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Shifting attention between macro and firm-specific information around earnings announcements

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Abstract

Theoretical models predict that investors with limited capacity to process information will shift attention to macro information when macro uncertainty is high, which may lead to neglect of firm-specific information such as earnings announcements. I predict that stock prices will therefore initially underreact to earnings in times of high uncertainty, and display a delayed reaction thereafter. I also predict that attention allocation will affect trading volume. My tests reject the predictions for returns, but show that trading volume is lower for firms that report earnings in times of high uncertainty. Returns are also consistent with the hypotheses in the period before the collapse of Lehman Brothers.

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1 Introduction

Every day, investors are exposed to a wealth of new information. Traditional models of financial markets assume that investors can instantly distill this information and incorporate it into prices. In contrast, psychological evidence suggests that attention is limited and must therefore be selective. Recent research, e.g. Peng (2005) and Peng and Xiong (2006) therefore suggests that investors allocate their limited attention between macroeconomic and firm-specific information in order to minimize the total uncertainty of their portfolios. The predictions of dynamic attention allocation have also been confirmed in empirical studies. Peng, Bollerslev, and Xiong (2007) find that shocks to the discount rate lead to an initial increase in covariation between individual stocks, consistent with less attention being allocated to firm-specific factors, and subsequent decrease in covariation, consistent with attention being shifted back to firm-specific factors.

Recent research has also proposed attention constraints as an explanation to the puzzling anomaly of the post-earnings announcement drift, i.e. the tendency for stocks to have abnormally high returns for an extended period of time following positive earnings surprises, and vice versa for negative surprises. Hirshleifer, Lim, and Teoh (2009) find stronger return predictabilities for firms that announce on days when there are many earnings announcements competing for investors' attention; Hou, Peng, and Xiong (2009) find stronger predictability for firms with low trading activity, and DellaVigna and Pollet (2009) reach the same result for firms announcing on Fridays, when investors may be distracted by the coming weekend.

In this thesis I seek to bring these streams of literature together, and thereby hope to contribute to an improved understanding of how dynamic attention allocation can help explain a well-known anomaly in finance. I measure macro uncertainty by the level of the VIX (an index of expected market-wide volatility). I hypothesize that the announcement day return will be less sensitive to earnings surprises when VIX is high (underreaction) as investors are preoccupied with resolving macro uncertainty at that time, and therefore cannot fully appreciate the earnings information. Since the initial disregard of the signal may give rise to arbitrage opportunities, returning attention to the stock should be worthwhile for investors when they are less distracted by macro factors. I therefore predict that the pattern will reverse in the post-announcement period, i.e. that there will be a drift of the stock price in the direction of the earnings surprise which is stronger in high-uncertainty times. If investors allocate less attention, this should also be reflected in the trading volume. I hypothesize that higher VIX should make the announcement day volume lower and less sensitive to (absolute) earnings surprises. If attention is reallocated to the firm in the post-announcement period, this should once again imply a reversal of these tendencies.

My empirical tests give ambiguous results, especially since the return patterns seem to change after the collapse of the investment bank Lehman Brothers at the end of the sample period. The announcement date return hypothesis is rejected for the full sample since higher VIX makes announcement day return *more* sensitive to earnings surprises, contrary to the hypothesis. However, when the post-Lehman observations (3% of all observations) are omitted, the results are in line with the predicted. I suggest that this may be due to the statistical leverage that the extreme levels of VIX give to observations from the post-Lehman period, and the market dislocation that followed the collapse. Higher announcement date uncertainty makes returns more sensitive to earnings in the post-announcement period, consistent with attention being reallocated to firms that were initially neglected due to the distraction from macro uncertainty. The results for trading volume are mixed in the sense that higher VIX leads to lower announcement day volume as predicted, whereas the results for the post-announcement period are ambiguous.

The remainder of this paper is structured as follows: section 2 reviews related literature, from which I develop my hypotheses in section 3. Section 4 describes the data, section 5 describes my empirical testing methods, and section 6 presents and discusses the results. Section 7 concludes.

2 Review of related literature

In this section, I review first the literature on limited attention theories, then the post-earnings announcement drift, and then the research that brings these phenomena together. Further, I go through some arguments for why attention constraints should matter even in a highly efficient market.

2.1 Limited attention models

The psychological foundations for attention constraints are well founded; attention requires effort and is by nature selective (Kahneman (1973)). Despite this, the effect of limited attention has largely been ignored in modern finance. Recently however, researchers in finance and economics have explored this issue in theoretical and empirical settings.

Of particular interest to this thesis is Peng (2005) who models an investor who is rational but has limited attention capacity. By allocating her attention among systematic and firm-specific uncertainty factors, the agent seeks to minimize the total uncertainty of her portfolio and maximize the utility from intertemporal consumption decisions. The model proves the intuitive result that investors will allocate more attention to market-wide factors and less to firm-specific factors when there is more macro uncertainty. Peng and Xiong (2006) extend the model by introducing the psychological bias of overconfidence, and show that when agents are overconfident and attention-constrained, the comovement between stocks can become higher than what is fundamentally motivated. Further, they show that stocks with stronger comovement with other stocks in their sector have higher bias-driven predictability and lower price informativeness.

The predictions for time-varying allocation of attention between firm-specific and macro factors have been investigated empirically by Peng, Bollerslev, and Xiong (2007). The authors use high-frequency data to study the reaction to macroeconomic discount rate shocks, proxied by the volatility in 30-year Treasury futures. They find that such shocks initially lead to an increase in macro volatility (measured by the volatility in S& 500-futures) and increase in comovement between stocks, consistent with an increased allocation of attention to macro factors and reduced allocation to firm-specific factors. In subsequent days, macro volatility and comovement between stocks decrease, indicating that investors shift attention back to firm-specific factors.

While the theoretical models described above treat attention allocation as a rational response to attention constraints, other studies assume that investors' attention allocation is driven by the saliency of the information provided (e.g. Barber and Odean (2008)). Experimental evidence suggests that both rational considerations and saliency determine agents' attention allocation (e.g. Gabaix and Laibson (2005), Gabaix et al. (2006)). This thesis is built on the rational attention allocation literature, but it seems likely that the "saliency" theory would give the same predictions, as there is for instance probably a higher likelihood of vivid media coverage of the macroeconomic structure in times of high macroeconomic uncertainty.

Another indication of the importance of attention effects comes from the literature on "neglected stocks". Ho and Michaely (1988), Huberman and Regev (2001) and Tetlock (2008) analyze cases where delayed reporting in wide-spread media of already public information had significant price impact. Klibanoff, Lamont, and Wizman (1998) find that news on the front page of the N*ew York Times* about a country decreases the underreaction to changes in net asset value (NAV) among stock prices of closed end funds focusing on the country in question. These articles reach different conclusions as to whether or not the results are compatible with investors reacting optimally to information costs.

2.2 Post earnings announcement drift

The post-earnings announcement drift (henceforth drift) is the tendency for stocks of companies that have announced higher (lower) earnings than expected to have abnormally high (low) returns, not only on the announcement day, but also for an extended period thereafter. Since the return is predictable after the announcement day, this pattern is puzzling from the perspective of efficient market theories.

After the initial discovery of the drift by Ball and Brown (1968), researchers have sought to explain it using rational and behavioral models. Among the rational explanations, Ball, Kothari and Watts (1993) find some evidence of increased risk level among companies with positive earnings surprise, which could explain the abnormally high return; however, the increase is too small to fully explain it (e.g. Mendenhall (2004)). Further, theoretical studies such as Lewellen and Shanken (2002) and empirical studies like Francis et al. (2006) and Kovacs (2007) seek to explain the drift by rational structural uncertainty, i.e. the patterns that arise when agents use earnings announcements to update their estimates of valuation-relevant parameters. Additionally, Sadka (2006) finds that the drift is reduced when accounting for liquidity risk. Researchers in behavioral finance have attributed the drift to cognitive biases like conservatism (Barberis, Schleifer, and Vishny (1998)), overconfidence (Daniel, Hirshleifer, and Subramanyam(1998)), or the interaction between agents with simplified models (Hong and Stein (1998)). Consistent with the notion of some agents being irrational and rational arbitrageurs failing to fully exploit this, researchers have found more drift among stocks where arbitrage activity is more difficult. For instance, more drift has been found among stocks/firms that are smaller (e.g. Foster, Olsen, and Shevlin (1984)), less liquid (Chordia et al. (2006), Sadka (2006)), have higher transaction costs (Ng, Rusticus, and Verdi (2008)), or have higher idiosyncratic volatility (Mendenhall (2004)).

2.3 Limited attention as a cause for post-earnings announcement drift

If investors are only attention constrained but otherwise rational, it is not immediately clear that this would generate a predictable return pattern around earnings announcements.

Hirshleifer and Teoh (2006) and DellaVigna and Pollet (2009) construct models that explain why inattention may cause a drift. In the models, a fraction of the investors ignore earnings-relevant signals prior to the announcement. After earnings have been realized, the price moves in the same direction as the earnings surprise as inattentive investors gradually recognize their mistake. Since the unconstrained attentive investors are risk-averse, they do not fully exploit the other investors' neglect, and there is therefore predictability in prices. The higher the fraction of inattentive investors in the models, the stronger is the pattern of initial underreaction and subsequent drift. A related model of how boundedly rational investors can create predictable patterns is offered by Hong and Stein (1999). In their model, there are two groups of agents that only use subsets of all information. Fundamental traders only pay attention to fundamental signals, whereas momentum traders only pay attention to past prices. In their model, there is a drift in the direction of the initial signal since the information is gradually spread among the fundamental traders. This drift is also reinforced by the technical traders who seek to trade on momentum strategies. The interaction between those two groups therefore creates initial underreaction and subsequent drift to public information signals. Rational arbitrageurs (who "really have to be very smart" in a computational sense in the model) can reduce the anomalies, but do not wipe it out entirely as long as they are risk averse or wealth constrained.

A number of studies use different proxies for attention constraints to explain the drift. Hirshleifer, Lim, and Teoh (2009) use the number of earnings announcements on the same day, arguing that more simultaneous reports makes it harder to direct attention to a specific firm. They find that stocks of firms that report on "high-news" days have weaker initial reaction and stronger delayed reaction. Further, they find lower announcement day abnormal trading volume for such stocks. DellaVigna and Pollet (2009) study earnings announced on Fridays, assuming that investors' attention is distracted by the coming weekend. They find the same return and volume patterns as described above. In addition, the authors find that managers seem to act strategically in releasing negative news on Fridays, which however is not fully taken into account by investors. Hou, Peng, and Xiong (2009) use pre-announcement stock turnover as a proxy, arguing that attention is a precondition for trading. Further, they argue that high trading activity raises the "visibility" of a stock, which may increase the attention investors allocate to it (Gervais, Kaniel, and Mingelgrim (2001)). This study also finds lower direct reaction and higher delayed reaction for stocks that have received less attention. The authors also find that the drift is stronger in recessions, which they attribute to the “ostrich effect” where investors take great interest in their portfolios during good times but “put the head in the sand” during bad times (Karlsson, Lowenstein, and Seppi (2009)). Finally, Peress (2008) finds the same volume and return patterns for firms that have not received media coverage of their earnings announcements, which indicates that less attention is being allocated to these stocks. This study also incorporates the findings from the studies above by showing that the effect of media coverage is lower on days when many announcements are mentioned in the media and on Fridays.

While the empirical studies mentioned above use proxies for differing attention constraints over time and across companies, Engelberg (2008) considers the differences in processing costs of different kinds of information. Using so-called natural language tools which measure the “mood” in articles surrounding the earnings announcement, Engelberg finds that this qualitative information creates a more delayed response in the stock price than the quantitative information of surprise in earnings per share (EPS).

2.4 Limited attention and traditional financial theories[1]

While the psychological feasibility of attention constraints on the individual level is indisputable, “traditional” (i.e. efficient markets, rational expectations) financial theory raises a number of concerns as to whether it should affect securities prices. I will outline and respond to those concerns below.

A central theme in the behavioral finance literature is to what extent rational arbitrageurs can exploit the irrationality of other traders and thereby squeeze out anomalies. For theories based on limited attention, the constraints to arbitrage activities are even more problematic. First of all, while it is feasible to assume a totally bias-free agent, an agent without attention constraints is clearly unrealistic. Obviously, investors can extend their attention by employing agents and computers, but managing those requires attention in itself, so processing capacity is still finite. One strategy would be to fully direct one’s attention to a small subset of stocks, and when several agents do this, the prices of all stocks should move as predicted by the efficient markets hypothesis (EMH). However, if arbitrage is risky and the agents or their investors are risk averse, they may not find this strategy attractive (cf. Schleifer and Vishny (1997)). Since attention is costly, either in terms of the alternative use of time or expenditure on e.g. IT equipment, it is also not necessarily the

[1] This section builds heavily on Hirshleifer and Teoh (2006), and Hirshleifer, Lim, and Teoh (2009).

case that the “smart” investors in models of trading between differentially attentive agents (e.g. Hong and Stein (1999), and Hirshleifer and Teoh (2006)) fare better than less attentive ones after these costs have been accounted for. For this reason, there need not be a “natural selection” via flows of funds from less to more attentive investors.

Even if some investors ignore earnings signal, one could expect them to “free ride” on the more attentive ones by inferring information from market prices. However, doing this may be a relatively complex problem, since it requires knowledge about factors such as market microstructure and other traders’ information, risk preferences and liquidity needs (Grossman and Stiglitz (1980)). Hence, attention constrained investors may not find this worthwhile either.

Finally, one could argue that rational investors would be unwilling to trade if they know they have not attended to all available information. However, the same mechanisms that prevent investors from attending to public signals are also likely to stop them from considering the consequences of this. Calculating on the probability and possible consequences of an ignored signal can be more cumbersome than processing the signal itself. If people are overconfident as suggested by the psychological and behavioral finance literature, this can prevent them from questioning their own estimates. Experimental evidence also indicates that people are unable to fully take into account the deficiencies in the information they receive (Tversky and Kahneman (1981)).

3 Hypothesis development

I hypothesize that investors attention may be “distracted” not only by information from other firms, but also by macroeconomic information. Following the theoretical predictions in Peng (2005) and Peng and Xiong (2006), and the empirical evidence in Peng, Xiong, and Bollerslev (2007), it is reasonable to believe that investors direct more attention to macro information when there is more market-wide uncertainty, which limits their ability to process firm-specific information such as earnings announcements. If there is a group of inattentive agents and attentive ones cannot fully wipe out the consequences of the former group’s behavior, we would expect the patterns of initial underreaction to earnings announcements and subsequent correction predicted by Hirshleifer and Teoh (2006) and DellaVigna and Pollet (2009). This leads me to the following hypotheses:

Hypothesis 1.1. Higher macro uncertainty will make abnormal return less sensitive to the earnings surprise on the announcement day.

If information provided in the earnings announcement is initially partially neglected, there is an incentive for investors to reallocate attention to the firm in the subsequent period. This should lead to a reversal of the patterns above:

Hypothesis 1.2. Higher announcement date macro uncertainty will make abnormal return more sensitive to the earnings surprise in the post-announcement period.

Attention provision is a precondition for information-based trading. If higher macro uncertainty decreases the processing of firm-specific information, one would also expect the following patterns for trading volume:

Hypothesis 2.1a. Higher macro uncertainty will lead to lower abnormal volume on the announcement day.

Hypothesis 2.1b. Higher macro uncertainty will make abnormal volume less sensitive to the absolute earnings surprise on the announcement day.

Note that the hypotheses for volume predict a change in the reaction to the *absolute* earnings surprise, since positive and negative surprises are likely to have symmetric effects. Further, note that I expect both a conditional effect where volume becomes less sensitive to absolute earnings surprises and an unconditional effect where volume becomes lower. The reason for this is that if attention allocation is decreased and the earnings surprise is therefore partially neglected, this should initially make the volume reaction less sensitive to the (absolute) earnings surprise (Hypothesis 2.1b). Additionally, one may expect that other information items than EPS provided in the earnings announcement (e.g. additional accounting information and management commentary) are also partially neglected, which should result in lower trading volume unconditional of the earnings surprise (Hypothesis 2.1a). The reason why I only hypothesize a conditional effect for the abnormal return is that abnormal return *per se* cannot be seen as a function of attention allocation, in contrast to abnormal volume.

As for the return hypotheses, I hypothesize that there will be a reversal in the volume patterns in the subsequent period:

Hypothesis 2.2a. Higher announcement date macro uncertainty will lead to higher abnormal volume in the post-announcement period.

Hypothesis 2.2b. Higher announcement date macro uncertainty will make abnormal volume more sensitive to the absolute earnings surprise in the post-announcement period.

4 Sample and data

This section describes the data sources and the filters I use to exclude inappropriate observations. Further, I provide variable definitions and show descriptive statistics.

I start with all quarterly EPS forecasts for the years 1999 through 2008 for US companies in the IBES database. I then collect accounting data from Compustat and equity data from CRSP. Actual EPS is taken from IBES rather than Compustat for technical reasons.[2]

I apply filters that are common in earlier research[3] and seek to drop erratic observations and stocks where arbitrage activity is not feasible. The filters are outlined in detail below. Following the suggestion in Shumway (1997), I replace missing delisting returns by -30% when a firm delists for performance-related reasons.[4] [5] Apart from this, I do not apply any particular data inspection or cleaning procedures as the data is from premier providers and has been tested extensively in earlier research.

Data for the VIX is obtained from the CBOE web site.[6] Value-weighted returns for the $5 \times 5 = 25$ portfolios formed on size and book-to-market as well as their breakpoints are obtained from Kenneth French's web site.[7] From his web site I also obtain classifications for 10 industry categories which are used in alternative expected return specifications, and the value-weighted returns of the industry category portfolios. For the Unclassified/other category, I use the CRSP value-weighted index return.

4.1 Filters

To avoid forecasts that had lost relevance at the time of the announcement, I require that the forecast be one- or two-period-ahead and issued within 60 calendar days prior to the

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[2] Both the forecast and actual earnings in IBES refer to *pro forma* earnings whereas Compustat use GAAP earnings, which would make the use of Compustat actual earnings inconsistent. Further, Compustat regularly updates information when accounts are filed with the SEC, which usually takes place after the preliminary announcement and may differ from it. Therefore, using Compustat earnings figures implicitly assumes that investors had access to information that may not have been released at the time. See Livnat and Mendenhall (2006).

[3] See eg. Hirshleifer, Lim, and Teoh (2009) and Livnat and Petrovits (2009).

[4] CRSP delisting codes 500 and 520-584.

[5] Delisting returns may be missing in the CRSP daily database either because they are genuinely missing or because the proceeds were paid out later than ten trading days after the delisting. See CRSP (2001).

[6] http://www.cboe.com/micro/vix/historical.aspx

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

earnings announcement day. If an analyst makes multiple forecasts in that interval, I use only the most recent one. To ensure that the earnings announcement date is correct, I require that the earnings announcement dates given by IBES and Compustat differ by no more than one trading day. In case of discrepancies, I use the earlier of the two dates, following DellaVigna and Pollet (2009). I drop a small number of cases where either the end date of the fiscal period or the announcement date of the forecast is given as a later date than the earnings announcement date; these cases are likely due to database errors (Glushkov (2007)). Further, I set up a number of filters that seek to exclude companies where trading may be difficult. Specifically, I require that total book assets at the end of the year before the earnings announcement be at least $10 million, and book equity at least $5 million. Further, I require that the market cap be a least $10 million and nominal stock price at least $1 from the end date of the fiscal period through the announcement day. I also require that the stock is a "standard stock" during the same time span, by which I mean that it is traded actively on one of the major exchanges (NYSE, Alternext – formerly AMEX, and Nasdaq), and that it is the common stock of an operating company.[8] In addition, I require that the stock price on the announcement day is higher than both the median forecast and the actual EPS. Finally, I require stock return history to be available in CRSP for at least 365 calendar days prior to the announcement.

4.2 Sample characteristics

After all the filters are put in place, the sample consists of 5,919 firms and 75,887 announcements, i.e. on average approximately 13 announcements per firm. Characteristics of the announcing firms are presented in *Table 1*.

For obvious reasons, the sample is limited to firms that have analyst coverage, which implies that it will mainly consist of large firms. The filters for size and "regular" trading also tilts the sample towards larger firms. As the table shows, the sample firms are on average larger than the average firm in the CRSP-Compustat Merged universe, both in terms of market cap and in terms of book equity. The book to market ratio is lower in the sample than in the full universe. When studying the assignations of the sample firms into size and book-to-market quintiles (*Table 2*), we see however that the sample is overweighted in firms in the lowest size quintile. The reason for this is that the breakpoints

[8] CRSP share codes 10 or 11, which means that I exclude preferred stocks, REITS, closed-ended funds and companies incorporated outside the US.

for the quintiles are for NYSE stocks, whereas the sample includes stocks from Nasdaq and Alternext, which are on average smaller. The distribution of book-to-market quintiles shows that the sample is heavy in growth firms, which is also partly due to the same reason.[9] When studying the distribution of industry categories, the category Other/unclassified looks rather large (around 30% both in sample and in full universe). For the sample firms, 52% of the firms in this category are financial services companies.

After all filters for size and liquidity are put in place, the sample includes approximately 44% of all firms in the CRSP-Compustat universe.[10]

Table 1. Sample characteristics

The table presents market cap, book equity and book-to-market ratio of a) sample companies (measured at the time of announcements) and b) companies in the CRSP-Compustat merged database which are traded actively on NYSE, Alternext or Nasdaq, have non-negative book equity, and have CRSP share codes 10 or 11 (measured at month end). Book equity is defined as total book value of common equity (Compustat item CEQ) plus balance sheet deferred taxes and investment tax credit if they are available, measured at the end of year T-1.

	Sample companies					Full Compustat-CRSP Merged universe				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Market cap (M$)	75,887	5,968	22,045	10	518,168	630,142	2,669	14,461	0.1	602,432
Book Equity (M$)	75,887	2,119	7,407	5	163,258	630,142	998	5,001	0	163,258
Book to Market Ratio	75,887	0.6	0.79	0	38.01	630,142	0.86	1.86	0	222.61

[9] In unreported tabulations, I test the quintile distribution using only the NYSE firms in the sample. The results show that this sample is heavily tilted towards larger firms and growth firms. In further unreported tabulations, I inspect the distribution when using breakpoints obtained from the entire universe of CRSP-Compustat firms. Once again, the sample is then tilted towards large firms and growth firms.

[10] Before those filters, I am able to match approximately 56% of all firms with IBES, which is slightly lower than e.g. Hong, Lim and Stein (2000) and Livnat and Mendenhall (2009) who are able to match approximately 60% of the firms.

Table 2. Size and book to market quintiles of sample

The table presents the assignations of sample firms into size and book to market quintiles, based on the breakpoints and methodology provided by Kenneth French.

	Book-to market quintile					
Size quintile	1	2	3	4	5	Total
1	5,345	4,256	4,457	4,189	4,666	22,913
2	4,706	3,597	3,050	2,508	1,576	15,437
3	4,618	3,211	2,334	1,645	1,134	12,942
4	4,776	3,032	2,050	1,469	991	12,318
5	5,900	2,684	1,576	1,323	784	12,267
Total	25,345	16,780	13,467	11,134	9,151	75,877

Table 3. Industry categories

Firms are assigned into industry categories provided by Kenneth French based on their SIC codes, which are taken from Compustat, or if unavailable there, from CRSP.

	Sample		Full CCM universe	
Industry group	Freq.	Percent	Freq.	Percent
Durables	1,796	2.4	14,165	2.3
Energy	3,564	4.7	19,746	3.1
Hi-Tech	14,883	19.6	130,931	20.8
Health	7,463	9.8	67,638	10.7
Manufacturing	9,288	12.2	73,505	11.7
Non-durables	3,814	5.0	32,212	5.1
Shops	8,742	11.5	62,916	10.0
Telecoms	2,096	2.8	14,724	2.3
Utilities	3,013	4.0	15,256	2.4
Other / unspecified	21,218	28.0	199,049	31.6
Total	75,877	100	490,898	100

4.3 Variable definitions

4.3.1 Dependent variables

The abnormal return for the announcement date and the post-announcement period are respectively defined as:

$$BHAR1_{i,T} = \prod_{t=T}^{T+1}\left(1 + R_{i,t}\right) - \prod_{t=T}^{T+1}\left(1 + R_{FF,t}\right) \quad (1.1)$$

$$BHAR60_{i,T} = \prod_{t=T+2}^{T+61}\left(1 + R_{i,t}\right) - \prod_{t=T+2}^{T+61}\left(1 + R_{FF,t}\right), \quad (1.2)$$

where R_{FF} is the return on a portfolio matched to firm *i* on size and book to market, using the procedure in Davis, Fama, and French (2000).

The abnormal volume is defined as the average of the log dollar volume in the period in question, less its average value in the pre-announcement period. To avoid cases where the measure is not defined, I add 1 to the dollar volume before taking the log. Using the log transformation alleviates the problems that result from the positive skew of the dollar volume. The pre-announcement reference period is set to end 11 trading days before the announcement, since Chae (2005) finds that volume tends to be abnormally low starting from that date until the announcement date. The definitions of abnormal volume are thus

$$ABVOL1_{i,T} = \frac{1}{2}\sum_{t=T}^{T+1}\ln\left(P_{i,t}VOL_{i,t} + 1\right) - \frac{1}{21}\sum_{\mathrm{t=T-31}}^{\mathrm{T-11}}\ln\left(P_{i,t}VOL_{i,t} + 1\right) \quad (2.1)$$

$$ABVOL60_{i},T = \frac{1}{60}\sum_{t=T+2}^{T+61}\ln\left(P_{i,t}VOL_{i,t} + 1\right) - \frac{1}{21}\sum_{\mathrm{t=T-31}}^{\mathrm{T-11}}\ln\left(P_{i,t}VOL_{i,t} + 1\right) \quad (2.2)$$

If the stock is traded on Nasdaq, the volume measure is harder to interpret since it includes inter-dealer trades. I follow earlier literature (e.g. LaPlante and Muscarella (1997)) and divide volume by two for Nasdaq firms. The volume results are qualitatively similar if these firms are excluded (untabulated).

The drift period of 60 trading days is chosen because Bernard and Thomas (1989) find that most of the drift occurs during this period. Using a longer period would increase the risk that subsequent announcement days are included, which would complicate the analysis.[11] In cases where the firm is delisted or for other reasons excluded from the sample before the end of the sample period, I take the corresponding value from the available period to get the drift period variables.

For brevity, I will henceforth refer to abnormal return and abnormal volume as return and volume, respectively. Further, unless stated otherwise, announcement day will mean the time span (T,T+1), and drift period the time span (T+2,T+61).

4.3.2 Independent variables

4.3.2.1 Volatility

I measure macro uncertainty by the level of the VIX index, an index of the expected volatility (measured as annualized standard deviation) of the S&P 500 index in the coming 30 days, using volatility implied from option prices.[12] Henceforth, I will use the terms VIX and macro uncertainty/volatility interchangeably. A comment may be in place about the forward-looking nature of VIX. Since the index measures the expected volatility in the coming month, an assumption in this thesis is that investors are forward-looking when they allocate their attention, i.e. if they expect high macro uncertainty in the near future they will seek to resolve the underlying uncertainty immediately rather than postpone the effort. I test the robustness to this assumption in section 6.5 by using a proxy that only measures the macro volatility on the event day. Further, since VIX only measures expected volatility in S&P 500 stocks whereas my sample is broader, I need to assume that the S&P 500 stocks are representative of the wider US stock market.[13]

If VIX is high on the announcement day, it is likely to remain high also in the drift period, due to the “volatility clustering” first described by Mandelbroit (1963). If macro uncertainty remains high during the drift period, shifting attention back to firm-specific factors may be difficult for attention-constrained investors. To control for this possibility, the drift period tests also control for the volatility during this period. The drift period volatility is defined as:

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[11] Barber and Lyon (1995) and Cowan and Sergeant (1996) claim that overlapping event periods will yield misspecified tests.
[12] Technical details on the construction of the index can be found in Whaley (1993) and CBOE (2009).
[13] Since these stocks account for approximately 75% of the total US market capitalization (Standard & Poor’s (2007)), this assumption appears plausible.

$$VIX60_T = \frac{1}{60}\sum_{t=T+2}^{T+61} VIX_t \tag{3}$$

Indeed, the correlation between *VIX* and *VIX60* is around 0.8, which confirms the suspicion of clustering.[14]

4.3.2.2 Earnings surprise

I proxy the market's expectation of earnings by the median forecast from stock analysts. I normalize the measure by the stock price at the end of the quarter for which the firm is reporting. This measure is commonly referred to as standardized unexpected earnings (SUE) in the literature.

$$SUE_{i,T} = \frac{EPS_{i,T} - E[EPS_{i,T}]}{P_{i,T^*}}, \tag{4}$$

where P_{i,T^*} is the share price at the end of the fiscal quarter for which the firm is reporting, and $E[EPS_{i,T}]$ is the median forecast. All the variables are split-adjusted.[15]

I further transform the measure by taking the decile rank of SUE compared to other announcements in the previous quarter;[16] the measure is then called $SUEq$. This transformation is also in standard in previous research and has many benefits. By comparing only to previous values, the measure avoids a "look-ahead bias", i.e. using data in the regressions that was not available to investors at the time they would have had to make a decision (Holthausen (1983), cited in Foster, Olsen and Shevlin (1984)). An additional benefit is that the distribution of earnings surprises seems to change over time (see e.g. Chan, Karceski, and Lakonishkok (2003)). Further, the method alleviates the problems caused by the non-linear relation between earnings surprises and abnormal returns (Kinney, Burgstahler, and Martin (2002)).

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[14] The relation between the measures also arises mechanically since VIX is a forward-looking measure of volatility; loosely speaking it can be stated that $VIX_T = f(E[\sigma_{T+1}, \dots, \sigma_{T+30}], \Omega)$ and $VIX60_T = f(E[\sigma_{T+2}, \dots, \sigma_{T+30}, \dots, \sigma_{T+90}], \Omega)$ where Ω is the required premium in excess of the expected volatility (see Bollerslev, Gibson, and Zhou (2008)). As seen above, the functions for VIX and $VIX60$ have the terms $\sigma_{T+2}, \dots, \sigma_{T+30}$ in common. Note that the expressions above ignore the fact that expectations and risk premia may be time-varying.

[15] The split adjustment factors are taken from CRSP rather than from IBES since the latter tend to be imprecise; see Payne and Thomas (2003), and Robinson and Glushkov (2006).

[16] I define the previous quarter as the preceding ${}^{252}/_{4} = 63$ trading days. Previous research has generally used quintile ranks compared to the values in the previous calendar quarter; the reason for basing the definition on trading days is that it allows me to use more recent values.

An assumption behind the use of the *SUE* measure is that the expectations of analysts are an appropriate proxy for the aggregate expectations of all investors.[17]

As mentioned before, it appears plausible that positive and negative surprises have symmetric effects on volume. For these tests, I therefore use the decile rank of the absolute value of *SUE*, denoted *ASUEq*.

For brevity, "earnings" and "absolute earnings" will henceforth mean the decile rank of the surprise in the respective measure as defined above, unless stated otherwise.

4.3.2.3 Additional controls

I use a number of controls that have previously been found to be important for the drift. Since the amount of earnings announcements might affect systematic volatility, I control for the number of concurrent reports, defined as in Hirshleifer, Lim, and Teoh (2009)[18] and denoted *NUMREP*. I also control for turnover, which can be interpreted as an indicator of investor attention as mentioned before (Hou, Peng, and Xiong (2009)) as well as a liquidity measure (Amihud (2002)). Turnover is defined as

$$TURNO_{i,T} = \frac{1}{21}\sum_{t=T-31}^{T-11}\frac{VOL_{i,t}}{SHROUT_{i,t}}, \tag{5}$$

where $SHROUT_{i,t}$ is the number of shares outstanding.

The number of analysts that have supplied a forecast might affect the quality of the information transmitted by analysts and the amount of attention investors allocate to the firm. I therefore control for this number, which I denote *NUMFORC*.

All the controls described above are normalized by taking the decile rank as described before, and referred to as *NUMREPq*, *TURNOq* and *NUMFORCq*, respectively. The reason for this transformation is primarily to avoid the problems that arise from the apparent non-stationarity in some of the variables, as well as to reduce the influence of outliers.

To ensure that the abnormal volume tests are not influenced by market-wide trends, I include controls for the market's average abnormal volume in those tests:

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[17] Brandt et al. (2008) propose a more inconclusive measure for the surprise of all investors to the full information in the earnings announcement, namely the announcement date return. However, applying this measure in the context of limited attention would be difficult since the announcement date return is also hypothesized to depend on attention allocation.

[18] Following Hirshleifer, Lim, and Teoh (2009), I define the number of reports as the number of quarterly reports registered in Compustat for the date in question. Note that this implies that the sample of firms included is substantially larger than the test sample, since approx. 33% of all Compustat firms are not covered by IBES.

$$MKTABVOL1_T = \sum_i \left(\frac{1}{2} \sum_{t=T}^{T+1} \ln\left(P_{i,T}VOL_{i,T} + 1\right) - \frac{1}{21} \sum_{\mathrm{t=T-31}}^{\mathrm{T-11}} \ln\left(P_{i,t}VOL_{i,t} + 1\right) \right) \quad (6.1)$$

$$MKTABVOL60_T = \sum_i \left(\frac{1}{60} \sum_{t=T+2}^{T+61} \ln\left(P_{i,T}VOL_{i,T} + 1\right) - \frac{1}{21} \sum_{\mathrm{t=T-31}}^{\mathrm{T-11}} \ln\left(P_{i,t}VOL_{i,t} + 1\right) \right) \quad (6.2)$$

Finally, I include the 5×5 size and book to market quintiles *SIZEq* and *BMq* as controls, since those characteristics may affect pre-announcement attention to the firm (Peress (2008)) and have been found to affect how firms react to earnings surprises (eg. Skinner and Sloan (2002) and Foster, Olsen, and Shevlin (1984)).

4.4 Summary statistics

Table 4 shows summary statistics for the dependent variables and untransformed forms of the independent variables. The table shows that the variables *TURNO*, *NUMREP* and *NUMFORC* have maximum values several standard deviations above their means, which indicates that these values may be outliers. This problem is solved by the quintile transformation. The table shows that the mean *SUE*, *BHAR1* and *BHAR60* are statistically indistinguishable from zero, while the *ABVOL1* and *ABVOL60* are clearly positive. The latter result is hardly surprising given that trading volume tends to concentrate around earnings announcements (Chae (2005)). The variable means by year are displayed in *Table 5*. As seen in the table, the mean level of VIX varied substantially during the period, which can also be seen from *Figure 1*. The figure shows that after the Chapter-11 filing of Lehman Brothers on September 15, 2008, VIX reached extreme levels that had not been seen before. *Table 5* also shows that there is a slight upward trend in the number of analyst forecasts *NUMFORC*, and a clear upward trend in turnover. There was also a downward trend in the number of simultaneous reports

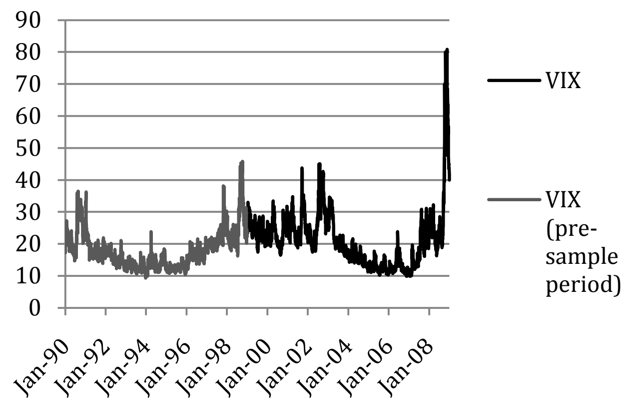

Figure 1. VIX over time

NUMREP, in line with the general decline in the number of listed stocks during the period.[19] Note that the quintile transformation resolves this non-stationarity problem. The average earnings surprise *SUE* became negative during the last two years, possibly because analysts underestimated the effects of the financial crisis.

Table 4. Summary statistics

				Percentiles				
Variable	*N*	*Mean*	*Std. Dev.*	90th	95th	99th	*Min*	*Max*
BHAR1	75,877	0.001	0.085	.089	.131	.237	-0.76	2.02
BHAR60	73,769	0.002	0.236	.230	.349	.725	-1.33	8.47
ABVOL1	75,876	0.552	0.775	1.41	1.72	2.57	-11.2	8.84
ABVOL60	73,769	0.024	0.549	.603	.865	1.62	-5.36	6.85
SUE	75,877	-0.001	0.065	.004	.008	.029	-7.87	7.37
VIX	75,877	21.4	9.71	30.4	35.1	60.9	9.89	80.9
TURNO	75,877	6,619	7,278	13,648	18,616	32,876	9.3	428,826
NUMREP	75,877	289	168	493	535	622	4	1510
NUMFORC	75,877	3.8	4.06	2.30	2.56	3.04	1	37
MKTABVOL1	75,877	0.073	0.169	.264	.355	.485	-1.01	0.791
MKTABOL60	73,769	0.02	0.14	.192	.250	.350	-0.543	0.399

Table 5. Variable means by year

	Year									
Variable	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008
BHAR1	0.002	0.001	0.003	0.001	0.003	0.001	0.002	-0.001	0.001	0.002
BHAR60	-0.012	0.014	0.015	-0.003	0.019	0.005	0.008	0	-0.009	-0.019
ABVOL1	0.466	0.339	0.401	0.45	0.593	0.659	0.653	0.718	0.756	0.438
ABVOL60	0.07	-0.082	-0.052	-0.071	0.133	0.049	0.051	0.061	0.101	-0.038
SUE	0	0	0	0	0	0	0	0	-0.003	-0.005
VIX	23.7	23.7	26	27.8	21.8	15.8	13.3	12.6	17	33.2
TURNO	4,583	5,478	5,882	5,890	5,919	6,165	6,213	6,950	7,720	10,496
NUMREP	312.4	314.4	317.3	296.7	278.2	277.6	281.5	283.6	276.2	265
NUMFORC	3.348	3.238	4.165	3.865	3.887	3.912	3.916	3.686	3.742	4.099
MKTABVOL1	0.087	0.028	0.012	0.082	0.06	0.123	0.062	0.108	0.191	-0.025
MKTABOL60	0.106	-0.02	-0.105	-0.073	0.068	0.028	0.033	0.044	0.105	0.012

[19] During the sample period, the number of NYSE/Alternext/Nasdaq stocks with a valid stock price in the CRSP database decreased from 9,090 to 6,068, showing a generally declining trend with a few exceptions of small increases.

4.5 Subsample characteristics

Table 6. Number of observations in categories

The table shows the number of observations from the period before and after the Lehman Brothers collapse as well as the number of observations grouped based on whether VIX was above its 95th percentile (VIX_{95}).

	$VIX \leq VIX_{95}$	$VIX > VIX_{95}$	Total
Pre-Lehman	72,018	1,642	73,660
Post-Lehman	36	2,181	2,217
Total	72,054	3,823	75,877

In the coming tests, I will re-run the regressions separately for the periods before and after the collapse of Lehman Brothers, since this event had the effect of pushing VIX up to “extreme” levels. As an alternative way of reducing the influence of extreme observations, I winsorize VIX at its 95th percentile. *Table 6* shows that there is a substantial overlap between the observations that are from the post-Lehman period and those that are affected by the winsorize transformation; in particular, 98.4% of all post-Lehman observations have values of VIX above its 95th percentile.

5 Hypothesis tests

I test my hypotheses using linear pooled regressions where the standard errors are robust to heteroscedasticity and clustering on the announcement date, using the corrections from Huber (1967) and White (1980), and Froot (1989), respectively. As mentioned above, I run the regressions separately for the full sample, before and after the Lehman collapse,[20] and with winsorized VIX.

The model for announcement day return is:

$$BHAR1_{i,T} = \alpha_0 + \alpha_1 SUEq_{i,T} + \alpha_2 VIX_T + \alpha_3 SUEq_{i,T} \times VIX_T + \sum_{j=1}^{5} \beta_j x_{i,T}^{j} + \sum_{j=1}^{5} \gamma_j SUEq_{i,T} \times x_{i,T}^{j} + \varepsilon_{i,T}, \tag{7.1}$$

where $x_{i,T} = \{NUMREPq_T, TURNOq_{i,T}, NUMFORCq_{i,T}, SIZEq_{i,T}, BMq_{i,T}\}$.

The model for drift period return also includes the drift period volatility:

$$BHAR60_{i,T} = \alpha_0 + \alpha_1 SUEq_{i,T} + \alpha_2 VIX_T + \alpha_3 SUEq_{i,T} \times VIX_T + \alpha_4 VIX60_T + \alpha_5 SUEq_{i,T} \times VIX60_T + \sum_{j=1}^{5} \beta_j x_{i,T}^{j} + \sum_{j=1}^{5} \gamma_j SUEq_{i,T} \times x_{i,T}^{j} + \varepsilon_{i,T} \tag{7.2}$$

The set of controls $x_{i,T}$ is the same. The predicted sign of α_3 is negative on the announcement day (lower return sensitivity to earnings when VIX is high; Hypothesis 1.1)

[20] The drift period regressions are not conducted for the post-Lehman period since there are only 67 drift period observations from this time.

and positive in the drift period (higher sensitivity; Hypothesis 1.2).

The model for announcement day volume is:

$$ABVOL1_{i,T} = \alpha_0 + \alpha_1 ASUEq_{i,T} + \alpha_2 VIX_T + \alpha_3 ASUEq_{i,T} \times VIX_T + \alpha_4 MKTABVOL1_T + \sum_{j=1}^{4} \beta_j x_{i,T}^{j} + \sum_{j=1}^{4} \gamma_j ASUEq_{i,T} \times x_{i,T}^{j} + \varepsilon_{i,T}, \quad (8.1)$$

where $x_{i,T} = \{NUMREPq_{,T}, NUMFORCq_{i,T}, SIZEq_{i,T}, BMq_{i,T}\}$.

Note that I do not include *TURNO* in the set of controls for volume since the pre-announcement trading activity is already controlled for in the dependent variable. The model for the drift period also includes drift period volatility and replaces *MKTABVOL1* by *MKTABVOL60*:

$$ABVOL60_{i,T} = \alpha_0 + \alpha_1 ASUEq_{i,T} + \alpha_2 VIX_T + \alpha_3 ASUEq_{i,T} \times VIX_T + \alpha_4 VIX60_T + \alpha_5 ASUEq_{i,T} \times VIX60_T + \alpha_6 MKTABVOL60_T + \sum_{j=1}^{4} \beta_j x_{i,T}^{j} + \sum_{j=1}^{4} \gamma_j ASUEq_{i,T} \times x_{i,T}^{j} + \varepsilon_{i,T}, \quad (8.2)$$

Again, the set of controls $x_{i,T}$ is the same as in the announcement day model. The predicted *total effect* of α_2 and α_3 is negative on the announcement day, and positive in the drift period (hypotheses 2.1a and 2.2a, respectively). The *total effect* is defined as $\alpha_2 + \alpha_3 ASUEq$, which obviously implies that it will depend on the level of *ASUEq*.[21] Due to the controversy among statisticians as to whether the main effect (α_2 in the expression above) is meaningful to consider in isolation, and if so how it should be interpreted (see Jaccard, Turrisi, and Wan (1990) and references therein), I do not consider the main effect.

The coefficient for the effect of VIX on volume sensitivity to absolute earnings, α_3, is expected to be negative on the announcement day and positive in the drift period (hypotheses 2.1b and 2.2b).

6 Results and discussion

This section provides a presentation and discussion of the regression results, first for returns and then for the volume. For visibility, the coefficients are reported in parts per thousand (‰). *Table 7* summarizes how the results compare with the hypotheses.

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[21] The standard error of the total effect at the level x of the interacted variable X is $se_{totaleffect} = \sqrt{\sigma_{\alpha_2}^2 + 2x\sigma_{\alpha_2,\alpha_3} + x^2\sigma_{\alpha_3}^2}$ (where $X = \{SUEq, ASUEq\}$). Assuming that the population standard errors are normally distributed, the tests statistic $t_{totaleff\ ect} = \frac{\alpha_2 + X\alpha_3}{se_{totaleffect}}$ follows a t-distribution with $N - k - 1$ degrees of freedom (Jaccard, Turrisi, and Wan (1990)).

Table 7. Summary of results

The table summarizes the results obtained for the effect of VIX on returns and volume. "Confirmed" in this case means that the statistical null hypothesis of no effect of VIX on the respective property is rejected at the 5% level and the coefficient/the total effect has the expected sign. See the respective section for details.

Hypothesis	*Full-sample*	*Pre-Lehman*	*Winsorized VIX*
1.1: Announcement day return underreaction	Rejected	Confirmed	Inconclusive
1.2: Drift- period return delayed reaction	Confirmed	Confirmed	Confirmed
2.1a: Announcement day underreaction in total volume	Confirmed	Confirmed	Confirmed
2.1b: Announcement day underreaction in volume sensitivity to absolute earnings	Confirmed	Confirmed	Confirmed
2.2a: Drift period delayed reaction in total volume	Inconclusive	Inconclusive	Inconclusive
2.2b: Drift period delayed reaction in volume sensitivity to absolute earnings	Confirmed	Confirmed	Confirmed

6.1 Abnormal returns

Table 8 shows the regression results. The announcement date return hypothesis is rejected for the full sample, but confirmed in the pre-Lehman period. Drift period returns are consistent with the hypothesis.

6.1.1 Effect of VIX on announcement day return

The full-sample results for announcement date return are contrary to the prediction of reduced return sensitivity to earnings in high-uncertainty times (Hypothesis 1.1), as the estimated effect of VIX on earnings sensitivity is positive (α_3=.04‰, p-value<.1%). The effect is also economically significant: when VIX is at its 90th percentile, the estimated sensitivity to *SUEq* is approximately 7.5% higher than when it is at its 10th percentile.[22] However, closer inspection reveals that the unexpected result is heavily affected by extreme observations from the end of 2008. When announcements made after the collapse of Lehman Brothers are excluded, the coefficient becomes significantly negative, in line with expectations (α_3=-.04‰; p-value 1.8%). This indicates that higher macro uncertainty diverts investors' attention, making them less attentive to the earnings signal. The results are once again economically significant: the sensitivity to earnings is 8.9% lower when VIX

[22] This is obtained from the estimated coefficient for the main effect of *SUEq*, α_1, and the estimate for the interaction term between VIX and *SUEq*, α_3, where the sensitivity is estimated as $\hat{\alpha}_1 + \hat{\alpha}_3 \cdot VIX$. The 10th and 90th percentiles of VIX are, respectively, 12.01 and 30.44.

Table 8. Regression estimates for abnormal returns

BHAR1 is the buy-and-hold abnormal return over the announcement day T and the subsequent day T+1. BHAR60 is the post-announcement period [T+2,T+61] buy-and-hold abnormal return. The suffixes pre and post indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers. The subscript VIX95 indicates that the independent variable VIX (see below) has been winsorized at its 95th percentile. SUEq is the earnings surprise decile (1 lowest, 10 highest) compared to other announcements in the trading days [T-62,T]. VIX is the level of the VIX index of implied volatility. NUMREPq is the decile rank of the number of announcements on day T. TURNOq is the decile rank of turnover. NUMFORCq is the decile rank of the number of analysts that have given a forecast. SIZEq and BMq are the decile ranks of market cap and book-to-market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parentheses. Coefficients and standard errors are multiplied by 1,000.
(double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).*

Variable	BHAR1	BHAR60	BHAR1pre	BHAR1post	BHAR60pre	$BHAR1_{VIX95}$	$BHAR60_{VIX95}$
SUEq	8.80 (.693)***	2.30 (2.07)	1.4 (.735)***	9.09 (11.6)	2.34 (2.08)	9.56 (.738)***	2.53 (2.10)
VIX	-.244 (.095)**	1.28 (.617)**	.251 (.114)**	-.247 (.721)	1.31 (.625)**	-.025 (.123)	1.44 (.705)**
SUEq×VIX	.041 (.017)**	.256 (.097)***	-.043 (.018)**	.195 (.161)	.263 (.098)***	.002 (.020)	.330 (.111)***
VIX60		-1.05 (.648)			-1.09 (.666)		-1.27 (.767)*
SUEq×VIX60		-.302 (.096)***			-.31 (.098)***		-.390 (.116)***
NUMREPq	.105 (.359)	-1.85 (.997)*	.112 (.353)	1.27 (3.35)	-1.81 (.996)*	.106 (.358)	-1.82 (.996)*
SUEq×NUMREPq	-.073 (.059)	.348 (.165)**	-.074 (.058)	-.427 (.546)	.352 (.165)**	-.073 (.059)	.348 (.165)**
TURNOq	-3.03 (.271)***	.774 (1.01)	-2.98 (.268)***	-5.5 (2.96)*	.801 (1.01)	-3.02 (.271)***	.758 (1.01)
SUEq×TURNOq	.365 (.044)***	-.253 (.157)	.351 (.044)***	.95 (.468)**	-.254 (.157)	.362 (.044)***	-.256 (.157)
NUMFORCq	1.35 (.262)***	1.78 (.749)**	1.48 (.26)***	-1.12 (2.48)	1.84 (.75)**	1.34 (.264)***	1.78 (.749)**
SUEq×NUMFORCq	-.175 (.044)***	-.331 (.126)***	-.208 (.043)***	.622 (.42)	-.337 (.126)***	-.174 (.044)***	-.332 (.126)***
SIZEq	3.97 (.584)***	.682 (1.68)	3.33 (.574)***	21.1 (6.46)***	.661 (1.68)	3.90 (.590)***	.718 (1.68)
SUEq×SIZEq	-.502 (.100)***	-.436 (.289)	-.385 (.098)***	-4.1 (1.16)***	-.438 (.289)	-.492 (.101)***	-.427 (.289)
BMq	3.13 (.526)***	-5.47 (1.60)***	3.09 (.517)***	9.01 (4.93)*	-5.44 (1.61)***	3.00 (.526)***	-5.55 (1.61)***
SUEq×BMq	-.585 (.088)***	.733 (.249)***	-.575 (.086)***	-1.62 (.938)*	.732 (.249)***	-.565 (.088)***	.722 (.249)***
constant	-42.7 (4.23)***	2.06 (12.7)	-51.5 (4.42)***	-102 (6.8)*	1.46 (12.8)	-46.9 (4.54)***	3.10 (13.0)
N	75,877	73,769	73,662	2,215	73,662	75,877	73,769
R^2	7.12%	0.46%	7.26%	7.38%	0.46%	7.10%	0.40%
Total effect of VIX per SUEq							
SUEq=1	-.203 (.081)**	1.54 (.539)***	.207 (.099)**	-.052 (.572)	1.58 (.547)***	-.023 (.106)	1.77 (.619)***
SUEq=2	-.162 (.086)*	1.780 (.565)***	.164 (.104)	.144 (.636)	1.84 (.572)***	-.021 (.112)	2.10 (.648)***
SUEq=3	-.122 (.094)	2.05 (.605)***	.12 (.112)	.339 (.731)	2.10 (.613)***	-.019 (.121)	2.43 (.694)***
SUEq=4	-.081 (.104)	2.31 (.657)***	.077 (.122)	.534 (.845)	2.37 (.665)***	-.017 (.132)	2.76 (.754)***
SUEq=5	-.04 (.116)	2.56 (.718)***	.033 (.134)	.73 (.973)	2.63 (.727)***	-.015 (.146)	3.09 (.825)***
SUEq=6	.001 (.129)	2.82 (.787)***	-.01 (.147)	.925 (1.109)	2.89 (.796)***	-.013 (.160)	3.42 (.904)***
SUEq=7	.041 (.142)	3.08 (.861)***	-.054 (.161)	1.12 (1.25)	3.15 (.87)***	-.012 (.177)	3.75 (.989)***
SUEq=8	.082 (.157)	3.33 (.939)***	-.097 (.176)	1.32 (1.40)	3.42 (.949)***	-.010 (.193)	4.08 (1.08)***
SUEq=9	.123 (.172)	3.59 (1.02)***	-.14 (.192)	1.51 (1.55)	3.68 (1.03)***	-.008 (.211)	4.41 (1.17)***
SUEq=10	.164 (.187)	3.84 (1.11)***	-.184 (.208)	1.71 (1.70)	3.94 (1.12)***	-.006 (.229)	4.74 (1.27)***

is at its 90th percentile than when it is at its 10th.[23] The regression with winsorized VIX gives further interesting results; the coefficient is now positive but insignificant (α_3=.002‰; *p*-value 92.3%). Since virtually all (98.4%) of the observations from the post-Lehman period are affected by the winsorize transformation, this indicates that the full-sample results are not only driven by extreme post-Lehman levels of VIX, but also extreme announcement day returns in this period.[24]

Contrary to my expectations, there is a significant main effect of VIX on returns. This result is hard to explain based on the limited attention hypothesis, as the return in itself cannot be seen as a measure of attention allocation. There is once again a reversal of the pattern after the Lehman collapse: the effect is negative for the full sample (α_2=-.24‰; *p*-value 1.0%), positive for the pre-Lehman period (α_2=.25‰; *p*-value 2.9%), and negative but insignificant after the Lehman collapse (α_2=-.25‰; *p*-value 72%). Due to the significant main effect, I test the significance of the total effect even though my theories only predict a conditional effect. The total effect of VIX on the announcement day return is significant only for the two lowest *SUEq* deciles, where it is negative (*p*-value<5.9%). For the other deciles, the effect has varying signs but is insignificant. In the pre-Lehman period, the total effect is significantly positive only in the lowest *SUEq* decile (*p*-value 3.6%), for the other ones it has varying sign but lacks significance. The main and total effects on are insignificant when VIX is winsorized (main effect: coefficient -.03‰, *p*-value 83.7%; total effect: varying signs depending on *SUEq*, *p*-value>41%).

6.1.2 Effect of VIX on drift period return

In the post-announcement period, the effect of VIX on return sensitivity to earnings is positive, consistent with Hypothesis 1.2 (α_3=.26‰; *p*-value .7%). The results are qualitatively similar for the pre-Lehman period and when VIX is winsorized (see *Table 8* for details). Comparing this result to the negative effect of VIX on the announcement date return sensitivity in the pre-Lehman period, the pattern is consistent with the hypothesis that high VIX will initially make investors less attentive to earnings surprises which lowers return sensitivity to earnings, and that they will subsequently reallocate their attention to the neglected firms, which increases return sensitivity. The difference is also economically

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[23] See note 22 for details of the calculation.

[24] “Extreme” announcement day returns appear more common during the post-Lehman period, for instance, in this period 6.2% of all *BHAR1* observations are more than three standard deviations away from the (full-sample) mean; the corresponding measure for the pre-Lehman period is 1.6%.

significant: the sensitivity to earnings in the post-announcement return is 88% higher when VIX is at its 90th percentile compared to when it is at its 10th.[25]

There is a significant main effect of VIX on returns in the drift period as well (α_2=1.28‰; p-value 1.8%). The total effect of VIX on returns is significantly positive for all *SUEq* deciles (p-value<.2%). Considering the economic significance, it can be seen that a unit increase in VIX is estimated to lead to an additional 26 basis points abnormal return in the drift period (given that *SUEq*=5), equivalent to an annualized abnormal return of 1.0 percentage points. Once again, the results are qualitatively similar for the pre-Lehman period and when VIX is winsorized.

The coefficient for the interaction between *SUEq* and *VIX60* is negative (α_5-.30‰; p-value .2%), implying that returns become less sensitive to earnings when drift period volatility is high. Note that although VIX and *VIX60* are highly correlated, the coefficients for their respective interaction with *SUEq* have opposite signs. This indicates that high announcement date macro volatility gives rise to a delayed reaction to earnings, while post-announcement volatility impedes this reaction, as investors need to remain focused on macro factors and therefore cannot shift their attention to firm-specific ones.

6.1.3 Effects of control variables

The results for the control variables are largely in line with my expectations. Unless otherwise stated, the results for the pre-Lehman period and the regressions where VIX has been winsorized are qualitatively similar to the full-sample results presented below. The coefficients for *NUMREPq* largely reflect the results in Hirshleifer, Lim, and Teoh (2009); however the interaction term is insignificant in the regression for announcement day return. The effect of *NUMREPq* on drift period return sensitivity to earnings is significantly positive, consistent with their result. *TURNOq* has a positive effect on the sensitivity of announcement day return to earnings surprises, consistent with turnover being a proxy for attention as in Hou, Peng, and Xiong (2009). Note that this measure supposedly increases with attention, whereas the distraction proxies VIX and *NUMREPq* decrease with attention. The coefficient for drift-period return sensitivity is negative which is consistent with limited attention theory, but is insignificant. The number of analyst reports *NUMFORCq* makes announcement day return less sensitive to earnings, which may be due to more of the information already being foreseen and impounded into price when there have been many

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[25] See note 22 for details of the calculation.

forecasts in advance (Shores (1990)). The negative effect on earnings sensitivity persists in the drift period. From the coefficients for *SIZEq* we see that larger firms have higher return sensitivity to earnings on the announcement day but lower sensitivity in the drift period, consistent with information being impounded into price more quickly for larger firms; note however that the latter effect is insignificant. Higher book-to-market ratio *BMq* makes return less sensitive to earnings on the announcement day and the opposite in the drift period.

6.1.4 Resolving the failure of the theory post-Lehman

As discussed above, the results differ significantly when the period following the collapse of Lehman Brothers is omitted. Whether the omission of these observations is warranted is therefore a vital question. Although I do not test formally for a structural break, I will argue that there are good reasons to omit the observations. First, the extreme levels of VIX at that time makes the observations influential (in a statistical sense), which may distort the results.[26] Second, the Lehman collapse caused a shock to speculator capital,[27] which in turn caused dislocation in the equity markets which may have driven the relation between returns and earnings out of its equilibrium. This shock can be considered exogenous since many hedge funds lost significant amounts of money due not to their own trading strategies but rather due to the losses at Lehman Brothers and their own failure to protect their assets deposited there (see e.g. Senior Supervisors Group (2009) and Aragon and Strahan (2009)). From a more practical perspective, it seems reasonable to believe that arbitrageurs would be unwilling to open speculative positions in response to earnings surprises during the post-Lehman period, since there was a great degree of uncertainty and funding constraints at that time.[28] This failure of sophisticated traders to initiate positions could have driven stock prices away from their ordinary behavior at that time.

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[26] The fact that the post-Lehman observations only make up 3% of the observations but change the results significantly indicates that there are influential observations from this period. Further, there are two observations from the post-Lehman period which alone have a high influence on the estimated sensitivity of announcement date return to earnings, due to the announcement date return being in excess of 100% and the VIX being above its 99th percentile. Exclusion of these two observations decreases the estimated effect of VIX on return sensitivity to earnings by 41%, and reduces the significance level of the associated coefficient from 1.6% to 4.8%.

[27] See Aragon and Strahan (2009); cf. also the analysis in Khandani and Lo (2009) of the possibility of the "quant crisis" in August 2007 being caused by forced liquidation with ripple effects in the system.

[28] See Liu and Mello (2009) for a discussion of hedge funds' switch from risky securities to cash following the crisis.

6.2 Abnormal volume

Table 9 displays results for the volume regressions. Announcement date volumes support the hypotheses, while the drift period tests give ambiguous results.

6.2.1 Effect of VIX on announcement day volume

The volume predictions are fulfilled on the announcement day: higher VIX leads to lower volume (negative total effect; *p*-value <.1% for all *ASUEq* deciles) and lower sensitivity to absolute earnings (α_3=-.70‰; *p*-value <.1%). This indicates that higher VIX makes investors pay less attention to the earnings announcement and therefore trade less (Hypotheses 2.1a and-b). The difference in volume sensitivity to absolute earnings is economically significant as the estimated sensitivity is 62% lower when VIX is at its 90th percentile compared to when it is as its 10th.[29] The economic significance of the total effect may however be limited: a unit increase in VIX leads to a decrease in announcement day volume of approximately 1%.[30]

The volume results are qualitatively similar in the pre-Lehman period and the regressions where VIX has been winsorized. In the post-Lehman period the total effect of VIX on announcement day volume is significantly negative only for the four highest *ASUEq* deciles (*p*-value 5.7%); for the other ones it is of varying sign but insignificant.

6.2.2 Effect of VIX on drift-period volume

A troublesome pattern emerges for trading volume in the drift period: the estimated total effect is significantly negative for the two lowest *ASUEq* deciles (*p*-value<.8%), significantly positive for the two highest *ASUEq* deciles (*p*-value<5.8%) and insignificant in between. The dependence of the total effect on the *ASUEq* decile makes the results hard to interpret. My hypothesis was that the total effect in the drift period would be positive for all levels of *ASUEq* (Hypothesis 2.2a); the intuition being that high VIX on the announcement date would lead to underreaction on that date, which would increase trading volume in the subsequent period as investors re-direct attention to the firm. The conditional effect is however significantly positive (α_3=1.08‰; *p*-value<.1%); i.e. higher announcement-day VIX makes trading volume in the drift period more sensitive to absolute earnings surprises. This result

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[29] See note 22 for details of the calculation.
[30] The estimate is for *ASUEq*=5. I use the property that the estimate of the total effect of VIX ($\widehat{\alpha_2} + \widehat{\alpha_3} \cdot ASUEq$) can roughly be interpreted as a semielasticity; for closer details please see Appendix 3.

Table 9. Regression estimates for abnormal volume

ABVOL1 is the abnormal dollar trading volume over the announcement date and the subsequent day, and *ABVOL60* is the abnormal volume over the time span $[T+2, T+61]$. The suffixes *pre* and *post* indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers. The subscript VIX95 indicates that the independent variable VIX and its interaction term (see below) has been winsorized at its 95th percentile. *ASUEq* is the absolute earnings surprise decile rank (1 lowest, 10 highest) compared to other announcements in the trading days $[T-62, T]$. *VIX* is the level of the VIX index of implied volatility. *NUMREPq* is the decile rank of the number of announcements on day T. *MKTABVOL* denotes the abnormal volume of all CRSP stocks over the time span $[T, T+1]$ in the test for *ABVOL1*, and the time span $[T+2, T+61]$ in the test for ABVOL60. *NUMFORCq* is the decile rank of the number of analysts that have given a forecast. *SIZEq* and *BMq* are the decile ranks of market cap and book to market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parenthesis. Coefficients and standard errors are multiplied by 1,000. (* double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).

	ABVOL1	ABVOL60	ABVOL1pre	ABVOL1post	ABVOL60pre	$\text{ABVOL1}_{\text{VIX95}}$	$\text{ABVOL60}_{\text{VIX95}}$
ASUEq	29.0 (5.37)***	2.7 (5.02)***	27.9 (6.03)***	99.1 (32.6)***	20.5 (5.05)***	32.2 (5.91)***	23.6 (4.96)***
VIX	-7.84 (.881)***	-5.19 (1.22)***	-12.7 (1.04)***	5.15 (2.64)*	-5.31 (1.24) ***	-12.9 (.942)***	-6.77 (1.52)***
ASUEq×VIX	-.697 (.099)***	1.08 (.242)***	-.618 (.167)***	-1.82 (.465)***	1.13 (.245)***	-.799 (.158)***	1.73 (.280)***
VIX60		4.72 (1.2)***			4.65 (1.24)***		6.73 (1.59)***
ASUEq×VIX60		-1.97 (.215)***			-2.00 (.222)***		-2.77 (.285)***
MKTABVOL	593 (35.4)***	806 (3.3)***	628 (35)***	731 (88.7)***	807 (3.4)***	643 (31.3)***	816 (30.1)***
NUMREPq	-33.1 (3.04)***	-7.6 (2.08)***	-33.4 (3.01)***	-3.2 (16.1)*	-7.45 (2.09)***	-33.3 (2.92)***	-7.44 (2.08)***
ASUEq×NUMREPq	-1.71 (.469)***	-.201 (.399)	-1.78 (.478)***	-1.09 (2.25)	-.196 (.401)	-1.85 (.472)***	-.227 (.396)
NUMFORCq	-11.7 (1.67)***	-11.3 (1.25)***	-11.7 (1.7)***	-34 (7.77)***	-11.4 (1.25)***	-11.9 (1.67)***	-11.3 (1.25)***
ASUEq×NUMFORCq	-.069 (.31)	-.614 (.232)***	-.176 (.315)	2.32 (1.45)	-.605 (.232)***	-.205 (.309)	-.634 (.231)***
SIZEq	-11.9 (4.36)***	15.8 (3.46)***	-12.3 (4.45)***	65.1 (18.1)***	15.7 (3.46)***	-10.7 (4.37)**	15.5 (3.45)***
ASUEq×SIZEq	1.36 (.708)*	1.22 (.57)**	1.55 (.724)**	-3.97 (3.86)	1.2 (.571)**	1.57 (.709)**	1.30 (.567)**
BMq	-79.1 (4.67)***	1.96 (3.46)	-81 (4.79)***	-61.3 (16.1)***	1.9 (3.46)	-80.4 (4.66)***	2.06 (3.46)
ASUEq×BMq	5.98 (.756)***	.831 (.559)	6.1 (.773)***	5.13 (3.01)*	.837 (.559)	5.97 (.754)***	.752 (.557)
constant	1126 (35.1)***	66.4 (27)**	1224 (36.1)***	326 (169)*	69.3 (27.1)**	1221 (34.6)***	57.3 (27.6)**
N	75,876	73,769	73,661	2,215	73,662	75,876	73,769
R^2	7.18%	6.34%	6.00%	13.61%	6.31%	7.40%	6.40%
Total effect of VIX per ASUEq							
ASUEq=1	-8.54 (.813)***	-4.11 (1.06)***	-13.3 (.918)***	3.33 (2.26)	-4.18 (1.07)***	-13.7 (.830)***	-5.04 (1.33)***
ASUEq=2	-9.23 (.831)***	-3.02 (1.14)***	-14.0 (.963)***	1.5 (2.4)	-3.05 (1.15)***	-14.5 (.874)***	-3.31 (1.41)**
ASUEq=3	-9.93 (.86)***	-1.94 (1.26)	-14.6 (1.03)***	-.319 (2.62)	-1.93 (1.28)	-15.3 (.943)***	-1.58 (1.55)
ASUEq=4	-10.6 (.898)***	-.854 (1.41)	-15.2 (1.12)***	-2.14 (2.89)	-.799 (1.43)	-16.1 (1.03)***	.155 (1.72)
ASUEq=5	-11.3 (.946)***	.23 (1.59)	-15.8 (1.23)***	-3.96 (3.21)	.329 (1.61)	-16.9 (1.14)***	1.89 (1.91)
ASUEq=6	-12 (1.00)***	1.32 (1.78)	-16.4 (1.35)***	-5.79 (3.56)	1.46 (1.8)	-17.7 (1.25)***	3.62 (2.12)*
ASUEq=7	-12.7 (1.06)***	2.4 (1.98)	-17 (1.48)***	-7.61 (3.93)*	2.59 (2.01)	-18.5 (1.37)***	5.35 (2.35)**
ASUEq=8	-13.4 (1.13)***	3.48 (2.19)	-17.7 (1.61)***	-9.43 (4.33)**	3.71 (2.22)*	-19.3 (1.50)***	7.08 (2.59)***
ASUEq=9	-14.1 (1.2)***	4.57 (2.41)*	-18.3 (1.76)***	-11.3 (4.73)**	4.84 (2.44)**	-20.1 (1.64)***	8.82 (2.84)***
ASUEq=10	-14.8 (1.28)***	5.65 (2.63)**	-18.9 (1.9)***	-13.1 (5.15)**	5.97 (2.66)**	-20.9 (1.78)***	10.5 (3.09)***

is consistent with investors reconsidering the initially neglected earnings signal (Hypothesis 2.2b). The difference in sensitivities is once again economically significant: the sensitivity is 127% higher when VIX is at its 90th percentile than when it is as its 10th.[31] The results are again qualitatively similar in the pre-Lehman period and the regressions where VIX has been winsorized.

Studying the effect of drift period volatility on drift period volume, a similar ambiguity arises as for the effect of announcement date volatility on drift period volume. Higher *VIX60* makes drift period volume less sensitive to earnings, consistent with high drift-period VIX making it harder to reallocate attention to the firm (α_5=-1.97‰; *p*-value<.1%). However, the sign of the total effect varies depending on *ASUEq*.[32] Based on the theory of *VIX60* impeding a return of attention, one would expect a significantly negative total effect for all *ASUEq*.

6.2.3 Effects of control variables

The control variables have mixed success in the volume regressions. The number of announcements *NUMREPq* has a negative effect on announcement date volume and announcement date volume sensitivity to earnings, which can be expected based on the results of Hirshleifer, Lim, and Teoh (2009). However, the total and conditional effects on drift period volume are negative, inconsistent with a reversal of attention to firms that were initially neglected due to a high number of concurrent reports. Since Hirshleifer, Lim, and Teoh (2009) do not test for drift-period volume, this result cannot be compared to their work. The number of analysts *NUMFORCq* lowers the volume reaction (negative total effect) on the announcement day and in the drift-period. The effect on volume sensitivity to absolute earnings surprises is significantly negative for the announcement date and insignificantly negative for the drift period. These results again indicate that more information has already been incorporated when there are more forecasts prior to the announcements, which reduces the incentives for trading after the announcement. The volume patterns for *SIZEq* are mixed: larger firms have higher volume sensitivity to earnings both on the announcement day and in the drift period; the total effect is negative or insignificant on the announcement date (depending on *ASUEq*) and negative in the drift

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[31] See note 22 for details of the calculation.
[32] For brevity, the total effect of *VIX60* has not been tabulated. The total effect of *VIX60* on *ABVOL60* is positive for the lowest *ASUEq* (*p*-value .7%), negative for the seven highest *ASUEq* (*p*-value<1.8%), and insignificant in between.

period. Higher book-to-market ratio makes volume more sensitive to earnings on the announcement day and in the drift period, however only the former effect is significant. The total effect of book to market on volume is ambiguous for the announcement date and insignificant in the drift period.

6.2.4 Reconciling the ambiguous volume results

The trading volume results generally support the hypotheses, but the ambiguous total effect of VIX on drift period volume (effect may be either significantly negative, insignificant or significantly positive, depending on *ASUEq*) is hard to explain based on my theories. This indicates that the theory may be in need of further refinement, as the relation between macro volatility, earnings surprises and abnormal volume may be more complex than what my models capture.

One reason for the ambiguous result could be that trading volume is driven not only by information-based trading but also liquidity needs. Chae (2005) proposes that traders who seek liquidity but have discretion in the timing of their trades will prefer to time them after earnings announcements, since information asymmetries are lower at those times. It could be that the behavior of such traders is influenced by macro uncertainty. For instance, they may avoid trading in high-uncertainty times if they believe that information asymmetries are higher at such times (e.g. French and Roll (1986), Bardong, Bartram, and Yadav (2009)). If information asymmetries remain high or build up again in the drift period in such times, these traders may prefer to postpone their trades until after subsequent earnings releases. This could explain the lack of clear indications of reversal of trading volume in the drift period. Investigating the prediction that volume reverses around subsequent earnings announcements would be interesting, but would take me too far afield in this thesis.

6.3 Good and bad news

Good and bad news may have asymmetric effects. Barber and Odean (2008) find that attention-grabbing news such as extreme earnings surprises are on average associated with purchases from retail investors. Since these investors are largely short-sale constrained, this effect should be larger for good news. While retail investors may purchase just about any stock that has drawn their attention, their selling decisions are constrained to the stocks they already own. One would therefore expect the attention effects to be larger for good news. This result has also been confirmed in other studies that seek to explain the drift by attention constraints (e.g. DellaVigna and Pollet (2009); Hirshleifer, Lim, and Teoh (2009); and Hou, Peng, and Xiong (2009)). I therefore re-run the tests separately for positive and negative announcements to test this conjecture.[33]

The results, which are tabulated on the next page, are somewhat more in line with expectations for the "good news" subsample. For good news, the effect of VIX on announcement date return sensitivity to earnings remains positive, which is the opposite of Hypothesis 1.1, but is now insignificant (α_3 .02‰; p-value 72.6%). This contrasts with the significantly positive estimates from the full sample and the bad news sample (p-value <.1% for both regressions). The estimated coefficients for the drift period returns have opposite signs for good and bad news. Following good news, the drift period return sensitivity to earnings increases in VIX (α_3=1.79‰, p-value<.1%). This is consistent with the hypothesis of a larger delayed reaction for announcements made in high-VIX times (Hypothesis 1.2), and is in line with the full sample results. In contrast, the coefficient is negative following bad news (α_3=-.60‰; p-value 2.8%). Volume results are qualitatively similar to the full sample results for both good and bad news.

[33] Good news is defined as *SUEq*≥6. Similar results are obtained if good news is defined as *SUE*≥0 (untabulated).

Table 10. Separate regressions for returns following good and bad news

The prefix good indicates that the sample includes only announcements with SUEq (see below) greater than or equal to 6; the prefix bad indicates that SUEq<6. BHAR1 is the buy-and-hold abnormal return over the announcement day T and the subsequent day T+1. BHAR60 is the post-announcement period [T+2,T+61] buy-and-hold abnormal return. SUEq is the earnings surprise decile (1 lowest, 10 highest) compared to other announcements in the trading days [T-62,T]. VIX is the level of the VIX index of implied volatility. NUMREPq is the decile rank of the number of announcements on day T. TURNOq is the decile rank of turnover. NUMFORCq is the decile rank of the number of analysts that have given a forecast. SIZEq and BMq are the decile ranks of market cap and book-to-market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parentheses. Coefficients and standard errors are multiplied by 1,000. (double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).*

Variable	goodBHAR1	badBHAR1	goodBHAR60	badBHAR60
SUEq	6.36 (1.98)***	1.5 (1.79)***	-3.67 (5.9)	-8.30 (6.00)
VIX	-.096 (.375)	-.503 (.139)***	-11.3 (1.98)***	4.09 (1.03)***
SUEq×VIX	.018 (.052)	.139 (.038)***	1.79 (.266)***	-.601 (.273)**
VIX60			12.1 (1.69)***	-4.68 (1.04)***
SUEq×VIX60			-1.91 (.22)***	.865 (.268)***
NUMREPq	.078 (1.14)	-.121 (.542)	-8.57 (3.6)**	-3.9 (1.58)**
SUEq×NUMREPq	-.067 (.148)	.038 (.151)	1.12 (.475)**	1.31 (.448)***
TURNOq	-1.62 (1)	-3.64 (.428)***	-2.12 (3.2)	-1.13 (1.25)
SUEq×TURNOq	.195 (.127)	.58 (.129)***	.071 (.417)	.585 (.368)
NUMFORCq	-.11 (.88)	1.39 (.44)***	4.4 (2.36)*	2.65 (1.23)**
SUEq×NUMFORCq	-.002 (.114)	-.178 (.127)	-.625 (.312)**	-.733 (.354)**
SIZEq	7.1 (2.07)***	4.28 (.934)***	4.71 (6.07)	.247 (2.72)
SUEq×SIZEq	-.922 (.271)***	-.981 (.271)***	-.961 (.803)	-.692 (.816)
BMq	-5.92 (1.88)***	5.19 (.838)***	-13.3 (5.3)**	-2.85 (2.68)
SUEq×BMq	.529 (.241)**	-1.04 (.258)***	1.70 (.676)**	.070 (.832)
constant	-22.9 (15.0)	-47.2 (6.39)***	55.4 (44.1)	26.7 (21.1)
N	37,969	37,908	36,965	36,804
R^2	1.21%	3.87%	0.76%	0.42%
Total effect of VIX per SUEq				
SUEq=1		-.364 (.106)***		3.49 (.776)***
SUEq=2		-.225 (.124)*		2.89 (.909)***
SUEq=3		-.086 (.15)		2.29 (1.1)**
SUEq=4		.053 (.181)		1.68 (1.31)
SUEq=5		.193 (.214)		1.08 (1.55)
SUEq=6	.013 (.445)		-.608 (2.33)	
SUEq=7	.031 (.482)		1.18 (2.52)	
SUEq=8	.049 (.522)		2.96 (2.72)	
SUEq=9	.067 (.564)		4.75 (2.94)	
SUEq=10	.085 (.608)		6.53 (3.16)**	

Table 11. Separate regressions for abnormal volume following good and bad news

The prefix good indicates that the sample includes only announcements with *SUEq* (see below) greater than or equal to 6; the prefix *bad* indicates that *SUEq* <6. *ABVOL1* is the abnormal dollar trading volume over the announcement date and the subsequent day, and *ABVOL60* is the abnormal volume over the time span [T+2,T+61]. *ASUEq* is the absolute earnings surprise decile rank (1 lowest, 10 highest) compared to other announcements in the trading days [T-62,T]. *VIX* is the level of the VIX index of implied volatility. *NUMREPq* is the decile rank of the number of announcements on day T. *MKTABVOL* denotes the abnormal volume of all CRSP stocks over the time span [T,T+1] in the test for *ABVOL1,* and the time span [T+2,T+61] in the test for *ABVOL60. NUMFORCq* is the decile rank of the number of analysts that have given a forecast. *SIZEq* and *BMq* are the decile ranks of market cap and book to market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parenthesis. Coefficients and standard errors are multiplied by 1,000. (* double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).

	goodABVOL1	badABVOL1	goodABVOL60	badABVOL60
ASUEq	42.8 (11.0)***	5.67 (6.82)	35.4 (9.94)***	3.98 (5.99)
VIX	-5.48 (1.44)***	-8.70 (.906)***	-10.3 (2.72)***	-3.32 (1.34)**
ASUEq×VIX	-1.07 (.204)***	-.523 (.116)***	1.73 (.472)***	.811 (.269)***
VIX60			13.9 (2.64)***	1.75 (1.30)
ASUEq×VIX60			-3.12 (.440)***	-1.68 (.242)***
MKTABVOL	587 (39.1)***	587 (40.5)***	815 (35.7)***	800 (33.5)***
NUMREPq	-31.1 (6.33)***	-33.6 (3.22)***	-13.3 (4.80)***	-5.72 (2.18)***
ASUEq×NUMREPq	-2.24 (.974)**	-1.22 (.592)**	.673 (.807)	-.722 (.468)
NUMFORCq	-2.05 (3.74)	-14.9 (1.88)***	-5.26 (3.02)*	-13.3 (1.33)***
ASUEq×NUMFORCq	-1.81 (.579)***	1.20 (.412)***	-1.55 (.482)***	-.039 (.295)
SIZEq	-6.98 (9.30)	-12.5 (4.90)**	17.9 (6.93)***	17.9 (3.95)***
ASUEq×SIZEq	-1.54 (1.41)	4.36 (.936)***	-1.32 (1.09)	3.18 (.747)***
BMq	-133 (9.25)***	-66.2 (5.31)***	-21.6 (7.25)***	5.47 (3.90)
ASUEq×BMq	13.3 (1.36)***	4.38 (.983)***	3.86 (1.11)***	1.19 (.716)*
constant	1129 (71.9)***	1140 (37.5)***	37.8 (59.2)	82.5 (29.4)***
N	37,969	37,907	36,965	36,804
R^2	7.83%	6.68%	6.50%	7.35%
Total effect of VIX per ASUEq				
ASUEq=1		-9.23 (0.827)***		-2.51 (1.16)**
ASUEq=2		-9.75 (0.851)***		-1.7 (1.25)
ASUEq=3		-10.3 (0.889)***		-0.884 (1.39)
ASUEq=4		-10.8 (0.94)***		-0.0725 (1.56)
ASUEq=5		-11.3 (1)***		0.739 (1.76)
ASUEq=6	-11.9 (1.75)***		0.0789 (3.61)	
ASUEq=7	-13 (1.9)***		1.81 (3.99)	
ASUEq=8	-14 (2.06)***		3.54 (4.39)	
ASUEq=9	-15.1 (2.22)***		5.28 (4.8)	
ASUEq=10	-16.2 (2.39)***		7.01 (5.22)	

6.4 Alternative explanations

Macro uncertainty can of course affect investors in various ways other than by distracting their attention. In this section, I go through some other potential explanations to the results. The main challenge for competing theories is to explain why their properties should affect returns and trading volume of reporting firms more than others, as overall market moves are controlled for.

Previous research has found relations between macro volatility and other factors of relevance to real world arbitrageurs such as liquidity (e.g. Chordia, Roll, and Subrahmanyam (2001), idiosyncratic volatility (e.g. Campbell et al. (2001)), and funding conditions (e.g. Brunnermeier and Pedersen (2008) and Adrian and Shin (2008)). These factors are not necessarily “alternative” explanations since market liquidity can be affected by attention constraints among market makers (Corwin and Coughenour (2008)) and idiosyncratic volatility can be seen as a function of attention as mentioned before (Peng (2005), Peng and Xiong (2006)). Nevertheless, I test the robustness of the results to the inclusion of proxies for these factors in Appendix 2. The Appendix also contains a definition of the chosen proxies. Due to the simultaneity considerations above, I use lagged values of the variables. As can be expected, the proxy for funding conditions has a negative correlation with VIX (ρ=-.45), whereas the idiosyncratic volatility is positively correlated with VIX (ρ=.22), as is the illiquidity proxy, albeit with little economic significance (ρ= 0.02). The main difference from including the variables is that the effect of VIX on announcement date return sensitivity to earnings retains the predicted sign in the pre-Lehman period, but becomes insignificant (α_3=-.01‰, *p*-value 51%). Another difference is that the problem of ambiguous results for the total effect of VIX on drift period volume is partly resolved: the sign of the total effect still varies but it is now only significant for positive total effects (*p*-value<5.3% for the five highest *SUEq*). The positive sign is consistent with a reversal of attention in the drift period leading to higher trading volume (Hypothesis 2.2a)

The level of macro uncertainty could also affect the informativeness of the earnings statement. The direction is however unclear since plausible stories can be constructed as to why the earnings announcement should be either more or less informative in times of high macroeconomic volatility. An explanation along these lines is complicated by the fact that VIX measures uncertainty in systematic factors, whereas the return and volume reactions I measure are firm-specific. For instance, the value of an information signal could be higher when there is more macro uncertainty prior to the signal, while on the other hand there may be more noise in firm-specific signals like earnings announcements when macro uncertainty is high, implying that rational investors should put less weight on these signals. To my knowledge, the issue has not been tested empirically.[34] However, it should be acknowledged that information uncertainty theories could also be able to explain the results. Such theories are hard to distinguish from behavioral ones empirically since they not only predict the same underreaction/drift pattern, but also share proxy variables that are expected to reinforce the pattern (Brav and Heaton (2002)).

A phenomenon related to information uncertainty is opinion dispersion. Buraschi and Jiltsov (2006) find that dispersion measured from macroeconomic forecasts is increasing in VIX. The results could therefore be driven by disagreement rather than inattention. However, this explanation is hard to square with the reduced announcement date trading volume in high-VIX times, as disagreement is theoretically and empirically associated with higher trading volume (e.g. Harris and Raviv (1993), Kandel and Pearson (1995), Bamber, Barron, and Stober (1997)).

Finally, the lower trading volume in times of high macro uncertainty could be explained by information asymmetry being higher in such times (French and Roll (1986), Bardong, Bartram, and Yadav (2009)). Again, it is however hard to see why high macro volatility should raise information asymmetry more for reporting firms than other ones. Further, post-announcement volume may be *positively* correlated with pre-announcement information asymmetry; Chae (2005) finds that this result holds in the cross-section.

6.5 Robustness tests

This section tests the robustness of the results when definitions of key variables are changed. The most important features of the relation between macro uncertainty and return and volume reactions remain similar.

6.5.1 Measure of volatility

I re-define macro volatility as the effective range of the S&P 500 index, defined as in Graham, Koski, and Loewenstein (2006):

[34] Beber and Brandt (2009) find that higher *ex ante* macro volatility (measured from economic derivatives) is associated with a stronger reduction in uncertainty (measured by change in VIX) following announcements of macro data. Rogers, Skinner and Van Buskirk (2009) find that a higher log change in VIX makes earnings guidance from management more informative in the sense of having more effect on implied volatility of individual stock options.

$$RANGE_T = \frac{(P_{SP,T}^{HIGH} - P_{SP,T}^{LOW})}{\frac{P_{SP,T}^{HIGH} + P_{SP,T}^{LOW}}{2}} \tag{9}$$

, where $P_{SP,T}^{HIGH}$ and $P_{SP,T}^{LOW}$ are the intraday high and low prices of S&P 500 futures.[35] Since S&P 500 futures are among the most liquid contracts traded, (Peng, Bollerslev, and Xiong (2007)) market microstructure effects are unlikely to "contaminate" the measure (cf. Alizadeh, Diebold, and Brandt (2002)). The drift-period volatility *RANGE60* is constructed in the same way as *VIX60*, i.e. the mean of *RANGE* during the days (T+2,T+61).

The results are qualitatively similar for the full sample tests. The test again indicates that announcement date return sensitivity to earnings increases in macro volatility, contrary to expectations (p-value 3.4%). It also still holds that the effects of volatility on return sensitivity to earnings have the expected signs in the pre-Lehman period, but they are now insignificant (p-value 45% on the announcement date and 25% in the drift period). The results for announcement date volume have the expected signs and are significant (negative conditional and total effect; p-value<.1% for both effects), while the drift period volume measures have the opposite signs of the expected but are insignificant (negative total and conditional effect; p-value 60% for conditional effect and 50% for total effect). The volume results for the pre-Lehman period are similar to the full-sample results described above. The results are tabulated in Appendix 1. A possible interpretation of the lack of significant results from this measure is that it uses a very limited amount of the total information that could be obtained about prices on a specific date, namely only the intraday high and low. Further, the difference in results may be due to VIX being a forward-looking measure as described before, whereas *RANGE* only proxies for volatility that was realized on the event date. The lack of significant results for *RANGE* can therefore be interpreted as investors' attention allocation being driven more by their expectations of future macro volatility than by their reactions to macroeconomic shocks that occurred during the day.

6.5.2 Further robustness tests

I check the results when expected return is defined as the return of the industry portfolio, when financial and utility companies are excluded, and when the announcement date is

[35] I use futures rather than the index itself since I had access to longer time series for the former. The empirically observed lead-lag relation between the two is of minor relevance to my study since the lag tends to be in 5-10 minute periods. (Stoll and Whaley (1990))

changed from (T,T+1) to T.[36] The regression results are qualitatively similar. For brevity, only the first robustness test is tabulated; see Appendix 1 for estimates. In untabulated regressions, I also test the robustness of the "pre-crisis" results by changing the cutoff date to February 2007 (which Brunnermeier (2008) considers the start date of the crisis). The results are qualitatively similar to those that are obtained when the Lehman collapse is chosen as the cutoff.

6.6 Practical implications and suggestions for further research

The most interesting result from the perspective of a profit-seeking investor may be the significant total effect of VIX on drift period return. This indicates that trading strategies based on the drift should perform better in high-uncertainty times. Implementing a strategy to exploit this would however be associated with several difficulties.[37]

As discussed before, the economic significance of the volume results may be limited since a unit increase in VIX was estimated to decrease trading volume on the announcement day by only approximately 1%. It should be noted however that the property of interest to an investor is not total dollar volume *per se* but rather liquidity, and dollar volume is an imperfect proxy for this. Investigating the effect of VIX on the liquidity around earnings announcements using liquidity measures with stronger theoretical underpinning such as the Amihud (2002) measure may be an interesting avenue for future research.

There was support for all but one of the hypotheses in the period before the fall of Lehman Brothers. While I suggest that there may have been a structural break in the post-Lehman period, testing this more formally would be of interest. Further, it would be interesting to extend the sample period and check whether the results hold in other market crises. A more detailed examination of the performance of investment strategies based on the post-earnings announcement drift in the financial crisis would also be of interest, since that may expose "tail risks" in the strategies, which can help explain their abnormally high

[36] I use the time span T+1 instead when IBES' time stamp indicates that the report was released after market close (4 p.m.) and the announcement date given by IBES is not later than the announcement date given by Compustat.

[37] First, the regressions control for drift period volatility, which obviously cannot be foreseen on the announcement date when the positions would have to be started. Second, forming a "hedge" portfolio of firms that have announced in low-VIX times would be difficult since all firms announcing on the same day obviously have the same VIX. One might of course form that portfolio in firms that have announced in adjacent dates with lower VIX, but the variation in VIX over short time spans is likely low due to volatility clustering. Finally, transaction costs have not been taken into account in my analysis.

returns. Since I only have 67 drift period observations from this time, I could not test meaningfully for this possibility. It could also be of interest to extend the sample period to see if results went back to being more in line with my predictions when markets started to normalize.

7 Conclusions

Based on rational allocation of limited processing capacity between market-wide and firm-specific information, I hypothesize that returns and trading volume will follow predictable patterns around earnings announcements. I predict that the return will initially underreact to the information in the earnings announcement when investors are distracted by high macro uncertainty, as measured by a high level of the VIX. I also propose that these investors will subsequently reallocate their attention to the firm once the macro uncertainty is resolved, which will make post-announcement period returns more sensitive to earnings. This dynamic attention allocation could therefore help explain the post-earnings announcement drift. The regression tests of these hypotheses give conflicting results. The prediction that returns will be less sensitive to earnings in times of high uncertainty is rejected for the full sample; however this effect is largely driven by extreme observations from the time following the collapse of Lehman Brothers. When this part of the sample (3% of all observations) is omitted, the results are in line with the hypothesis. The returns in the post-announcement period become more sensitive to earnings in times of high uncertainty, consistent with a reversal of attention. Based on the limited attention theory I also hypothesize that trading volume will initially be more muted in high-uncertainty periods, and revert in the post-announcement period. These predictions are supported by the data on the announcement date, but the signs of subsequent reversal are mixed.

Together, these results indicate that returns and announcement date trading volume behaved in ways consistent with limited attention theory prior to the financial crisis, although the ambiguous post-announcement volume results indicate that more factors may need to be taken into account. I suggest that the counter-expected effects in the full-sample tests may be due to the dislocation that followed from Lehman's fall and the external shock it caused to other market participants, but further investigation is needed to support this conjecture.

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9 Appendix 1. Robustness tests

Table 12. Regression estimates for abnormal returns when defining volatility as intraday range

BHAR1 is the buy-and-hold abnormal return over the announcement day *T* and the subsequent day *T+1*. *BHAR60* is the post-announcement period [*T*+2,*T*+61] buy-and-hold abnormal return. The suffixes *pre* and *post* indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers.*SUEq* is the earnings surprise decile (1 lowest, 10 highest) compared to other announcements in the trading days [*T*-62,*T*]. *RANGE* is the intraday effective range of S&P 500 futures. *NUMREPq* is the decile rank of the number of announcements on day *T*. *TURNOq* is the decile rank of turnover. *NUMFORCq* is the decile rank of the number of analysts that have given a forecast. *SIZEq* and *BMq* are the decile ranks of market cap and book-to-market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parentheses. Coefficients and standard errors are multiplied by 1,000.
(* double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).

Variable	BHAR1	BHAR60	BHAR1pre	BHAR1post	BHAR60pre
SUEq	9.2 (.651)***	3.71 (1.98)*	9.64 (.665)***	17.8 (7.3)**	3.79 (1.99)*
RANGE	-147 (87.5)*	167 (315)	150 (107)	-79.6 (230)	181 (320)
SUEq×RANGE	32 (15.1)**	69.4 (59.9)	-13.3 (17.7)	36.8 (39.9)	7.4 (6.9)
RANGE60		91.1 (463)			112 (475)
SUEq×RANGE60		-220 (65.1)***			-226 (66.1)***
NUMREPq	.141 (.359)	-1.81 (1.01)*	.054 (.356)	1.24 (3.23)	-1.81 (1.01)*
SUEq×NUMREPq	-.081 (.059)	.326 (.164)**	-.068 (.059)	-.244 (.522)	.33 (.164)**
TURNOq	-3.03 (.271)***	.812 (1.01)	-3 (.268)***	-5.51 (2.92)*	.844 (1.01)
SUEq×TURNOq	.364 (.044)***	-.269 (.157)*	.354 (.043)***	.982 (.475)**	-.271 (.157)*
NUMFORCq	1.35 (.262)***	1.78 (.752)**	1.47 (.259)***	-1.04 (2.48)	1.84 (.752)**
SUEq×NUMFORCq	-.176 (.044)***	-.343 (.127)***	-.206 (.043)***	.635 (.416)	-.349 (.127)***
SIZEq	3.94 (.582)***	.703 (1.66)	3.37 (.574)***	21 (6.47)***	.671 (1.66)
SUEq×SIZEq	-.499 (.1)***	-.411 (.286)	-.397 (.098)***	-4.15 (1.18)***	-.412 (.287)
BMq	3.07 (.526)***	-5.67 (1.6)***	3.1 (.517)***	9.32 (5)*	-5.63 (1.61)***
SUEq×BMq	-.58 (.088)***	.749 (.25)***	-.58 (.086)***	-1.71 (.944)*	.746 (.25)***
constant	-45.6 (3.99)***	2.47 (12.4)	-48.2 (4)***	-113 (46.4)**	1.56 (12.5)
N	75,854	73,746	73,639	2,215	73,639
R^2	7.12%	. 31%	7.26%	7.09%	.32%
Total effect of RANGE per SUEq					
SUEq=1	-115 (74.9)	237 (268)	137 (93.2)	-42.3 (195)	253 (273)
SUEq=2	-83.4 (79.3)	306 (287)	123 (98.1)	-5.9 (207)	323 (292)
SUEq=3	-51.4 (86.3)	375 (317)	110 (106)	30.5 (225)	393 (323)
SUEq=4	-19.4 (95.1)	445 (354)	96.8 (116)	66.8 (249)	463 (361)
SUEq=5	12.7 (105)	514 (397)	83.5 (127)	103 (276)	534 (404)
SUEq=6	44.7 (117)	584 (444)	70.1 (140)	140 (306)	604 (452)
SUEq=7	76.7 (129)	653 (494)	56.8 (154)	176 (338)	674 (502)
SUEq=8	109 (142)	723 (546)	43.4 (169)	212 (372)	745 (555)
SUEq=9	141 (155)	792 (599)	30.1 (184)	249 (407)	815 (609)
SUEq=10	173 (168)	862 (654)	16.8 (199)	285 (442)	885 (665)

Table 13. Regression estimates for abnormal volume when defining volatility as intraday range

ABVOL1 is the abnormal dollar trading volume over the announcement date and the subsequent day, and *ABVOL60* is the abnormal volume over the time span [*T*+2,*T*+61]. The suffixes *pre* and *post* indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers. *ASUEq* is the absolute earnings surprise decile rank (1 lowest, 10 highest) compared to other announcements in the trading days [*T*-62,*T*]. *RANGE* is the intraday effective range of S&P 500 futures. *NUMREPq* is the decile rank of the number of announcements on day *T*. *MKTABVOL* denotes the abnormal volume of all CRSP stocks over the time span [*T*,*T*+1] in the test for *ABVOL1*, and the time span [*T*+2,*T*+61] in the test for ABVOL60. *NUMFORCq* is the decile rank of the number of analysts that have given a forecast. *SIZEq* and *BMq* are the decile ranks of market cap and book to market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parenthesis. Coefficients and standard errors are multiplied by 1,000.
(* double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).

Variable	ABVOL1	ABVOL60	ABVOL1pre	ABVOL1post	ABVOL60pre
ASUEq	21.9 (5.06)***	21.5 (4.34)***	21.2 (5.25)***	17.8 (27.5)	21.4 (4.36)***
RANGE	-4837 (702)***	-74.5 (625)	-6697 (1155)***	-863 (1043)	-165 (637)
ASUEq×RANGE	-527 (84.7)***	-91.3 (142)	-472 (134)***	-281 (203)	-77.9 (146)
RANGE60		1623 (805)**			1533 (825)*
ASUEq×RANGE60		-1217 (148)***			-1229 (152)***
MKTABVOL	759 (36.1)***	812 (30.4)***	777 (40.7)***	893 (98.9)***	812 (30.4)***
NUMREPq	-33.6 (3.10)***	-7.78 (2.09)***	-33.3 (3.16)***	-16.6 (15.3)	-7.60 (2.11)***
ASUEq×NUMREPq	-1.55 (.471)***	-.164 (.398)	-1.58 (.478)***	-2.83 (2.50)	-.164 (.400)
NUMFORCq	-11.5 (1.68)***	-11.2 (1.25)***	-11.4 (1.71)***	-31.0 (7.77)***	-11.2 (1.25)***
ASUEq×NUMFORCq	-.027 (.311)	-.639 (.231)***	-.066 (.316)	1.90 (1.45)	-.632 (.231)***
SIZEq	-13.9 (4.38)***	15.3 (3.48)***	-15.1 (4.46)***	61.1 (18.2)***	15.2 (3.48)***
ASUEq×SIZEq	1.34 (.712)*	1.33 (.572)**	1.44 (.725)**	-3.28 (3.99)	1.32 (.573)**
BMq	-78.9 (4.64)***	2.36 (3.46)	-79.9 (4.77)***	-60.3 (16.5)***	2.31 (3.46)
ASUEq×BMq	5.76 (.758)***	.792 (.559)	5.85 (.776)***	5.03 (3.19)	.795 (.559)
constant	1036 (31.6)***	36.2 (24.6)	1063 (34.0)***	609 (131)***	37.6 (24.6)
N	75,853	73,746	73,636	2,217	73,637
R^2	6.70%	6.40%	5.40%	13.30%	6.30%
Total effect of RANGE per ASUEq					
ASUEq=1	-5360 (645)***	-166 (558)	-7170 (1050)***	-1140 (869)	-243 (567)
ASUEq=2	-5890 (661)***	-257 (611)	-7640 (1080)***	-1420 (937)	-320 (621)
ASUEq=3	-6420 (688)***	-348 (689)	-8110 (1120)***	-1700 (1040)	-398 (703)
ASUEq=4	-6940 (723)***	-440 (786)	-8580 (1170)***	-1980 (1170)*	-476 (803)
ASUEq=5	-7470 (767)***	-531 (895)	-9050 (1240)***	-2260 (1320)*	-554 (916)
ASUEq=6	-8000 (816)***	-622 (1010)	-9530 (1320)***	-2540 (1480)*	-632 (1040)
ASUEq=7	-8530 (872)***	-713 (1140)	-10000 (1400)***	-2820 (1650)*	-710 (1160)
ASUEq=8	-9050 (931)***	-805 (1260)	-10500 (1500)***	-3100 (1830)*	-788 (1300)
ASUEq=9	-9580 (995)***	-896 (1390)	-10900 (1600)***	-3380 (2010)*	-866 (1430)
ASUEq=10	-10100 (1060)***	-987 (1530)	-11400 (1700)***	-3660 (2200)*	-943 (1570)

Table 14. Regression estimates for abnormal returns

indBHAR1 is the buy-and-hold abnormal return over the announcement day T and the subsequent day T+1, where expected return is the average return in the company's industry. indBHAR60 is the post-announcement period [T+2,T+61] buy-and-hold abnormal return. The suffixes pre and post indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers. SUEq is the earnings surprise decile (1 lowest, 10 highest) compared to other announcements in the trading days [T-62,T]. VIX is the level of the VIX index of implied volatility. NUMREPq is the decile rank of the number of announcements on day T. TURNOq is the decile rank of turnover. NUMFORCq is the decile rank of the number of analysts that have given a forecast. SIZEq and BMq are the decile ranks of market cap and book-to-market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. Standard errors robust to heteroscedasticity and clustering on the announcement day are in parentheses. Coefficients and standard errors are multiplied by 1,000. (double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).*

	indBHAR1	indBHAR60	indBHAR1pre	indBHAR1post	indBHAR60pre
SUEq	8.77 (.692)***	3.38 (2.11)	10.4 (.726)***	9.69 (11.5)	3.39 (2.12)
VIX	-.290 (.112)**	4.58 (.676)***	.220 (.126)*	-.474 (.922)	4.64 (.685)***
SUEq×VIX	.044 (.017)***	.219 (.096)**	-.044 (.018)**	.198 (.160)	.222 (.096)**
VIX60		-3.82 (.666)***			-3.89 (.686)***
SUEq×VIX60		-.282 (.092)***			-.286 (.094)***
NUMREPq	-.098 (.369)	-1.12 (1.06)	-.099 (.362)	1.67 (3.71)	-1.08 (1.06)
SUEq×NUMREPq	-.062 (.059)	.335 (.168)**	-.066 (.058)	-.357 (.532)	.340 (.169)**
TURNOq	-3.06 (.276)***	.015 (.970)	-3.00 (.273)***	-5.96 (2.88)**	.030 (.970)
SUEq×TURNOq	.370 (.045)***	-.223 (.156)	.355 (.044)***	1.03 (.461)**	-.222 (.156)
NUMFORCq	1.35 (.260)***	1.73 (.738)**	1.49 (.258)***	-1.04 (2.47)	1.78 (.739)**
SUEq×NUMFORCq	-.183 (.044)***	-.387 (.123)***	-.215 (.043)***	.534 (.427)	-.394 (.123)***
SIZEq	4.14 (.586)***	-2.58 (1.84)	3.46 (.580)***	22.7 (6.31)***	-2.63 (1.84)
SUEq×SIZEq	-.529 (.099)***	-.444 (.292)	-.405 (.096)***	-4.41 (1.26)***	-.447 (.292)
BMq	3.26 (.527)***	-2.20 (1.60)	3.18 (.517)***	10.3 (4.91)**	-2.13 (1.60)
SUEq×BMq	-.597 (.088)***	.575 (.244)**	-.585 (.085)***	-1.74 (.958)*	.573 (.244)**
constant	-40.8 (4.53)***	2.52 (13.5)	-49.7 (4.62)***	-98.6 (68.4)	2.02 (13.6)
N	75,877	73,769	73,662	2,215	73,662
R^2	7.17%	1.38%	7.30%	7.44%	1.39%
Total effect of VIX per SUEq					
SUEq=1	-0.246 (0.101)**	4.8 (0.608)***	0.177 (0.112)***	-0.276 (0.78)	4.86 (0.616)***
SUEq=2	-0.202 (0.105)*	5.01 (0.63)***	0.133 (0.116)***	-0.0783 (0.828)	5.09 (0.638)***
SUEq=3	-0.158 (0.112)	5.23 (0.665)***	0.0895 (0.123)***	0.12 (0.902)	5.31 (0.674)***
SUEq=4	-0.114 (0.12)	5.45 (0.712)***	0.046 (0.132)***	0.317 (0.996)	5.53 (0.72)***
SUEq=5	-0.0707 (0.13)	5.67 (0.767)***	0.00247 (0.142)	0.515 (1.11)	5.75 (0.776)***
SUEq=6	-0.0269 (0.142)	5.89 (0.83)***	-0.0411 (0.154)	0.713 (1.23)	5.97 (0.839)***
SUEq=7	0.0169 (0.154)	6.11 (0.899)***	-0.0846 (0.166)	0.911 (1.36)	6.2 (0.909)***
SUEq=8	0.0606 (0.168)	6.33 (0.972)***	-0.128 (0.18)	1.11 (1.49)	6.42 (0.982)***
SUEq=9	0.104 (0.182)	6.55 (1.05)***	-0.172 (0.194)	1.31 (1.63)	6.64 (1.06)***
SUEq=10	0.148 (0.196)	6.77 (1.13)***	-0.215 (0.209)	1.5 (1.77)	6.86 (1.14)***

10 Appendix 2. Inclusion of additional controls

Liquidity is defined as the average value of the Amihud (2002) measure over the time span (T-31,T-11)

$$ILLIQ_{i,T} = \frac{1}{21} \sum_{\mathrm{t=T-31}}^{\mathrm{T-11}} \frac{|R_{i,t}|}{P_{i,t} VOL_{i,t}} \cdot 1000 \tag{10}$$

Idiosyncratic volatility is defined as

$$IV_{i,T} = \frac{1}{21} \sum_{\mathrm{t=T-31}}^{\mathrm{T-11}} \left(R_{i,t} - R_{FF,t}\right)^2 \tag{11}$$

Funding conditions are measured as the gross repo positions of the primary dealers with which the Federal Reserve Bank of New York conducts its open market operations.[38] These dealers tend to be important both as funding parties and trading parties in speculative trades (Adrian and Fleming (2005)). Following Kambhu (2006), I use only continuing and overnight positions, using gross volumes in both repos and reverse repos, since the dealers may both fund clients' positions and take own positions funded with such instruments. I also follow Kambhu (2006) in defining the gross repo position as its deviation from its one-year moving average, so as to correct for the apparent stationarity in the time series. The data is released at weekly frequency, and I use lagged values for intermediate dates. A similar measure is used by Boyson, Stahel, and Stulz (2008).[39]

The added controls are also interacted with *SUEq*/*ASUEq.*

Table 15. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ILLIQ	75,877	2.3E-04	3.4E-03	3.3E-9	.517
IV	75,877	.024	.052	1.43E-04	3.398
FUNDING	75,877	149,108	138,418	- 1,152,814	676,497

Table 16. Correlations with VIX

Variable	Correlation with VIX
ILLIQ	0.019
IV	0.219
FUNDING	-0.445

[38] Available at http://www.newyorkfed.org/markets/gsds/search.cfm.
[39] Note however that they define repo volume differently since they are only interested in repos from the perspective of funding provision to hedge funds.

Table 17. Regression estimates for abnormal returns with additional controls (continued on next page)

BHAR1 is the buy-and-hold abnormal return over the announcement day *T* and the subsequent day *T+1*. *BHAR60* is the post-announcement period [*T*+2,*T*+61] buy-and-hold abnormal return. The suffixes *pre* and *post* indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers. *SUEq* is the earnings surprise decile (1 lowest, 10 highest) compared to other announcements in the trading days [*T*-62,*T*]. *VIX* is the level of the VIX index of implied volatility. *NUMREPq* is the decile rank of the number of announcements on day *T*. *TURNOq* is the decile rank of turnover. *NUMFORCq* is the decile rank of the number of analysts that have given a forecast. *SIZEq* and *BMq* are the decile ranks of market cap and book-to-market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. *ILLIQ* is the Amihud (2002) measure of trading impact, *IV* is the idiosyncratic volatility, and *FUNDING* measures funding conditions in repo volumes; previous page for closer details Standard errors robust to heteroscedasticity and clustering on the announcement day are in parentheses. Coefficients and standard errors are multiplied by 1,000. (* double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).

Variable	BHAR1	BHAR60	BHAR1pre	BHAR1post	BHAR60pre	$BHAR1_{VIX95}$	$BHAR60_{VIX95}$
SUEq	8. 00 (.777)***	2.26 (2.2)	9.12 (.78)***	11.9 (12.2)	2.36 (2.21)	9.13 (.792)***	2.00 (2.19)
VIX	-.391 (.103)***	1.46 (.618)**	.125 (.118)	-.184 (.712)	1.48 (.627)**	-.119 (.126)	1.43 (.634)**
SUEq×VIX	.073 (.018)***	.259 (.096)***	-.012 (.019)	.183 (.159)	.267 (.098)***	.029 (.021)	.285 (.099)***
VIX60		-1.22 (.663)*			-1.23 (.681)*		-1.13 (.653)*
SUEq×VIX60		-.299 (.099)***			-.311 (.101)***		-.311 (.098)***
NUMREPq	.067 (.357)	-1.89 (.996)*	.041 (.35)	1.66 (3.47)	-1.86 (.995)*	.079 (.357)	-1.92 (.997)*
SUEq×NUMREPq	-.063 (.059)	.348 (.165)**	-.061 (.058)	-.403 (.596)	.352 (.165)**	-.065 (.059)	.350 (.165)**
TURNOq	-3.14 (.272)***	1.24 (.998)	-3.04 (.272)***	-5.64 (2.92)*	1.27 (.999)	-3.10 (.273)***	1.24 (.998)
SUEq×TURNOq	.409 (.044)***	-.272 (.16)*	.386 (.044)***	1.01 (.47)**	-.273 (.16)*	.401 (.044)***	-.268 (.160)*
NUMFORCq	1.39 (.262)***	1.84 (.746)**	1.56 (.259)***	-.86 (2.5)	1.9 (.747)**	1.36 (.264)***	1.85 (.747)**
SUEq×NUMFORCq	-.183 (.044)***	-.335 (.126)***	-.221 (.043)***	.612 (.424)	-.341 (.126)***	-.177 (.044)***	-.337 (.126)***
SIZEq	4.16 (.598)***	-.374 (1.73)	3.24 (.592)***	21.9 (6.3)***	-.395 (1.73)	4.09 (.606)***	-.368 (1.73)
SUEq×SIZEq	-.583 (.103)***	-.422 (.298)	-.424 (.1)***	-4.36 (1.14)***	-.425 (.298)	-.576 (.104)***	-.429 (.299)
BMq	3.13 (.527)***	-5.65 (1.61)***	3.07 (.519)***	8.3 (5.13)	-5.61 (1.61)***	3.01 (.527)***	-5.66 (1.61)***
SUEq×BMq	-.599 (.089)***	.734 (.25)***	-.586 (.087)***	-1.49 (.947)	.731 (.25)***	-.580 (.089)***	.736 (.250)***
ILLIQ	206 (179)	478 (486)	156 (159)	1251 (1599)	481 (487)	204 (178)	477 (485)
SUEq×ILLIQ	-6.44 (268)	-127 (8.7)	-.595 (25)	-71 (264)	-127 (8.8)	-6.16 (26.8)	-128 (80.6)
IV	24.6 (18.9)	-103 (67.8)	12.6 (2.1)	59 (46)	-103 (67.9)	15.9 (19.1)	-104 (67.9)
SUEq×IV	-1.8 (2.48)***	.237 (9.96)	-8.56 (2.6)***	-23.5 (11.3)**	.283 (9.96)	-9.54 (2.45)***	-.038 (9.98)
FUNDING	-2E-5 (8E-6) *	-3E-5 (2E-5)	-3E-5 (8E-6) ***	-3E-5 (4E-5.)	-4E-5 (2E-5)	-5E-6 (8E-6)	-3E-5 (2E-5)
SUEq×FUNDING	2E-6 (1E-6) **	2E-7 (3E-6)	8E-6 (1E-6) ***	3E-6 (7E-6)	-1E-7 (3E-6)	8E-7 (1E-6)	3E-7 (3E-6)
constant	-38 (4.76)***	9.73 (13.8)	-44 (4.84)***	-121 (66.1)*	8.76 (13.8)	-44.9 (4.92)***	8.89 (13.8)
N	75,877	73,769	73,662	2,215	73,662	75,877	73,769
R^2	7.24%	0.52%	7.39%	7.69%	0.52%	7.20%	0.52%

Table 17. Regression estimates for abnormal returns with additional controls (continued)

Total effect of VIX per SUEq

Variable	BHAR1	BHAR60	BHAR1pre	BHAR1post	BHAR60pre	$BHAR1_{VIX95}$	$BHAR60_{VIX95}$
SUEq=1	-.319 (.087)***	1.72 (.539)***	.113 (.102)	-.002 (.565)	1.75 (.547)***	-.089 (.108)	1.71 (.553)***
SUEq=2	-.246 (.093)***	1.98 (.565)***	.1 (.107)	.181 (.629)	2.01 (.573)***	-.060 (.114)	2.00 (.580)***
SUEq=3	-.173 (.102)*	2.24 (.604)***	.088 (.115)	.364 (.722)	2.28 (.613)***	-.030 (.123)	2.28 (.621)***
SUEq=4	-.1 (.113)	2.5 (.656)***	.075 (.125)	.547 (.836)	2.55 (.665)***	-.001 (.134)	2.57 (.674)***
SUEq=5	-.028 (.125)	2.76 (.717)***	.063 (.138)	.73 (.963)	2.82 (.726)***	.028 (.148)	2.85 (.737)***
SUEq=6	.045 (.139)	3.02 (.785)***	.05 (.151)	.913 (1.1)	3.08 (.795)***	.058 (.163)	3.14 (.808)***
SUEq=7	.118 (.154)	3.27 (.859)***	.038 (.166)	1.1 (1.24)	3.35 (.869)***	.087 (.179)	3.42 (.883)***
SUEq=8	.191 (.169)	3.53 (.937)***	.025 (.181)	1.28 (1.38)	3.62 (.948)***	.116 (.196)	3.71 (.964)***
SUEq=9	.263 (.185)	3.79 (1.02)***	.013 (.197)	1.46 (1.53)	3.88 (1.03)***	.146 (.213)	3.99 (1.05)***
SUEq=10	.336 (.202)*	4.05 (1.1)***	.0006731 (.213)	1.65 (1.68)	4.15 (1.11)***	.175 (.231)	4.27 (1.13)***

Table 18. Regression estimates for abnormal volume with addition controls (continued on next page)

ABVOL1 is the abnormal dollar trading volume over the announcement date and the subsequent day, and *ABVOL60* is the abnormal volume over the time span [*T*+2,*T*+61]. The suffixes *pre* and *post* indicate that the regressions include only observations from the time before/after the Chapter-11 filing of Lehman Brothers. *ASUEq* is the absolute earnings surprise decile rank (1 lowest, 10 highest) compared to other announcements in the trading days [*T*-62,*T*]. *VIX* is the level of the VIX index of implied volatility. *NUMREPq* is the decile rank of the number of announcements on day *T*. *MKTABVOL* denotes the abnormal volume of all CRSP stocks over the time span [*T*,*T*+1] in the test for *ABVOL1*, and the time span [*T*+2,*T*+61] in the test for ABVOL60. *NUMFORCq* is the decile rank of the number of analysts that have given a forecast. *SIZEq* and *BMq* are the decile ranks of market cap and book to market equity, respectively, based on the breakpoints and methodology provided by Kenneth French. For closer definitions, see Section 4.3. *ILLIQ* is the Amihud (2002) measure of trading impact, *IV* is the idiosyncratic volatility, and *FUNDING* measures funding conditions in repo volumes; previous page for closer details Standard errors robust to heteroscedasticity and clustering on the announcement day are in parentheses. Coefficients and standard errors are multiplied by 1,000. (* double-sided p-value ≤ 10% ** p≤ 5% *** p ≤ 1%).

Variable	ABVOL1	ABVOL60	ABVOL1pre	ABVOL1post	ABVOL60pre	$ABVOL1_{VIX95}$	$ABVOL60_{VIX95}$
ASUEq	37.8 (5.90)***	25.0 (5.27)***	36.5 (6.34)***	96.3 (36.1)***	24.9 (5.28)***	37.0 (6.27)***	23.9 (5.19)***
VIX	-4.67 (.906)***	-2.27 (1.32)*	-9.59 (1.07)***	5.01 (2.72)*	-2.44 (1.35)*	-9.24 (1.02)***	-2.03 (1.39)
ASUEq×VIX	-.859 (.119)***	.990 (.258)***	-.709 (.182)***	-1.78 (.446)***	1.03 (.261)***	-.866 (.176)***	1.12 (.261)***
VIX60		4.81 (1.26)***			4.99 (1.32)***		4.56 (1.24)***
ASUEq×VIX60		-2.01 (.221)***			-2.06 (.229)***		-2.08 (.223)***
MKTABVOL	543 (33.2)***	748 (29.2)***	574 (31.9)***	757 (104)***	748 (29.3)***	-.866 (.176)***	750 (29.2)***
NUMREPq	-30.9 (2.92)***	-6.65 (2.06)***	-30.7 (2.88)***	-20.1 (18.8)	-6.72 (2.07)***	-30.9 (2.83)***	-6.65 (2.06)***
ASUEq×NUMREPq	-1.82 (.465)***	-.284 (.394)	-1.91 (.474)***	-1.02 (2.58)	-.264 (.395)	-1.93 (.469)***	-.292 (.392)
NUMFORCq	-9.88 (1.66)***	-8.38 (1.24)***	-10.3 (1.69)***	-24.8 (8.44)***	-8.40 (1.24)***	-10.1 (1.66)***	-8.40 (1.24)***
ASUEq×NUMFORCq	-.190 (.309)	-.704 (.231)***	-.260 (.315)	1.36 (1.51)	-.695 (.231)***	-.315 (.309)	-.690 (.230)***
SIZEq	-18.7 (4.21)***	.654 (3.61)	-17.2 (4.36)***	54.4 (16.6)***	.603 (3.62)	-16.5 (4.24)***	.665 (3.61)
ASUEq×SIZEq	1.42 (.715)**	1.83 (.642)***	1.46 (.749)*	-3.06 (3.36)	1.82 (.643)***	1.58 (.721)**	1.79 (.641)***
BMq	-84.4 (4.65)***	-6.29 (3.36)*	-85.9 (4.76)***	-64.1 (14.5)***	-6.38 (3.37)*	-84.7 (4.64)***	-6.26 (3.36)*
ASUEq×BMq	6.20 (.746)***	.945 (.545)*	6.23 (.767)***	6.66 (2.73)**	.956 (.546)*	6.16 (.743)***	.948 (.545)*
ILLIQ	11598 (8594)	6286 (7020)	9329 (9015)	51623 (17849)***	6226 (7010)	11422 (8667)	6303 (7002)
ASUEq×ILLIQ	-1201 (1175)	411 (1046)	-910 (1253)	-5705 (3222)*	417 (1046)	-1154 (1192)	406 (1043)
IV	-2124 (258)***	-3131 (292)***	-1948 (266)***	-1789 (740)**	-3128 (293)***	-1907 (250)***	-3140 (294)***
ASUEq×IV	115 (37.3)***	174 (48.4)***	97.3 (40.8)**	106 (83.9)	174 (48.5)***	96.3 (36.5)***	174 (48.7)***
FUNDING	3E-4 (6E-5)***	2E-5 (4E-5)	4E-4(6E-5)***	2E-4 (2E-4)	2E-5 (4E-5)	3E-4 (5E-5)***	2E-5 (4E-5)
ASUEq×FUNDING	3E-8 (8E-6)***	2E-5 (7E-6)***	4E-5 (9E-6)***	3E-6 (3E-5)	2E-5 (7E-6) ***	2E-5 (8E-6)***	2E-5 (7E-6)***
constant	1053 (37.1)***	99.0 (27.5)***	1125 (37.3)***	237 (183)	99.8 (27.6)***	1131 (36.6)***	99.5 (27.7)***
N	75,876	73,769	73,661	2,215	73,662	75,876	73,769
R^2	7.99%	9.30%	6.80%	16.79%	9.27%	8.19%	9.34%

Table 18. Regression estimates for abnormal volume with addition controls (continued)

Total effect of VIX per ASUEq

Variable	ABVOL1	ABVOL60	ABVOL1pre	ABVOL1post	ABVOL60pre	$ABVOL1_{VIX95}$	$ABVOL60_{VIX95}$
ASUEq=1	-5.53 (.823)***	-1.27 (1.14)	-10.3 (.931)***	3.23 (2.37)	-1.40 (1.16)	-10.1 (.895)***	-.901 (1.20)
ASUEq=2	-6.39 (.849)***	-.285 (1.22)	-11.0 (.982)***	1.45 (2.49)	-.368 (1.24)	-11.0 (.946)***	.222 (1.28)
ASUEq=3	-7.25 (.889)***	.706 (1.35)	-11.7 (1.06)***	-.330 (2.68)	.665 (1.37)	-11.8 (1.02)***	1.35 (1.40)
ASUEq=4	-8.11 (.943)***	1.70 (1.51)	-12.4 (1.17)***	-2.11 (2.93)	1.70 (1.54)	-12.7 (1.13)***	2.47 (1.56)
ASUEq=5	-8.97 (1.01)***	2.69 (1.70)	-13.1 (1.29)***	-3.89 (3.22)	2.73 (1.72)	-13.6 (1.24)***	3.59 (1.75)**
ASUEq=6	-9.83 (1.08)***	3.68 (1.90)*	-13.8 (1.42)***	-5.67 (3.55)	3.76 (1.93)*	-14.4 (1.38)***	4.72 (1.95)**
ASUEq=7	-10.7 (1.16)***	4.67 (2.12)**	-14.6 (1.56)***	-7.45 (3.89)*	4.80 (2.14)**	-15.3 (1.52)***	5.84 (2.17)***
ASUEq=8	-11.5 (1.25)***	5.66 (2.34)**	-15.3 (1.72)***	-9.23 (4.26)**	5.83 (2.37)**	-16.2 (1.66)***	6.96 (2.39)***
ASUEq=9	-12.4 (1.34)***	6.65 (2.57)***	-16.0 (1.87)***	-11.0 (4.64)**	6.86 (2.60)***	-17.0 (1.81)***	8.09 (2.62)***
ASUEq=10	-13.3 (1.44)***	7.64 (2.81)***	-16.7 (2.03)***	-12.8 (5.03)**	7.90 (2.84)***	-17.9 (1.97)***	9.21 (2.86)***

11 Appendix 3. Derivation of estimate for economic significance of abnormal volume

The estimate is built on the assumption that the difference between $\ln(P \cdot VOL + 1)$ and $\ln(P \cdot VOL)$ will be negligible for most firm-dates and that the pre-announcement "normal" volume is constant with respect to *VIX*$_T$.

Assuming that the pre-announcement volume $\frac{1}{21}\sum_{\mathrm{t=T-31}}^{\mathrm{T-11}} \ln\left(P_{i,t}VOL_{i,t} + 1\right)$ is constant with respect to VIX_T, the estimated total effect $\widehat{\alpha_2} + \widehat{\alpha_3} \cdot ASUEq$ can be interpreted as the semielasticity of the average dollar volume during the drift period with respect to VIX. Using these assumptions and the additive property of derivatives, we can write that

$$\frac{\partial ABVOL\,1}{\partial VIX_T} \approx \partial \frac{1}{2}\sum_{t=T}^{T+1} \ln(P_tVOL_t) \Big/ \partial VIX_T = \frac{1}{2}\sum_{t=T}^{T+1} \frac{\partial \ln(P_tVOL_t)}{\partial VIX_T} = \frac{1}{2}\sum_{t=T}^{T+1} \frac{\partial P_tVOL_t}{P_tVOL_t} \Big/ \partial VIX_T \tag{12a}$$

Similarly for *ABVOL60*:

$$\frac{\partial ABVOL\,60}{\partial VIX_T} \approx \partial \frac{1}{60}\sum_{t=T+2}^{T+61} \ln(P_tVOL_t) \Big/ \partial VIX_T = \frac{1}{60}\sum_{t=T+2}^{T+61} \frac{\partial \ln(P_tVOL_t)}{\partial VIX_T} = \frac{1}{60}\sum_{t=T+2}^{T+61} \frac{\partial P_tVOL_t}{P_tVOL_t} \Big/ \partial VIX_T \tag{12b}$$