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The Effect of Security and Market Order Flow Shocks on Co-movement

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ABSTRACT

In this paper we apply the smooth transition conditional correlation model to examine the impact that shocks to order flow imbalance have on stock market co-movement. We show that positive and negative shocks to security order flow reduce co-movement. Market order flow shocks have only a small impact on post shock correlations. Our results suggest that investors can increase diversification opportunities when forming dynamic portfolio strategies if they take account of security order flow information. We show that pre-shock firm characteristics allow investors to identify those stocks with the greatest diversification benefits.

Keywords: Order flow shock, co-movement, smooth transition model
JEL: G12, G14

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Highlights

In this paper we apply the smooth transition conditional correlation model to examine the impact that shocks to order flow imbalance have on stock market co-movement.

We find that positive and negative shocks to security order flow reduce co-movement.

When firms face net buying pressure positive shocks that raise net buying pressure lead to larger correlation reductions than negative shocks which raise net selling pressure. However, when firms face net selling pressure negative shocks lead to greater reductions in correlation than positive shocks.

Security level order flow shocks reduce correlations more for non S&P 500 constituents than for S&P 500 constituents.

Market order flow shocks have only a small impact on post shock correlations.

Our results suggest that investors can increase diversification opportunities when forming dynamic portfolio strategies if they take account of order flow information.

We find that sorting first by pre-shock correlation with the market and then by illiquidity provides opportunities for the largest post shock reduction in correlation.

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ABSTRACT

In this paper we apply the smooth transition conditional correlation model to examine the impact that shocks to order flow imbalance have on stock market co-movement. We show that positive and negative shocks to security order flow reduce co-movement. Market order flow shocks have only a small impact on post shock correlations. Our results suggest that investors can increase diversification opportunities when forming dynamic portfolio strategies if they take account of security order flow information. We show that pre-shock firm characteristics allow investors to identify those stocks with the greatest diversification benefits.

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The Effect of Security and Market Order Flow Shocks on Co-movement[1]

1. Introduction

This paper examines the effects that a shock to order flow imbalance has on co-movement. We are motivated to undertake this study because there is strong evidence that order flow and trading activity affects returns but the relationship between order flow shocks and co-movement has not previously been examined. This is an important issue to study as correlations between securities are believed to be at a high historically due to record usage of derivatives and exchange traded funds. A consequence of high market co-movement is that diversification becomes increasingly difficult leading to an elevated cost of capital for firms. Understanding better the link between order flow and co-movement is therefore important for portfolio selection strategies and may offer a route to achieving greater diversification benefits from portfolios.

To capture the effects of order flow shocks on return co-movement we utilize the framework of a GARCH smooth transition conditional correlation model. The main advantage of the model is that shocks to order flow are determined endogenously. This overcomes the problems associated with exogenously determined shocks noted by Boyer et al (2008) and Forbes and Rigobon (2002).[2] Another advantage of the model is its ability to capture non-linearities which allow the relationship between correlations and positive and negative shocks to be examined. This feature is important because Hong and Stein (1999), Vuolteenaho (2002), Chan (2003) and Kothari, Lewellen, and Warner (2006) have all found that investors respond

[1] We would like to acknowledge an outstanding contribution made by the referee of this paper whose detailed discussions and analysis has enabled us to enhance the paper significantly.
[2] These include which sample periods to use in estimation, bias due to heteroscedasticity and selection bias.

asymmetrically to good and bad news. The model also allows responses to be time varying.

Order flow information is believed to exert a strong influence over stock returns because it projects new information to the market, see for example Evans and Lyons (2002) or Underwood (2008). Kyle's (1985) model shows how order flow can contain private information and have a permanent impact on prices. Easley, Kiefer, O'Hara and Paperman (1996), and Easley, Kiefer and O'Hara (1997) also highlighted the positive connection between private information and trading pressure. A link between prices and order flow is also predicted from inventory models. Stoll (1978) and Ho and Stoll (1983) for example, show that order imbalances cause inventory adjustments that require dealers to adjust prices.

Order flow has been shown to have both a firm specific and a market wide component. Commonality in trading activity has been established by Chordia, Roll and Subrahmanyam (2002) and Huberman and Halka (2001) who show that security liquidity is correlated with both market and industry level liquidity[3]. Hasbrouck and Seppi (2001) use a principal components model to extract common components from order flow information and show that these are correlated with market returns but firm level returns are primarily influenced by their own order flow. Chordia et al (2001) show that security order imbalances are associated with changes in the market return for securities trading within the S&P 500. While Chordia and Subrahmanyam (2004) has shown that daily security returns are also influenced by security level order imbalances and provide a theoretical model in support of such a relationship. Harford

[3] Longer horizon volume has also been shown to display common effects by Tkac (1999) and by Lo and Wang (2000).

and Kaul (2005) show that commonality of order flow is stronger for S&P 500 listed securities than for those trading outside the index.

A primary difference between our paper and previous studies of order flow imbalances is that our analysis is concerned with the impact of *shocks* to order flow imbalance on stock market *correlation* rather than the study of order flow imbalance on stock returns. Our paper therefore extends the growing literature on the effects of order imbalance on stock returns but in a pioneering way. We augment the Berben and Jansen (2005) GARCH smooth transition time varying correlation model to allow for shocks in order flow. This enables us to capture the return correlation between stock returns and the market portfolio, in response to order flow shocks. The advantage of this framework is that order flow shocks are identified endogenously and characterize the transition path to the new regime in terms of its smoothness and avoids a self-selection bias when estimating the relationship between order flow shocks and co-movement. Moreover, the relationship between order flow shocks and co-movement is estimated without the need to rely on an equilibrium framework.

We estimate the smooth transition model for all NYSE/AMEX ordinary common stocks listed on the CRSP/COMPUSTAT merged database which also have intraday quote and transaction information on TAQ during the period January 1993 to December 2011[4]. Shleifer (1986) noted that S&P 500 constituents experience higher buying pressure while Harford and Kaul (2005) show that order flow commonality increases substantially when securities are indexed. Encouraged by these findings that suggest indexing can alter the relationship between order flow imbalance and return

[4] We begin in 1993 as transaction by transaction information provided by TAQ begins in this year.

correlation we partition the results for S&P 500 and non S&P 500 constituents. Motivated by the literature that shows that both security and market level order flow can influence stock returns (therefore possibly co-movement) we examine the effect of shocks to security level order flow and shocks to market aggregate order flow separately.

Roll (1988) showed that in a frictionless market the higher the ratio of market-wide information to firm specific information the higher the level of co-movement between stocks will be. This suggests that if order flow contains firm specific information a shock will lead to a reduction in correlation between the security return and the market return. Correlation is reduced because the security return variation contains a higher individual security component triggered by the firm specific information within the order flow shock. If part of an order flow shock is also experienced by firms in general the shock will also contain a market-wide component. The presence of a market-wide component in the order flow increases the influence of market returns offsetting the negative change in correlation resulting from the security specific component of the order flow shock. If the market-wide effect of the order flow shock dominates, the effect of an order flow shock will be to raise correlation between the security and the market.

The results from our analysis suggest a range of new findings. We show that positive security order flow shocks that raise net buying pressure and negative security order flow shocks that increase net selling pressure reduce average correlations. This is important as it suggests that order flow information can be used to enhance diversification opportunities because order flow shocks reduce co-movement.

However, market order flow shocks have little impact on co-movement when they raise net buying pressure or when they raise net selling pressure. We also show that the characteristics of firms can influence the extent to which co-movement alters in response to an order flow shock.

When firms are characterised by net buying pressure positive security order flow shocks lead to larger changes in correlation than when firms are subject to net selling pressure. But when firms are subject to net selling pressure, positive security order flow shocks lead to smaller decreases in correlation than negative shocks. An examination of S&P 500 constituents and non-constituents shows that security order flow shocks reduce correlations by more on average for non-members than for members. For S&P and non S&P securities positive security order flow shocks reduce correlations by more than negative shocks. Although, non S&P firms have larger post shock changes in correlation following a positive security order flow shock the difference between the effect of positive and negative shocks on co-movement is larger for S&P 500. When firms are grouped by the industry they belong to we find that the industry has a strong influence over the size of pre and post shock correlations suggesting that there are strong industry specific common factors driving co-movement.

Our examination of positive and negative *market* order flow shocks indicates that shocks to market order flow have a weak impact on post shock correlations. Whether firms are subject to buying or net selling pressure tends to increase the change in correlations slightly for both S&P and non S&P firms. These results suggest that changes in co-movement due to order flow shocks stem from security order flow changes not market ones.

We also examine the characteristics that might be able to explain the size of the correlation changes we have identified and find that friction, habitat, liquidity and information asymmetry all affect the post shock change in correlations although there are some differences between firms with positive and negative shocks. In addition to these broad features the pre shock level of correlation is also important. After allowing for firm characteristics differences between S&P and non S&P firms disappear indicating it is the characteristics of the firms rather than membership per se that accounts for the diverse responses to order flow shocks.

Our results make an important contribution and show that shocks to security level order flow are important because they reduce correlation between securities. Our conclusion therefore is that security order flow analysis should be an important component of dynamic portfolio diversification strategies. Order flow shocks lead to greater reductions in co-movement for portfolios comprising of non S&P 500 firms. However, knowledge of order flow shocks may be extremely useful for investors with portfolios containing S&P 500 securities because these securities are typically characterized by extremely high levels of correlation. The remainder of this paper is set out as follows. Section 2 describes the smooth transition model methodology. Section 3 explains the data we use in this study. Section 4 provides the results, Section 5 contains some robustness tests. Section 6 provides a summary and conclusion to the paper.

2. Smooth Transition Model

In this section we introduce the bi-variate GARCH model with time-varying correlations proposed by Berben and Jansen (2005) and Silvennoinen and Teräsvirta (2005), which allows us to test and model the time-varying behavior of stock return correlations.[5]

Consider a bi-variate time series of stock returns $\{y_t\}$, $t = 1, \ldots, n$, $y_t = (y_{1,t}, y_{2,t})'$, the stochastic properties of which are assumed to be described by the following model

$$y_t = \mu_{t-1} + \phi_1 HML_t + \phi_2 SMB_t + \varepsilon_t \, , \tag{1}$$

$$\mu_{t-1} = E[y_t \mid \Psi_{t-1}] \, , \tag{2}$$

where $y_{1,t}$ denotes the returns of firm *i* and $y_{2,t}$ the market returns. HML and SMB are Fama and French (1993) risk factors. In order to capture any temporal effects in the error volatilities and correlations, the error process of (1) is assumed to follow the process

$$\varepsilon_t \mid \Psi_t \sim N(0, H_t) \tag{3}$$

where Ψ_{t-1} is the information set consisting of all relevant information up to and including time $t-1$, and N denotes the bivariate normal distribution. The conditional covariance matrix of ε_t, H_t, is assumed to follow a time-varying structure given by

$$H_t = E[\varepsilon_t \varepsilon_t' \mid \Psi_{t-1}] \tag{4}$$

$$h_{11t} = w_1 + \alpha_1 \varepsilon_{1,t-1}^2 + \beta_1 h_{11,t-1} \tag{5}$$

$$h_{22t} = w_2 + \alpha_2 \varepsilon_{2,t-1}^2 + \beta_2 h_{22,t-1} \tag{6}$$

[5] Similar models (that capture possible regime switches) have been used in the context of stock market integration (Kearney and Poti, 2006; Silvennoinen and Teräsvirta, 2009; Savva, 2011), business cycles synchronization (Savva et al, 2010) and various macroeconomic relationships (Kapetanios and Tzavalis, 2010; Koop and Potter, 2007; Li, Philippopoulos and Tzavalis, 2000; among others). The test indicates that a firm may experience one or more double smooth transition shocks but does not specify the number.

$$h_{12,t} = \rho_t(h_{11,t}h_{22,t})^{1/2}, \quad (7)$$

$$\rho_t = \rho_0(1-G(s_t;\gamma,c)) + \rho_1 G(s_t;\gamma,c), \quad (8)$$

where we assume that the conditional variances $h_{11,t}$ and $h_{22,t}$ both follow a GARCH(1,1) specification. Our choice is motivated by the empirical literature that has found that this specification adequately captures persistence of stock return second moments.[6]

Equation (8) denotes the contemporaneous conditional correlations (ρ_t) which are assumed to change smoothly over time depending on a transition variable. In our application the conditional correlation coefficient is between the return of stock *i* and the return of the market. The advantage of measuring co-movement in this way is that we can estimate the model simultaneously for all stocks without loss of information rather than by estimating the model *n x n-1*.

To capture temporal changes in ρ_t we follow Berben and Jansen (2005) and Silvennoinen and Teräsvirta (2005) by letting $G(s_t;\gamma,c)$ be the logistic function

$$G(s_t;\gamma,c) = \frac{1}{1+\exp(-\gamma(s_t - c))}, \qquad \gamma > 0, \quad (9)$$

where s_t is the transition variable, in our case the lag values of the percentage change in order flow imbalance is the transition variable. Parameters γ and c determine the smoothness and location, respectively, of the transition between the two correlation

[6] The sizes of α and β, determine the short and long run dynamics of the resulting volatility series, respectively. Large β coefficients indicate that shocks to conditional variance take a long time to die out, implying persistent volatility. Large α parameters indicate that volatility reacts quite intensively to new information. Consequently, if α is large (and significant) and β is small, this means the volatility process is characterized by spikes.

regimes.[7] The starting values of γ and c are determined by a grid search and are estimated in one step by maximizing the likelihood function.

The resulting Smooth Transition Conditional Correlation (STCC) GARCH model is able to capture a wide variety of patterns of change. ρ_0 and ρ_1 represent the two extreme states of correlation between which the conditional correlations can vary over time according to the transition variable s_t. Differing ρ_0 and ρ_1 imply that the correlations increase ($\rho_0 < \rho_1$) or decrease ($\rho_0 > \rho_1$), with the pace of change determined by the slope parameter γ. This change is abrupt for large γ, and becomes a step function as $\gamma \rightarrow \infty$, with more gradual change represented by smaller values of this parameter. Parameter c defines the location of the transition (i.e. the percentage change in the buy-sell ratio our measure of order flow). This is the order flow *threshold* used in this study to identify shocks. It is determined endogenously by the model for each firm using the daily time-series data. The model uses all-time series data of the firm to determine the percentage change in the order flow (our threshold) where the correlation between firm stock returns and market portfolio exhibits substantial change.[8]

In this paper we utilize two measures of order flow. The first captures security specific order flow changes and is measured as the daily ratio of buyer initiated trades to seller initiated trades for each firm. Our market measure of order flow is the cross-sectional average of daily buyer initiated trades to seller initiated trades, calculated using all firms in the sample[9]. For each firm, when the percentage change in daily

[7] The transition function $G(s_t; \gamma, c)$ is bounded between zero and one, so that, provided there are valid correlations lying between -1 and +1, the conditional correlation ρ_t will also lie between −1 and +1.
[8] Whether this change is statistically significant, is determined by the model (Eqs. 1-10).
[9] When calculating the market buy-sell ratio we give equal weight to each firm's buy-sell ratio. We experimented with a value weighting and found that shocks lead to small negative changes in correlation. This was due to the individual firms having greater weight. However, even with value weighs we find that market shocks have a much smaller impact on correlation changes.

security or market order flow is less (greater) than the corresponding threshold (parameter c), the correlation between the return of stock *i* and the market return is closer to the state defined by ρ_0 (ρ_1) for this day. Accordingly, by comparing the percentage change in order flow imbalance each day with the corresponding threshold of the firm we determine the firm's daily correlation for the whole period. The constant conditional correlation model (Bollerslev, 1990) is a special case of the STCC-GARCH model, obtained by setting either $\rho_0 = \rho_1$ or $\gamma = 0$.

Prior to employing the STCC specification, a Lagrange Multiplier (LM) test against a constant conditional correlation model (Berben and Jansen, 2005, Silvennoinen and Teräsvirta, 2005) is estimated. Since the constant correlation null hypothesis is almost always rejected, STCC models are estimated for all firms with the market index using the percentage change in daily order flow (or market order flow) as a transition variable.[10] In addition to the above, we examine whether a second transition (in correlations) exists by performing the LM test developed by Silvennoinen and Teräsvirta (2009).[11] If such evidence is found, then we extend the original STCC-GARCH model to the Double Smooth Transition Conditional Correlation (DSTCC-GARCH) model by allowing the conditional correlations to vary according to two transition variables allowing each where each transition function has the logistic form of equation (9).

The second transition variable is also the percentage change in order flow, and hence allows for the possibility of a non-monotonic change in correlation over the sample. The pre and post shock parameters are interpreted in the same manner as for the STCC-GARCH model, but to ensure identification we require the second shock to be

[10] Individual results for each combination are available from authors upon request.
[11] See Silvennoinen and Teräsvirta (2009) for more details on that test.

larger than the first shock so that the two correlation transitions occur at different levels of order flow imbalance. Estimates are obtained simultaneously by maximizing the log-likelihood function of a bivariate GARCH model (ignoring the constant term and assuming normality):

$$l_t(\theta_t) = -\frac{1}{2}\ln|H_t| - \frac{1}{2}\varepsilon_t{}' H_t \varepsilon_t, \tag{10}$$

where θ is the vector of all the parameters to be estimated. The log-likelihood for the whole sample from time 1 to n, $L(\theta)$, is given by

$$L(\theta) = \sum_{t=1}^{n} lt(\theta) \tag{11}$$

To allow for potential non-normality of $\varepsilon_t | \psi_{t-1}$, robust "sandwich" standard errors (Bollerslev and Wooldridge, 1992) are used for the estimated coefficients.

In addition to the LM test suggested by Silvennoinen and Terasvirta (2009) we have applied the misspecification (diagnostic) tests suggested by Eitrheim and Terasvirta (1996) on our model.[12] These tests (such as testing for serial correlation, remaining nonlinearity, parameter constancy) suggest that our specification is appropriate and motivates further analysis.

3. Data and Summary Statistics

The data used in this sample comprises of all NYSE/AMEX ordinary common stocks listed on the CRSP/COMPUSTAT merged database between the period January 1993 to December 2011.[13] We do not examine NASDAQ stocks due to the difficulty in

[12] See Franses and van Dick (2000, p. 108-115) for more details on these tests.
[13] We begin in 1993 to coincide with availability of data on the TAQ database. Ordinary common stocks are identified using the CRSP share codes 10 and 11. This sample reflects a much longer sample than is usually studied by work that examines the influence of order flow.

assigning trades as noted by Christie and Schultz (1999). From CRSP/COMPUSTAT, we extract daily security price and shares outstanding information along with value weighted market returns.

We use the TAQ database to obtain tick-by-tick data for the NYSE/AMEX stocks. This includes quotes, transaction prices and trade quantities associated with each trade undertaken. We infer whether trades are buyer or seller initiated by applying the Lee and Ready (1991) algorithm which Lee and Radhakrishna (2000) have shown to be highly accurate at separating buyer and seller initiated trades in equity markets. This algorithm has been used extensively in previous studies to capture order flow information, see for example Chordia et al (2002), Barberis et al (2005), Harford and Kaul (2005) or Barber, Odean and Zhu (2008).

Application of the algorithm requires comparison of transaction price to the contemporaneous quote in the same stock to ascertain whether a buyer or seller initiated trade has taken place. The number of trades examined ranges from just over 300,000 in 1995 to over six million after 2005, representing a huge data analysis exercise. In cases where this trade-quote comparison can not be undertaken, the algorithm classifies buy trades as those that take place on an uptick and sells as those that take place on a downtick. Some trades such as those that take place at the opening auction cannot be classified. Using all intraday trades, we calculate the aggregate number of buyer initiated and seller initiated trades each day associated with each stock and create the security buy-sell ratio which is our measure of order flow imbalance. The market buy-sell ratio is a measure of aggregate imbalance and is the cross-sectional average of daily buyer initiated to seller initiated trades obtained from all available firms[14].

A value above (below) unity on day *t* arises when buyer initiated (seller initiated) trades exceed seller initiated (buyer initiated) trades giving rise to net buying (selling) pressure. We examine separately the effect of order flow shocks on firms with net buying pressure (buy-sell ratio >1) on that day and net selling pressure (buy-sell ratio <1) on that day separately. Positive shocks to order flow raise the buy-sell ratio (increase net buying pressure) while negative shocks reduce the buy-sell ratio (raise net selling pressure).

The number of firms vary each year as firms are listed/delisted or move between other exchanges. The average number of firms used each year is 1720; the minimum number being 748 and the maximum 2030, in all information on over 7,000 companies is used over the sample period being studied. From our analysis we exclude any firm that has less than 100 days of trading in a calendar year. Firms that are listed for less than 100 days, are transferred to another exchange, have suspended trading or exhibit high levels of thin trading are therefore excluded from the sample[15]. A small number are also excluded because we can not achieve convergence of the model(average of ten per year). From the smooth transition model we collect the correlations in each regime and the corresponding threshold of each firm. We use this

[14] The number of firms from which we calculate the market is therefore the same number in total as available for the security specific analysis.
[15] The number of firms is determined by the number that both exist on CRSP and TAQ with more than 100 days trading activity in a year. In the early years of our sample there are many less companies listed on TAQ and CRSP which is why the minimum number of firms is small relative to the maximum number.Moreover, the effects of thin trading on the sample lead to a much higher level of exclusions during the early period because thin trading has diminished over time. Motivated by the filters employed by Chordia and Subrahmanyam (2004) we also experimented with a range of additional filters by excluding high priced stocks, and stock splits but did not find our results to be sensitive to these exclusions, for brevity we do not report these results. We did not have an economic argument to exclude firms with dividends, share repurchases, reverse splits, stock splits etc as these events contain information just as other news events do.

information to identify those daily firm observations where the change in the buy-sell ratio is greater than the corresponding threshold of each firm (shocks).

Shleifer (1986) discovered that significant abnormal returns accrue to new S&P 500 constituents, see also Chen et al (2004) and Dennis et al (2003). Beneish and Whaley (1996, 2002) have documented that the size of this premium has been growing over time, increasing from 2.79% in the period 1976-1983 to 8% in the period 1996-2001. Vijh (1994) and Barberis et al (2005) have shown that inclusion in the S&P raises co-movement because market betas increase for securities admitted to the S&P. The "traditional" explanation for higher co-movement between S&P constituents is that greater return co-movement reflects greater synchronicity of fundamentals. See for example, Edminster et al (1994) who find that new S&P constituents exhibit rising prices in the two years prior to membership. Behavioral theories have also been developed to explain higher levels of co-movement between S&P securities. Barberis and Shleifer (2003) and Barberis, Shleifer and Wurgler (2005) suggest a sentiment view of co-movement in which a common factor drives S&P constituent returns. This happens because investors treat S&P securities as a category or style of investment in their own right allocating investment funds by category, rather than by security. Sentiment can also influence co-movement if investors trade within their preferred habitat rather than making stock selections across all available stocks. As investor risk aversion, sentiment or liquidity change investors alter their exposure to securities in their habitat and introduce a common factor to returns. Motivated by these findings we analyze S&P and non S&P securities separately. Since the industrial sector may influence the results we also examine the smooth transition model for groups of firms segregated by industrial classification (SIC)[16].

We also obtain information on a range of firm characteristics that may have an influence on co-movement. These can be broadly organized into four groups representing friction, liquidity, habitat and information asymmetry. Roll (1988) showed that co-movement between stocks will be low when there is little price friction because in an efficient market price changes will be driven primarily by firm specific news, lower friction therefore reduces co-movement. To capture friction we calculate RHO, the one period serial correlation coefficient of each firm. Higher levels of positive serial correlation indicate that observed returns persist while negative serial correlation captures short term return reversals. We include C-lag, the one period cross autocorrelation coefficient between firm and market returns. This captures the speed and amount of information diffusion from market to security. Hutton et al (2009), Jin and Myers (2006) and Wurgler (2000) all show that less synchronicity is consistent with more firm specific information and greater price efficiency. Higher cross autocorrelations are consistent with more market information being reflected at a security level with a lag and therefore can indicate a higher level of inefficiency[17].

We also examine a range of variables related to liquidity. The daily effective spread (SPREAD) is important as higher spreads drive a wedge between intrinsic and observed prices. In response to Chelley-Steeley et al (2013) who show that liquidity

[16] We use the Fama and French 10-industry classification available in their website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.
[17] Although this measure will also capture the extent to which firms are influenced by market returns so that firms with more market information will have higher one lag correlations.

shocks lead to changes in correlation we also include ill, the Amihud (2002) illiquidity ratio, calculated from the ratio of daily absolute returns to volume, scaled by the market ratio. We also include daily volume (VOL) and the number of trades (NT) as alternative measures of liquidity as more trading activity improves the quality of price information.

The effect of frictions on co-movement may be ambiguous since, Barberis, Shleifer and Wurgler (2005) show that friction can have a positive effect on co-movement. They argue that noise traders with correlated sentiment can adjust portfolios in a coordinated way introducing a common factor, unrelated to fundamentals, increasing co-movement (see also Barberis and Shleifer, 2003). Moreover, some assets exist in a preferred habitat, as investors sentiment or liquidity needs change, a common factor is introduced between asset returns. We incorporate two types of variables to capture sentiment. The first category is based on firm characteristics, the second on retail trading activity. We include SIZE, the mean of the July logarithm of market value, size was identified previously as an important habitat for investors, see for example Barberis et al (2005). We also include b/m the book to market ratio of firms as a possible habitat characteristic along with security price (P).

A range of studies have shown that retail investors earn lower returns than institutional investors and are more likely to follow sentiment while institutional investors are more likely to undertake informed trading. For example, Odean (1999) shows that stocks bought by individual investors underperform stocks by institutional investors by as much as 23 basis points. Moreover, Barber, Odean and Zhu (2008) show that order imbalances of individual traders are highly correlated and indicative of herding.

We therefore separate retail and institutional trades by using the Lee and Radhakrishna (2000) algorithm which assigns trades below \$5,000 as retail and those above \$50,000 as institutional. These cut offs have been shown by Lee and Radhakrishna (2000) to be accurate enough not to cause miss-assignment problems while Barber et al (2008) has shown that small trade order imbalance is strongly correlated with trade imbalance arising from retail brokers. Using this information we calculate the buy-sell ratio for retail and institutional trades. Retail imbalances are likely to reflect sentiment while the institutional ratio will reflect information asymmetries related to informed trading. To capture frictions stemming from information asymmetry we also include the number of analysts following a security obtained from I/B/E/S. Arbel and Strebel (1982) show that firms with less analyst following are more likely to be underpriced while Piotroski and Roulstone (2004) show that greater analyst following is associated with a more rapid transmission of industry and market information which leads to greater synchronicity of returns. Spread will also reflect to some extent information asymmetries which cause the adverse selection component of the effective spread to increase.

We also include information on the average return of securities in the pre-shock period (R) and the correlation of a security with the market RSQ. RSQ is the R^2 from an asset pricing regression containing $beta_{rm}$, $beta_{HML}$ and $beta_{SMB}$ which according to Barberis et al (2005) is a useful co-movement indicator. C-cor is the correlation between the security buy-sell ratio and the buy-sell ratio of the market. We report pre shock summary statistics along with non-shock averages in Table 1 for each of these variables reporting separately for S&P and non S&P firms and for firms that face net buying and net selling pressure. Comparisons of pre shock averages and non-shock sample averages will indicate whether characteristics are elevated or depressed prior to a shock.

Table 1 provides pre shock and non-shock averages of the firm characteristics for single shock firms (firms with at least one smooth transition shock) along with non-shock values for firms in the double smooth transition sample (firms with at least one double smooth transition shock). The results suggest that there is heterogeneity in the characteristics of firms within the different samples. S&P firms are larger, more liquid (lower spreads, illiquidity ratios, higher volume and a greater number of trades). S&P firms also display less information asymmetry, average institutional order imbalances are lower[18], firms on average have greater analyst following than non S&P firms and are more highly correlated with the market. We also find that S&P firms display less friction as average values of RHO are smaller[19]. Firms with buy-sell ratios > 1 are on average larger, have higher book to market ratios, are characterized by more liquidity, less friction, larger institutional and retail order imbalances, higher prices and greater co-movement with the market than firms with buy-sell ratios <1.

The distinguishing characteristics of double shock firms is that they tend to have lower prices, higher returns, are larger in size with higher book to market ratios, higher levels of institutional imbalances but lower retail imbalances have larger

[18] We would expect order imbalances to be smaller for S&P firms because there will be more information available for these stocks leading to lower levels of information asymmetry. Information asymmetry is likely to be an important determinant of order flow imbalance due to the actions of informed traders.
[19] We find that C-lag is higher for S&P firms and believe that C-lag reflects the strength of correlation with the market more than inefficiency due to delayed price reactions.

spreads and illiquidity ratios but higher volume and more trades per day. The characteristics of the market comprise of all shock and non-shock firms as the firms used to calculate the market order flow are all firms listed on CRSP-COMPUSTAT. Since there are many more firm months without shocks than with shocks average characteristics of firms prior to a market shock are almost the same as the averages of non-shock firms.

Comparisons of pre shock to non-shock characteristic values indicates that prior to a shock liquidity tends to be lower than at other times as the spread and illiquidity ratio are higher while volume and number of trades are lower in the pre shock period. We also find that the pre shock return of firms is lower than during non-shock periods and firms appear to be less influenced by the market as RSQ is lower for pre shock firms. We can not determine conclusively whether information asymmetry is higher in the pre shock period. The spread is higher which is consistent with a rise in the adverse selection component but the average order imbalance of institutional traders is lower than during non-shock periods which is not consistent with a rise in informed trading. We also examine the size of institutional order flow as a proportion of all order flow at the time of a positive (negative) shock and find that institutional order flow represents 23% (21%) of all order flow, larger shocks are associated with a larger proportion of institutional order flow while smaller shocks are associated with a lower proportion which suggests that there may higher levels of informed trading taking place. [20] There is a rise in the average imbalance of individual traders in the pre shock period which suggests that there may be a rise in sentiment motivated trading.

[20] We divide shocks into three groups based on the size of the shock. For the smallest shocks institutional order flow is 24% for positive shocks and 15% for negative shocks rising to 24% for positive shocks and 26% for negative shocks when shocks are in the largest group.

We also analyse the characteristics of positive and negative shock firms separately. For brevity we do not report these results but find that positive shock firms are on average larger, have a higher analyst following, have higher prices and higher pre shock returns when compared to negative shock firms. We find that both retail and institutional imbalances are slightly larger for positive shock firms although the average pre shock imbalance between buy and sell orders is not different for positive and negative shock firms. This suggests overall that positive shock firms are less neglected than negative shock firms.

Negative shock firms are characterized by a higher number of trades although positive shock firms experience slightly more volume. This suggests that trades in positive shock firms are on average larger and have larger price impacts because the average illiquidity ratio is higher for these firms. When we examine friction levels in positive and negative shock firms we find that RHO is more negative for positive shock firms indicating a higher level of friction through higher levels of return reversals.

In Figure 1 we trace out the average positive and negative shocks to order flow imbalance during the sample period and shows that average positive and negative shocks declined very slightly until 2000. Decimalization and high frequency trading appears to have had little impact on the size of order flow shocks. However, the financial crisis beginning in 2007 appears to have led to an increase in the average shock. Larger shocks during this period are consistent with Adrian and Shin (2009) who find evidence of higher trading activity during the crisis and Anand et al (2013) who find evidence of significant portfolio rebalancing during the recent financial crisis.

4. Empirical Results

4.1 Security Specific Results

In Table 2 we present the conditional correlations obtained prior and subsequent to an order flow shock. On average the mean correlation of all NYSE/AMEX stocks prior to a positive security shock is 0.2979 and 0.2844 prior to a negative shock indicating that firms experiencing positive and negative order flow shocks display on average similar levels of co-movement. The impact of positive and negative order flow shocks are not symmetrical. Positive shocks lead to a 20.98% reduction in average correlation while negative shocks reduce average correlation by 14.77%. This difference is also reflected in the proportions of securities that experience a rise or fall in correlation after a shock. Following a positive shock 74.7% of firms experience a reduction in correlation, following a negative shock only 65.4% of firms experience a negative change in correlation. These patterns suggest that good news leads to more firm specific variation in returns than bad news which causes a greater reduction in co-movement.

Whether a firm is subject to net buying or net selling pressure also influences the pattern of results[21]. When securities are characterized by net buying pressure (buy-sell ratio >1) both positive and negative order flow shocks reduce correlation but positive shocks have the greatest impact. However, when firms are subject to net selling pressure (buy-sell ratio <1) this asymmetry is reversed as on average positive shocks reduce average correlations by less than negative shocks (correlations fall by 6.89% for positive shocks and by 14.03% for negative shocks). This suggests that when

[21] Net buying (selling) are those firm-day observations with daily buy/sell ratio higher (lower) than one.

firms face buying pressure, positive order flow shocks contain more security information than negative order flow shocks. But for firms facing net selling pressure, positive order flow shocks contain less security specific information than negative shocks.

An explanation for this asymmetry is that increases in buying pressure contain more security relevant news than increases in selling pressure. Previously Gemmill (1996), Keim and Madhavan (1996) and Conrad et al (2001) have shown that prices go up following increased buys but do not fall as much after increased sales. Chan and Lakonishok (1997) suggest that this asymmetry arises because when investors sell it does not necessarily convey negative information as their reason for selling may be liquidity motivated. However, when an investor buys they are discriminating between all other stocks they could buy in favor of specific ones so even if their buying is liquidity motivated it is a more positive selective choice than the decision to sell and therefore conveys more information to the market.

Motivated by these findings we sort firms into three additional groups based on the size of the shock to the buy-sell ratio. Small contains firms with the smallest shock while Large contains firms with the greatest. We provide results for each of these three divisions in Panel B of Table 2. This table shows that larger shocks lead to monotonically larger increases in correlations for negative shocks, especially for firms with a buy-sell ratio > 1. For positive shocks bigger imbalances do lead to larger shocks but differences between medium and large shocks are small and not monotonically defined.

The higher co-movement of S&P 500 firms is evident in Panel C as prior to a positive (negative) shock the average correlation for S&P members is 0.4037(0.4042) but for non-members 0.2810(0.2707). We find that positive order flow shocks reduce average correlations for both S&P and non S&P constituents by a broadly similar magnitude. However, negative shocks have less impact on S&P constituents than on non-constituents. This suggests that S&P membership is much less important for positive shocks than for negative shocks suggesting that negative news of the order flow shock has less security specific information for S&P constituents. This suggests that when the negative news of a rise in selling pressure is experienced by an S&P firm other S&P firms also face a rise in selling pressure at the same time which increases the common element in returns causing a weaker reduction in correlation after the shock. However, for non S&P firms a negative shock is less universally experienced by firms so contains a weaker common element which causes the shock to have a stronger impact on correlation than for S&P firms.

An examination of firms characterized by net buying pressure reveals that positive shocks reduce average correlations for both S&P and non S&P firms However, a negative shock leads to much larger correlation reductions for non S&P firms than for S&P firms. When firms are subject to net selling pressure positive order flow shocks reduce average correlations by less than when firms are subject to net buying pressure, a feature that is especially strong for S&P firms.

In Figure 2 we show the conditional correlation of each security plotted against the percentage shock to the buy-sell ratio. Panel A of Figure 2 provides the results for positive order flow shocks while Panel B provides the results for negative order flow shocks. The darker plots are the pre shock conditional correlation and the lighter line is the post shock conditional correlations. Panel A shows most shocks are between 0 and 100% of the buy-sell ratio, although some firms experience even larger shocks. As the size of the shock to the buy-sell ratio increases the conditional correlation tends to decrease, a pattern that also emerges for negative shocks in Panel B. In Figure 3 we plot the relationship between the average conditional correlation and the percentage change in the buy-sell ratio for positive and negative order flow shocks respectively. Panel A shows that the average pre shock correlation is approximately 0.3 prior to a positive order flow shock but about 0.24 afterwards, when the shock to the buy-sell ratio is in the range of 40-50%, providing a relatively steep transition function. Panel B shows that prior to a negative shock average correlations are just above 0.28 but fall to almost 0.24 afterwards when shocks are in the range 35-55% of the buy-sell ratio.

4.2 *Security Specific Results by Industry*

Table 3 contains the correlation results for firms segregated by industry and show that average co-movement and the impact of an order flow shock is related to the industry securities belong to. Utility, Manufacturing and Other firms have the highest pre shock correlation while Health firms have the lowest pre shock correlation. Across all firms positive shocks tend to lead to a greater average decline in correlations than negative shocks but there are also noticeable differences dependent on the industry[22].

4.3 Market Wide Order Flow Shocks

[22] In analysis not presented for brevity we also find that S&P constituents segregated by industry experience in general larger changes in correlation following a positive order flow shock than a negative order flow shock. We also find that positive shocks lead to larger average reductions in correlation for non S&P firms, although precise patterns depend upon the industry.

In this section we will consider the impact of market order flow shocks on correlation. Table 4 Panel A, B and C contains the results for all firms, S&P and non S&P constituents and for industry segregated firms respectively. Table 4 shows that pre shock correlations are lower than prior to security order flow shocks. This suggests that on average a market shock is more likely during periods of lower correlation than firm specific shocks or that firm security shocks influence firms with higher pre shock correlations more than market shocks. We find small almost symmetric impacts on correlation from positive and negative market order flow shocks that reduce average correlations slightly. Across all firms, positive shocks reduce mean correlation by 2.94% while negative shocks reduce mean correlation by 3.04%. This pattern is found to be consistent for S&P and non S&P firms, except that S&P firms have stronger negative correlations in response to negative shocks. Market shocks for firms segregated by industry lead to small negative changes in correlation. However, positive shocks lead to much larger changes in correlation and more variation across the industries. For the Non Durables sector a positive order flow shock leads to a 25% increase in correlation but for the Telecommunications industry there is a 20% fall in correlation.

Market shocks contain important information for the individual security as each security return has a theoretical relationship with the market return. As a market wide shock takes place each stock will respond by experiencing a corresponding change in returns to re-establish this relationship. If this response weakens the impact of market driven behavioral factors that strengthens co-movement then a reduction in correlation will be observed in the post shock period. These changes could lead to the reduction in some habitats (reducing correlations) while the reinforcement of others (raising correlations).

In Figure 4 we show the conditional correlation of each security plotted against the percentage shock to the market buy-sell ratio. Panel A and B shows that most market shocks are smaller than security shocks and as the size of the positive or negative shock to the market buy-sell ratio increases conditional correlation increases. In Figure 5 we plot the relationship between the average conditional correlation and the percentage change in the market buy-sell ratio for positive and negative order flow shocks respectively. Panel A shows that the average pre shock correlation is approximately 0.22 prior to a positive order flow shock but falls to about 0.215 following a shock, when the change in the buy-sell ratio is in the range 4-6% of the market buy-sell ratio. Panel B shows that prior to a negative shock average correlations are about 0.23 but almost 0.22 afterwards when shocks are in the range 5-6% of the market buy-sell ratio. Both panels A and B indicate much flatter transition functions than was evident for security shocks. We should anticipate smaller average shocks to the market buy-sell ratio as the effects of security changes will be diversified away as the positive security order flow shocks of some firms are offset by negative order flow shocks in others.

4.4 Cross-section regressions

Motivated by these findings, we now examine whether changes in correlation following an order flow shock is related to firm characteristics. We begin by calculating the change in correlation following an order flow shock for three groups of firms which are sorted by each of the firm characteristics in turn. This information is contained in Table 5, Group 1 contains firms with the smallest characteristic and group 3 contains firms with the largest characteristic. We find that for positive shocks, correlation reductions are highest for firms in RHO group 1(RHO values are negative so group 1 are firms with the highest friction). We also find that as the spread and illiquidity rise the change in correlation increases but changes in correlation do not alter noticeably as volume increases or the daily number of trades changes (although for firms with the smallest number of daily trades negative correlation changes and elevated). As firm size falls the change in correlation increases, and also increases as the size of the order imbalance of retail investors increase but does not appear to be consistently related to the firms book to market ratio, an alternative measure of habitat/sentiment. We do not find a strong association between the size of institutional order flow imbalances and the change in correlation but do find that as the number of analysts following a firm rises the effect of order flow shocks tend to decline. The higher a firm's co-movement is with the market return the higher is the change in co-movement, the change in co-movement rises with RSQ[23].

Overall, our results suggest that friction, liquidity, sentiment and information asymmetry may all have an impact on the size of the change in correlation following an order flow shock but also that the extent to which a firm is correlated with the market is also important. We examine this further by estimating the following random effects panel model.

[23] We also divide each group based on the pre shock order flow imbalance <1 and >1 into three further groups based on firm size to determine if firm size has an important influence within each group formed by the buy-sell ratio. We find that for positive shocks and buy-sell ratios >1 large and medium shocks lead to greater changes in co-movement and the scale of these changes diminishes as firms increase in size. For negative shocks co-movement changes tend to be higher for larger imbalances and smaller firms However, for firms with buy-sell ratios <1 there is a less clear cut pattern associated with the scale of the buy-sell ratio in a group and the size of firms. For brevity we do not report these results.

$$\Delta\rho=\alpha+\beta_1 PreCor+\beta_2 Buy\text{-}sell+\beta_3 RHO+\beta_4 C\text{-}lag+\beta_5 C\text{-}cor+\beta_6 RSQ+\beta_7 S\&P+\beta_8 SIZE+\beta_9 b/m+\beta_{10} RET+\beta_{11} IN+\beta_{12} SPREAD+\beta_{13} ANYST+\beta_{14} ill+\beta_{15} VOL+\beta_{16} Time+\varepsilon \quad (12)$$

where $\Delta\rho_i$ is the change in the correlation coefficient of security *i* following an order flow shock. α is a constant, β are coefficient values. Variables are as previously defined. In addition to these variables we also include a zero one indicator variable (S&P) that has a value of unity if a security is a S&P 500 constituent but has a zero otherwise, we include this variable as our results suggest there may be differences between these two groups but it is not clear whether it is S&P membership that is important or differences in the characteristics of firms. We also include the pre shock correlation coefficient of the firm and the pre shock buy-sell ratio. We include a dummy variable called Time that has a value of zero in the pre 2007 period and a value of one after 2007. The pre and post 2007 variable captures the influence of crisis and non-crisis periods as order flow shocks seem to be higher during the crisis period after 2007. ε_i is an error process[24]. The model is estimated for both firm and market shocks.

Results are contained in Table 6 and show that some firm characteristics influence the size and direction of the co-movement change after positive and negative firm order flow shocks. For positive and negative shocks the pre shock correlation is important and is negatively signed suggesting that larger pre shock correlations increase the size of the decline in correlation. The fall in correlation following positive and negative order flow shocks rises with friction (RHO is positively signed). For positive and

[24] We also estimate versions of the model with industry dummies but do not find a role for these. We also estimate a version with price level effects and do not find that there is a relationship between correlation change and price levels.

negative shocks habitat is an important determinant of correlation change as SIZE and b/m are both negatively signed. For positive shocks liquidity and volume also influence the change in correlations. More illiquid stocks with lower volume have larger negative changes in correlation. The C-cor coefficient is positive indicating that less negative changes in correlation are associated with higher correlations between security and market buy-sell ratios. We also find that the crisis period raises correlations causing them to be less negative as the Time variable capturing the post 2007 period is significant and positive. There are some interesting differences between positive and negative shocks. Most striking is that the pre shock buy-sell ratio has a positive impact on correlation so that buying pressure raises correlations but selling pressure increases the size of negative correlation changes. This contrasts with the impact of retail investor imbalance as buying pressure has a negative influence on correlation changes. Illiquidity and volume does not influence correlation changes if order flow shocks are negative. These differences might be explained by the firm characteristics as positive shock firms have higher illiquidity ratios, volume and higher retail imbalances than negative shock firms.

Our results show that the differences between S&P and non S&P firms and the differences between firms with buy-sell ratios >1 and < 1 disappear after we control for firm characteristics. This suggests that the differences between these groups of firms in terms of their responses to order flow shocks was due to the firm characteristics not the respective grouping. Table 6 also shows that not all the firm characteristics that Table 5 showed were associated with a fall in correlation are significant. The reason for this is that some of the firm characteristics are correlated, such as size and spread etc. The regression results therefore indicate which characteristics are the most important for stock selection because they identify the most independent characteristics that influence correlation.

The market regressions show that size, RHO, illiquidity and volume are firm characteristics that influence the size of the correlation change following a positive market order flow shock. For negative market shocks a much wider range of variables influence post-shock correlations including Size, C-lag, C-cor, Spread, Order imbalance associated with retail and institutional investors, Volume and Analyst coverage. For market shocks the pre-shock correlation of the security does not impact on the post shock correlation change.

Using the results of Table 5 and 6 we undertake further group analysis based on two way screening. We find that if we divide securities into three groups on the basis of the pre-shock correlation then further divide securities into three groups based on illiquidity we find that reductions in correlation are over 30% in response to order flow shocks. This suggests that a useful approach to selection of stocks would be to rank stocks on the basis of their pre-shock correlations then from the stocks with high pre-shock correlations select those with medium to high illiquidity ratios. Our analysis of all firm characteristics indicates this two way sort provides the largest fall in correlations following an order flow shock.

5. Robustness and other tests

In this section we undertake further tests to strengthen the robustness of our findings. Figure 1 indicated that there was a noticeable change in order flow imbalance for both positive and negative shock firms after 2007 which coincides with the period of the financial crisis. Moreover, the VIX index, a measure of financial instability has been elevated between 2008 and 2011. Motivated by these findings we analyze the pre and post shock correlations for two separate sample periods ranging from 1993-2006 and from 2007-2011. These results highlight a substantial rise in pre shock correlations during the later period which is consistent with a wealth of evidence that has suggested correlations between assets has increased recently. Our results for the period 1993-2006 indicate that positive and negative shocks have large negative impacts on co-movement and the asymmetries we have discovered for the 1993-2011 sample are maintained.

Our analysis of 2007-2011 indicates that during the period of financial crisis order flow shocks have had much less effect on correlation than during the earlier period. Negative order flow shocks lead to a reduction in co-movement but these changes are smaller than during the period 1993-2007 while positive shocks generally lead to economically small increases in correlation. When average imbalances are high and co-movement is high shocks have much less impact on co-movement a discovery consistent with Longin and Solnik (2001), Silvennoinen and Teräsvirta (2005) and Berben and Jensen, (2005) who showed that during crisis periods co-movement is unusually high.

We examine the relationship between a firms order flow shock and volatility in the pre and post 2007 period and find that prior to 2007 the average volatility of firm and market returns is substantially lower than during the post 2007 period. This offers an explanation for why during the crisis period average shocks are larger but the average decline in correlations is smaller. If volatility is high during periods of crisis the effect of covariance reductions will be suppressed[25]. However, we also believe that during this period correlation changes are lower due to more coordinated return behaviour. Together both impacts will lead to a reduction in correlation.

We examine further the impact that market conditions have on co-movement by examining the effects that rising market conditions (bull markets) and falling market conditions (bear markets) at the time of the order flow shock have on correlations. Longin and Solnik (2001) or Ang and Bekaert (2002) have suggested that market conditions affect co-movement. We do not find that changes in co-movement are related to market conditions prior to a shock.

In the growing literature on security order flow imbalance alternative measures have been utilized to the ones we employ, see for example Chordia and Subrahmanyam (2004). We estimate the effect of order flow shocks on co-movement using a range of other measures of order flow imbalance which includes the value of buys-sells and both this and our buy-sell ratio scaled by either the number of trades in a day or the value of buys and sells. Overall we find that unscaled measures give consistent results to the ones we provide in the paper while scaling by average number of daily trades shows that both negative and positive shocks leads to co-movement reductions which are smaller for positive shocks but larger for negative shocks. For example, using the Chordia and Subrahmanyam (2004) measure buys-sells scaled by the number of trades, reduces correlations following positive shocks by about 10% but negative correlations reduce correlation by 25%[26].

[25] The correlation coefficient is the covariance scaled by the standard deviation of firm returns times the standard deviation of market returns. As volatility rises the correlation coefficient becomes smaller in size. We also note that the larger order flow shocks may have contributed to the higher volatility in the post 2007 period.
[26] Although we find that scaled order flow shocks still lead to large percentage reductions in correlation, post shock changes are smaller than for the unscaled measure. The unscaled measure leads to a more volatile series than scaled measures as shocks are

As a final robustness exercise we test the smooth transition model using monthly data to gauge whether increasing the return interval reduces the effect that order flow shocks have on co-movement. As anticipated using buy-sell ratios aggregated from a whole months order flow rather than from a single day reduces the impact that order flow shocks have on co-movement in all samples but does not cause it to disappear[27], we also find that the number of shocks is much lower probably because there is less volatility of order flow imbalance as the interval increases. Across all firms we find that positive shocks lead to a change in correlation of about 10% while negative shocks lead to a change in correlation of about 14%. Our discovery that order flow shocks have less impact on correlations when using monthly return horizons suggests that over shorter horizons part of the correlation change is due to the effect of transitory price movements. Since the asymmetry between positive and negative shocks is reversed it suggests that negative returns following order flow shocks contain less transitory information than positive shocks[28]. However, our analysis of monthly data suggests that even for investors that are willing to trade their portfolio less frequently there are some advantages of using order flow shocks for diversification.

on average larger. The impact of scaling tends to reduce the number of shocks by almost a half if the Chordia and Subrahmanyam (2004) scaling of Buys-Sells/Buys+Sells is applied as there are 729201 positive and 685676 negative shocks without scaling and 477504 positive shocks and 351412 negative shocks with scaling. This suggests that scaling overlooks some order flow shocks that appear to influence correlation. Overall, scaling reduces average correlation changes because some informative shocks are omitted by scaling, the reversal of the asymmetry suggests that on average scaling omits more relevant positive shocks than negative shocks.

[27] This is anticipated because the effect of multiple positive or negative shocks within a month are likely to be diversified across time.

[28] This is supported by values of RHO, the one period serial correlation coefficient of returns which captures the impact of return reversals when negative. For positive shock firms it is on average -0.0404 and for negative shock firms it is -0.0355 indicating larger return reversals for positive shock firms..

As a further extension we undertake the LM test of Silvennoinen and Teräsvirta (2009) and identify 658 firms in total that experience a double order-flow shock[29]; we then employ the double smooth transition conditional correlation model for these firms to estimate the average correlation prior and subsequent to each shock.

In Table 7 we present the change in correlations measured from prior to the first shock to after the second shock. To obtain this measure we breakdown each initial positive and negative shock according to whether the second shock is positive or negative. This provides four possible outcomes for each sample, a positive first shock followed by a positive or negative shock and a first negative shock followed by either a positive or negative shock. This analysis on firm shocks shows that positive shocks followed by positive shocks reduce correlation while positive shocks followed by negative shocks increase correlation. The analysis of market shocks shows that two successive positive or negative shocks lead to small negative changes in correlation across all firms while a positive shock followed by a negative one leads to more substantial reductions in correlation. In contrast, a negative shock followed by a negative shock leads to very large increases in correlation.

6. Conclusion

This paper has introduced a modification to the GARCH smooth transition conditional correlation model, allowing order flow shocks to be the transition variable. We have shown that positive and negative security level order flow shocks reduce co-movement. When firms are characterized by net buying pressure positive shocks lead to larger changes in correlation than when firms are subject to net selling pressure. When firms are subject to net selling pressure positive shocks lead to

[29] The test for a double order flow shock indicates that a firm has at least one double smooth transition but each firm may have multiple double smooth transitions.

smaller decreases in correlation than negative shocks. We also find sizeable differences between how S&P and non S&P firms respond to an order flow shock as non S&P 500 firms experience a larger change in correlations after an order flow shock than S&P constituents. Market order flow shocks have less impact on co-movement changes. The effect of a positive or negative market order flow shock leads to only a very small change in average co-movement.

Our research raises a range of questions for further research. An issue we have been unable to address fully within the confines of this paper is the extent to which information trading and liquidity trading are the cause of order flow shocks. It seems a useful and interesting avenue for future research would be to answer this important question comprehensively perhaps by looking at different corporate information events and examining the interdependencies of information and liquidity trading and the impact this has on order flow imbalance.

These findings are very important as they offer investors a way of identifying stocks that should be able to offer better diversification opportunities, increasing the range of risk return trade-offs available. This is important for those investors who hold S&P 500 securities as correlations between these securities are at a high historically. Being able to reduce co-movement through usage of order flow information will also improve the allocation of resources, see Wurgler (2000) and Durnev et al (2004) who show that the efficient allocation of resources is inversely related to co-movement.

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Table 1 Summary Statistics

In this table we provide mean values of the characteristics of firms used in the different samples. Pre is the pre shock value of the single shock firms. Non is the average value of each characteristic across all firms during non-shock periods. RHO is the first order daily serial correlation coefficient of firms, C-lag is the correlation between the daily market return and firm returns lagged one period, C-cor is the correlation between the firms daily buy-sell ratio and that of the market, SPREAD is the daily effective spread, ill is the daily Amihud illiquidity ratio, VOL is average daily trading volume in US $000,000, NT is the average number of trades per day, SIZE is the average July market capitalization of firms, b/m is the average July book to market ratio, IN and RET are the daily order imbalances associated with institutional and retail investors respectively obtained using the Lee and Radhakrishna (2000) algorithm. ANYST is the number of analysts following firms on I/B/E/S, R is the average daily return of firms, RSQ is the R^2 from the extended market model estimated using monthly information, PRICE is the average daily share price.

All Firms

	RHO	C-lag	C-cor	SPREAD	ill	VOL	NT	SIZE	b/m	IN	RET	ANYST	R	RSQ	PRICE
Pre	-0.038	0.332	0.105	0.005	1.312	6.019	842	5786	0.423	1.601	1.304	9	0.001	0.181	26.055
Non	-0.037	0.350	0.103	0.004	1.032	8.153	899	9618	0.471	1.790	1.230	8	0.004	0.193	28.206
Double	-0.038	0.358	0.103	0.006	1.563	9.839	1455	10217	0.668	1.926	1.165	8	0.006	0.198	23.291

S&P

	RHO	C-lag	C-cor	SPREAD	ill	VOL	NT	SIZE	b/m	IN	RET	ANYST	R	RSQ	PRICE
Pre	-0.012	0.472	0.137	0.001	0.009	6.380	4856	25170	0.396	1.412	1.121	16	-0.002	0.285	44.395
Non	-0.013	0.478	0.137	0.001	0.006	8.735	4856	40951	0.415	1.275	1.076	14	0.003	0.289	47.410
Double	-0.015	0.485	0.136	0.001	0.007	12.255	13546	44339	0.554	1.128	1.030	14	0.005	0.292	40.291

Non S&P

	RHO	C-lag	C-cor	SPREAD	ill	VOL	NT	SIZE	b/m	IN	RET	ANYST	R	RSQ	PRICE
Pre	-0.044	0.299	0.097	0.007	1.757	5.917	759	1907	0.406	1.653	1.342	6	0.003	0.158	21.744
Non	-0.043	0.320	0.095	0.005	1.346	8.018	813	3517	0.483	1.930	1.259	6	0.005	0.171	23.830
Double	-0.044	0.327	0.095	0.008	2.102	9.217	1210	3131	0.687	2.173	1.196	6	0.007	0.174	19.052

Buy-sell>1

	RHO	C-lag	C-cor	SPREAD	ill	VOL	NT	SIZE	b/m	IN	RET	ANYST	R	RSQ	PRICE
Pre	-0.028	0.376	0.120	0.003	0.501	6.687	1022	7591	0.447	1.667	1.346	9	0.001	0.210	30.871
Non	-0.029	0.387	0.120	0.003	0.377	9.046	1101	12622	0.482	1.753	1.193	9	0.004	0.216	33.038
Double	-0.031	0.393	0.113	0.005	0.711	10.842	1519	12409	0.676	1.908	1.132	8	0.006	0.219	25.913

Buy-sell<1

	RHO	C-lag	C-cor	SPREAD	ill	VOL	NT	SIZE	b/m	IN	RET	ANYST	R	RSQ	PRICE
Pre	-0.050	0.280	0.087	0.008	2.742	4.995	686	3694	0.225	1.495	1.247	8	0.002	0.148	20.429
Non	-0.046	0.309	0.084	0.006	1.975	7.011	732	6420	0.435	1.836	1.272	7	0.004	0.167	23.033
Double	-0.046	0.313	0.091	0.009	3.071	8.343	1389	7456	0.639	1.960	1.214	7	0.007	0.171	19.950

Table 2: Security Shock Smooth Transition Correlation Results

This table shows the mean pre and post shock correlation coefficient of firms obtained from the smooth transition model. + shock indicates a positive shock and – shock indicates a negative shock. % change is the percentage change in correlation that takes place after an order flow shock. *, ** and *** indicates significance at 10%, 5% and 1% respectively of these changes. An a indicates that there is not a significant difference between positive and negative shock pre or post shock correlations. Small, Medium and Large in Panel B refers to the relative size of the order imbalance shock.

Panel A. All Firms and Divisions by pre Shock Buy-Sell Ratio

	All Firms		buy-sell>1		buy-sell<1	
	+ shock	- shock	+ shock	- shock	+ shock	- shock
mean correlation before	0.2979	0.2844	0.3031	0.2971	0.2596	0.2781
mean correlation after	0.2354	0.2424	0.2352	0.2506	0.2418	0.2391
mean change in correlation	-0.0625***	-0.0420***	-0.0679***	-0.0465***	-0.0178***	-0.0390***
% change	-20.98%	-14.77%	-22.40%	-15.65%	-6.86%	-14.02%

Panel B: Buy-Sell Ratio Analysis

		buy-sell >1		buy-sell <1	
		+ shock	-shock	+ shock	-shock
Small	mean correlation before	0.3556	0.3406	0.2941	0.3181
	mean correlation after	0.2879	0.3066	0.2780	0.2853
	mean change in correlation	-0.0677***	-0.0340***	-0.0161***	-0.0328***
	% change	-19.04%	-9.98%	-5.47%	-10.31%
Medium	mean correlation before	0.3195	0.3128	0.2670	0.2937
	mean correlation after	0.2390	0.2573	0.2354	0.2470
	mean change in correlation	-0.0805***	-0.0555***	-0.0316***	-0.0467***
	% change	-25.20%	-17.74%	-11.84%	-15.90%
Large	mean correlation before	0.2368	0.2419	0.2162a	0.2173
	mean correlation after	0.1815	0.1932	0.1998	0.1788
	mean change in correlation	-0.0553***	-0.0487***	-0.0164***	-0.0385***
	% change	-23.35%	-20.13%	-7.59%	-17.72%

Panel C:S&P and Non S&P Firms

	S&P		Non S&P	
	+ shock	-shock	+ shock	-shock
mean correlation before	0.4037a	0.4042	0.2810	0.2707
mean correlation after	0.3264	0.3784	0.2205***	0.2265
mean change in correlation	-0.0773***	-0.0258***	-0.0605***	-.0.0442***
% change	-19.15%	-6.38%	-21.53	-16.33%

Table 3: Correlation Results by Industry

This table shows mean pre and post shock correlations obtained from the smooth transition model following a security order-flow shock. Δcor is the change in correlation. % change is the percentage change in correlation following a security order flow shock. *, ** and *** indicates significance of a t test at a 10%, 5% and 1% respectively. An a indicates that pre or post shock positive and negative correlations are not statistically different from each other at a 5% level.

	Positive shock				Negative Shock			
	Pre-shock cor	Post-shock cor	Δcor	% change	Pre-shock cor	post-shock cor	Δcor	% change
NoDur	0.2794	0.1953	-0.0841***	-0.3010	0.2568	0.2268	-0.0300***	-0.1168
Durbl	0.2918	0.2414	-0.0504***	-0.1727	0.2751	0.2664	-0.0087***	-0.0316
Manuf	0.3232	0.2516	-0.0716***	-0.2215	0.2957	0.2436	-0.0521***	-0.1762
Enrgy	0.2869	0.2214	-0.0655***	-0.2283	0.2820	0.2230	-0.0590***	-0.2092
HiTec	0.2527	0.1973	-0.0554***	-0.2192	0.2297	0.2046	-0.0251***	-0.1093
Telcm	0.2865	0.2275	-0.0590***	-0.2059	0.2908	0.2486	-0.0422***	-0.1451
Shops	0.2791	0.2234	-0.0557***	-0.1996	0.2787	0.2298	-0.0489***	-0.1755
Hlth	0.2139	0.1530	-0.0609***	-0.2847	0.1692	0.1715	0.0023***	0.0136
Utils	0.3792	0.3122	-0.0670***	-0.1767	0.3104	0.2871	-0.0233***	-0.0751
Others	0.3154	0.2535	-0.0619***	-0.1963	0.3225	0.2673	-0.0552***	-0.1712

*NoDur: Consumer NonDurables
Durbl: Consumer Durables
Manuf: Manufacturing -- Machinery, Trucks, Planes, Chemicals, Off Furn, Paper, Com Print
Energy: Oil, Gas, and Coal Extraction and Products
HiTec: Business Equipment
Telcm: Telephone and Television Transmission
Shops: Wholesale, Retail, and Some Services (Laundries, Repair Shops)
Hlth: Healthcare, Medical Equipment, and Drugs
Utils: Utilities
Others: Mines, Constr, BldMt, Trans, Hotels, Bus Serv, Entertainment, Finance

Table 4: Correlation Results Market Shock

This table shows the mean pre and post shock correlation coefficient of firms obtained from the smooth transition model following a shock to market order flow. These are reported separately for positive and negative shock firms. The *, ** and *** indicates the change in correlation was significant at a 10%, 5% or 1% level respectively. An a indicates that the positive and negative correlation is not statistically different at a 5% level.

Panel A. All Firms

	All Firms		buy-sell>1		buy-sell<1	
	+ shock	-shock	+ shock	-shock	+ shock	-shock
mean correlation before	0.2213	0.2303	0.2578	0.2811	0.2247	0.2560
mean correlation after	0.2148	0.2233	0.2467	0.2616	0.2183	0.2427
mean change in correlation	-0.0065***	-0.0070***	-0.0111***	-0.0195***	-0.0064***	-0.0133***
% change	-2.94%	-3.04%	-4.31%	-6.94%	-0.0285	-0.0520

Panel B:S&P and Non S&P Firms

	S&P 500 Stocks		Non S&P 500 Stocks	
	+ shock	-shock	+ shock	-shock
mean correlation before	0.3668a	0.3667	0.2107	0.2172
mean correlation after	0.3495	0.3377	0.2054	0.2121
mean Δ in correlation	-0.0173***	-0.0290***	-0.0053***	-0.0051***
% change	-4.72%	-7.91%	-2.52%	-2.35%

Panel C:Industry Analysis

Positive Shocks	NoDur	Durbl	Manuf	Enrgy	HiTec	Telcm	Shops	Hlth
mean correlation before	0.1593	0.1642	0.1823	0.2172	0.1916	0.2863	0.2338	0.1786
mean correlation after	0.1992	0.1777	0.1998	0.2341	0.1879	0.2283	0.2054	0.1588
mean change in correlation	0.0399***	0.0135***	0.0175***	0.0169***	-0.0037***	-0.0580***	-0.0285***	-0.0198***
% change	0.2505	0.0821	0.0958	0.0778	-0.0192	-0.2026	-0.1217	-0.1108
Negative Shocks								
mean correlation before	0.2272	0.2603	0.2422	0.2439	0.1593	0.2335	0.2313	0.1562
mean correlation after	0.2098	0.2369	0.2268	0.2264	0.1519	0.2397	0.2474	0.1537
mean change in correlation	-0.0174***	-0.0234***	-0.0155***	-0.0175***	-0.0074***	0.0062***	0.0161***	-0.0025***
% change	-0.0768	-0.0899	-0.0638	-0.0716	-0.0463	0.0265	0.0696	-0.0161

Table 5: Percentage Change in Correlations by Firm Characteristic

This table presents the percentage change in correlation between the pre shock and post shock period for three groups sorted by each characteristic value. RHO is the first order daily serial correlation coefficient of firms, C-lag is the correlation between the daily market return and firm returns lagged one period, C-cor is the correlation between the firms daily buy-sell ratio and that of the market, SPREAD is the daily effective spread, ill is the daily Amihud illiquidity ratio, VOL is average daily trading volume in US $000,000, NT is the average number of trades per day, SIZE is the average July market capitalization of firms, b/m is the July average book to market ratio, IN and RET are the daily order imbalances associated with institutional and retail investors respectively obtained using the Lee and Radhakrishna (2000) algorithm. ANYST is the number of analysts following firms on I/B/E/S, R is the average daily return of firms, RSQ is the R^2 from the extended market model estimated using monthly information, PRICE is the average daily share price. x indicates that the correlation change is not significant at a 5% level.

	All		S&P		Non S&P			All		S&P		Non S&P	
RHO	+	-	+	-	+	-	C-lag	+	-	+	-	+	-
1	-24.40%	-17.49%	-20.80%	-13.12%	-25.01%	-16.87%	1	-17.69%	-3.5 50%	-17.50%	-7.07%	-19.10%	-2.21%x
2	-21.63%	-16.24%	-19.69%	7.34%	-22.72%	-18.11%	2	-20.56%	-14.87%	-18.95%	-6.00%	-18.83%	-15.37%
3	-17.98%	-11.25%	-17.88%	2.7. %	-18.22%	-14.20%	3	-22.76%	-17.97%	-21.53%	-8.58%	-24.58%	-21.07%
C-cor	+	-	+	-	+	-	SPREAD	+	-	+	-	+	-
1	-19.53%	-14.61%	-21.66%	-12.78%	-23.19%	-13.60%	1	-20.24%	-13.92%	-19.82%	-7.81%	-20.90%	-16.72%
2	-22.49%	-20.08%	-17.44%	-3.83%	-23.20%	-22.22%	2	-21.31%	-15.17%	-18.64%	-10.63%	-21.85%	-15.91%
3	-18.71%	-10.56%	-18.87%	-5.30%	-19.64%	-13.01%	3	-22.49%	-18.26%	-20.04%	-9.71%	-22.88%	-18.61%
Ill	+	-	+	-	+	-	VOL	+	-	+	-	+	-
1	-19.25%	-10.98%	-21.53%	-9.04%	-19.68%	-14.22%	1	-21.20%	-19.15%	-19.95%	-7.85%	-21.67%	-20.23%
2	-20.94%	-16.64%	-18.32%	-6.28%	-21.84%	-17.19%	2	-20.65%	-14.49%	-19.73%	-7.30%	-21.15%	-16.77%
3	-24.66%	-20.38%	-18.51%	-8.01%	-25.09%	-20.35%	3	-21.78%	-12.59%	-19.13%	-8.13%	-22.59%	-13.91%
NT	+	-	+	-	+	-	RSQ	+	-	+	-	+	-
1	-33.67%	-20.68%	-37.48%	-29.11%	-22.93%	-19.37%	1	-15.37%	-4.18%	-17.06%	-9.26%	-15.50%	-3.13%
2	-29.22%	-9.34%	-32.32%	-23.96%	-17.39%	-9.25%	2	-22.02%	-16.59%	-20.78%	-4.28%	-21.60%	-16.07%
3	-28.92%	-10.41%	-30.85%	-22.34%	-17.16%	-9.81%	3	-22.51%	-16.78%	-20.76%	-9.13%	-23.81%	-20.28%
Size	+	-	+	-	+	-	b/m	+	-	+	-	+	-
1	-24.51%	-17.17%	-18.38%	-7.78%	-25.02%	-17.34%	1	-22.48%	-15.78%	-20.88%	-8.44%	-23.19%	-18.28%
2	-21.96%	-17.11%	-19.61%	-8.88%	-22.50%	-17.08%	2	-22.70%	-16.79%	-19.86%	-8.42%	-23.78%	-18.27%
3	-20.34%	-12.63%	-19.78%	-9.76%	-21.60%	-15.83%	3	-19.90%	-12.10%	-17.88%	-9.12%	-20.35%	-12.34%
IN	+	-	+	-	+	-	RET	+	-	+	-	+	-
1	-21.02%	-12.86%	-19.64%	-6.60%	-21.37%	-15.56%	1	-18.16%	-10.66%	-18.37%	-10.02%	-18.49%	-11.82%
2	-20.35%	-14.81%	-19.30%	-7.75%	-21.21%	-16.03%	2	-22.10%	-15.43%	-20.05%	-7.97%	-22.61%	-16.95%
3	-21.13%	-15.55%	-18.57%	-7.83%	-21.64%	-16.55%	3	-23.43%	-19.83%	-20.20%	-9.79%	-23.98%	-20.56%
ANYST	+	-	+	-	+	-	PRICE						
1	-22.59%	-17.69%	-18.01%	-8.05%	-23.01%	-18.02%	1	-17.58	-13.48	-16.18	-13.38	-15.92	-12.38
2	-22.31%	-15.73%	-19.52%	-6.76%	-22.82%	-16.42%	2	-12.59	-8.38	-10.38	-9.22	-11.39	-10.01
3	-20.62%	-12.75%	-20.28%	-8.64%	-21.97%	-16.21%	3	-14.82	-12.82	-13.28	-10.45	-12.34	-11.38

Table 6. Correlation Changes and Firm Characteristics

Panel A of this table shows the panel regression with random effects for the following variables. The dependent variable ($\Delta\rho_i$) is the change in the correlation coefficient of security *i* following an order flow shock. Pre shock correlation is the correlation prior to an order flow shock. Pre shock buy-sell ratio is the buy-sell ratio prior to an order flow shock, RHO is the one period serial correlation coefficient, C-lag is the one period cross autocorrelation between the security return and the market, C-cor is the correlation between the security buy-sell ratio and market buy-sell ratio,RSQ is the R^2 from a market model that contains market return, size and book to market. S&P is a dummy variable with a value of one if the security is a member of the S&P but has a value of zero otherwise, b/m is the book to market ratio, RET, is the buy-sell ratio of retail investors, IN is the institutional buy-sell ratio, ANYST is the analyst following of a firm, SPREAD is the effective spread, ill is the Amihud Illiquidity ratio, VOL is volume, Time is a dummy variable which has a value of 0 in the pre 2007 period but a value of unity otherwise,.x 100 indicates the coefficient value has been multiplied by 100. Panel B provides the pre and post shock correlations from the two way sorts, where firms are grouped first by pre-shock correlation and then by illiquidity. The *, ** and *** indicates the change in correlation was significant at a 10%, 5% or 1% level respectively.

Panel A: Full Sample

	Firm Shock		Market Shock	
Variable	+ shock	- shock	+ shock	-shock
Constant	0.0106***	0.0198***	-0.0011	-0.0005***
Size	-0.6634***	-1.4322***	-0.5197***	-0.1718***
Pre shock cor	-1.1674***	-0.4173***	0.0027	0.0003
Buy-Sell	-0.0273	0.4327***	-0.0264	0.0006
RHO	0.7087***	0.8210***	0.4783***	0.0566
C-lag	-0.3479	0.1847	-0.0286	0.0936***
C-cor	0.0535**	0.0398***	-0.0027	-0.0020***
RSQ	-0.0031	-0.0068	-0.0004	0.0003
S&P	0.0001	0.0006	0.0001	0.0001*
b/m	-0.2668***	-0.1266***	-0.0110	0.0107***
Spread	0.0002	0.0015	0.0011	-0.0001***
IN	-0.0001	-0.0012	-0.0002	0.0005***
Ret	0.0007	-0.0013***	0.0053	-0.0036***
Ill	-0.0010***	-0.00136*	-0.0004***	0.0069
VOL	0.2104***	-0.0443	0.0039***	0.0002***
ANYST	0.1830	-0.0044	0.0238	0.0155***
Time ^{X100}	0.3314***	0.0189***	0.0004*	0.0001
Adjusted R2	16.55%	1.24%	1.33%	3.38%

Panel B: Groups by Pre-shock Correlation and Illiquidity

		1-Low cor		2		3-High cor	
		+shock	-shock	+shock	-shock	+shock	-shock
1-Low Ill	mean correlation before	0.1944	0.2571	0.1552	0.1341	0.1245	0.1093
	mean correlation after	0.1925	0.2605	0.1654	0.1736	0.1137	0.1156
	mean change in correlation	-0.0019	0.0034	0.0102**	0.0395***	-0.0108***	0.0063**
	% change	-1.00%	1.32%	6.57%	26.46%	-8.67%	5.76%
2	mean correlation before	0.3178	0.2999	0.3032	0.2833	0.2941	0.2670
	mean correlation after	0.2649	0.2784	0.2332	0.2304	0.1976	0.1779
	mean change in correlation	-0.0550***	-0.0215***	-0.0700***	-0.0529***	-0.0965***	-0.0891***
	% change	-17.28%	-7.17%	-23.09%	-18.67%	-32.81%	-33.37%
3-High Ill	mean correlation before	0.4505	0.4469	0.4419	0.4341	0.4049	0.3939
	mean correlation after	0.3521	0.3805	0.3219	0.3250	0.2810	0.2640
	mean change in correlation	-0.0984***	-0.0664***	-0.1200***	-0.1091***	-0.1239***	-0.1299***
	% change	-21.84%	-14.86%	-27.16%	-25.13%	-30.60%	-32.98%

Table 7: Breakdown of Firm Double Smooth Transition Results

This table provides a breakdown of the double smooth transition results to show the difference between the correlation prior to the first shock and following the second shock. Positive 1st shock indicates that the first shock was positive, negative 1st shock indicates the first shock was negative. This is followed by either a positive or negative second shock.

Panel A: Firm Shocks

All Firms	Positive 1st Shock		Negative 1st shock	
	Positive 2cd shock	Negative 2cd shock	Positive 2cd shock	Negative 2cd shock
Pre 1st shock	0.3211	0.3211	0.5009	0.5009
Post 2cd shock	0.2608	0.4773	0.2608	0.4773
Mean change	-0.0603***	0.1562***	-0.2401***	-0.0236***
% Diff	-18.78%	48.65%	-47.93%	-4.71%

S&P 500	Positive 1st shock		Negative 1st shock	
	Positive 2cd shock	Negative 2cd shock	Positive 2cd shock	Negative 2cd shock
Pre 1st shock	0.4165	0.4165	0.5644	0.5644
Post 2cd shock	0.3463	0.5879	0.3463	0.5879
Mean change	-0.0702***	0.1714***	-0.2181***	0.0235***
% Diff	-16.85%	41.15	-38.64	4.16%

Non S&P 500	Positive 1st Shock		Negative 1st shock	
	Positive 2cd shock	Negative 2cd shock	Positive 2cd shock	Negative 2cd shock
Post 1st shock	0.2952	0.2952	0.4893	0.4893
Post 2cd shock	0.2468	0.4542	0.2468	0.4542
Mean change	-0.0484***	0.1590***	-0.2425***	-0.0351***
% Diff	-16.41%	53.86%	-49.56%	-7.17%

Panel B: Market Shocks

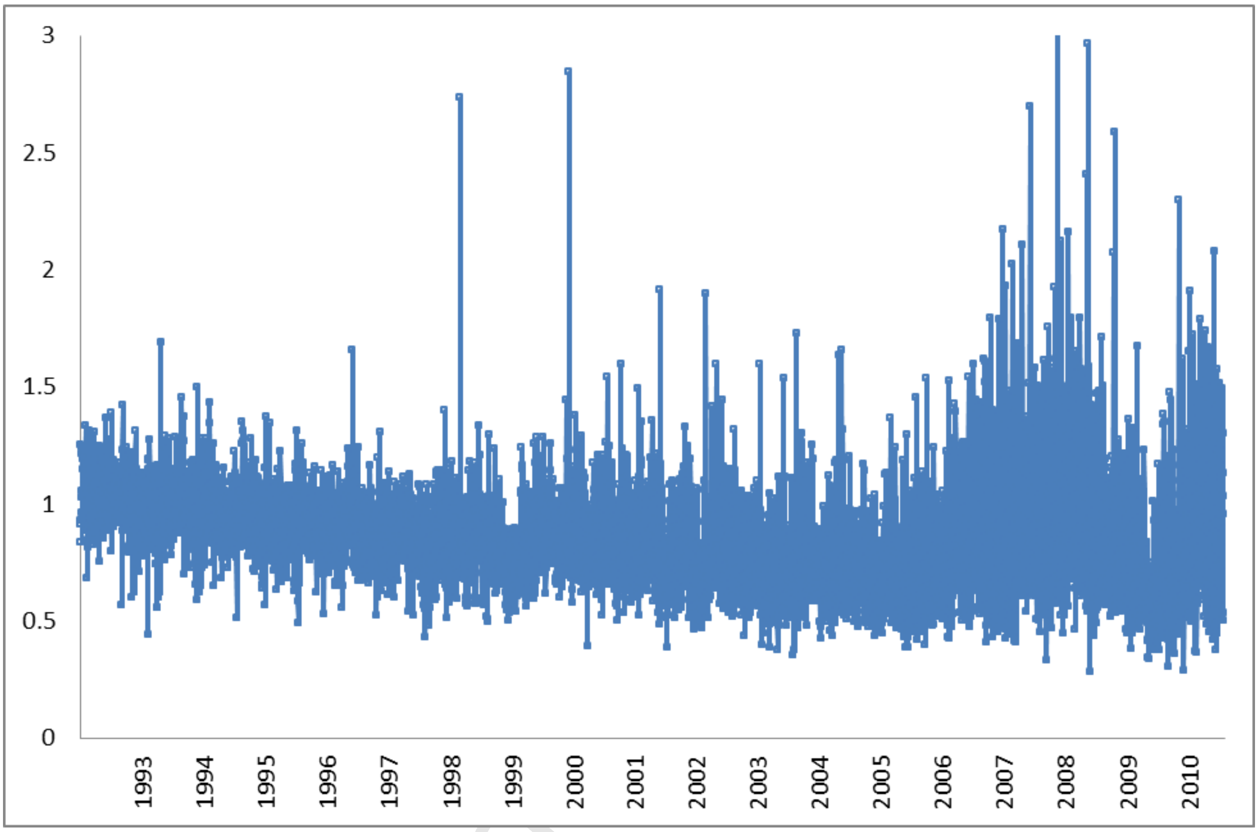
All Firms	Positive 1st Shock		Negative 1st shock	
	Positive 2cd shock	Negative 2cd shock	Positive 2cd shock	Negative 2cd shock
Pre 1st shock	0.3316	0.3316	0.2467	0.2467
Post 2cd shock	0.3198	0.2194	0.2194	0.4773
Mean Change	-0.0118	-0.1122	-0.0273	-0.0236
% Diff	-0.0356	-0.3384	-0.1107	-0.9347

S&P 500	Positive 1st shock		Negative 1st shock	
	Positive 2cd shock	Negative 2cd shock	Positive 2cd shock	Negative 2cd shock
Pre 1st shock	0.4614	0.4614	0.3505	0.3505
Post 2cd shock	0.3198	0.2194	0.2194	0.5879
Mean Change	-0.1416	-0.2420	-0.1311	-0.0235
% Diff	-0.3069	-0.5245	-0.0876	0.6773

Non S&P 500	Positive 1st Shock		Negative 1st shock	
	Positive 2cd shock	Negative 2cd shock	Positive 2cd shock	Negative 2cd shock
Post 1st shock	0.3123	0.3123	0.2331	0.2331
Post 2cd shock	0.3198	0.2193	0.2194	0.4542
Mean Change	0.0075	-0.0930	-0.0137	0.2211
% Diff	0.0240	-0.2978	-0.0588	0.9485

Figure 1: Average Security Order Flow Shocks over Time

Panel A: Positive Order Flow Shocks



Panel B:Negative Order Flow Shocks

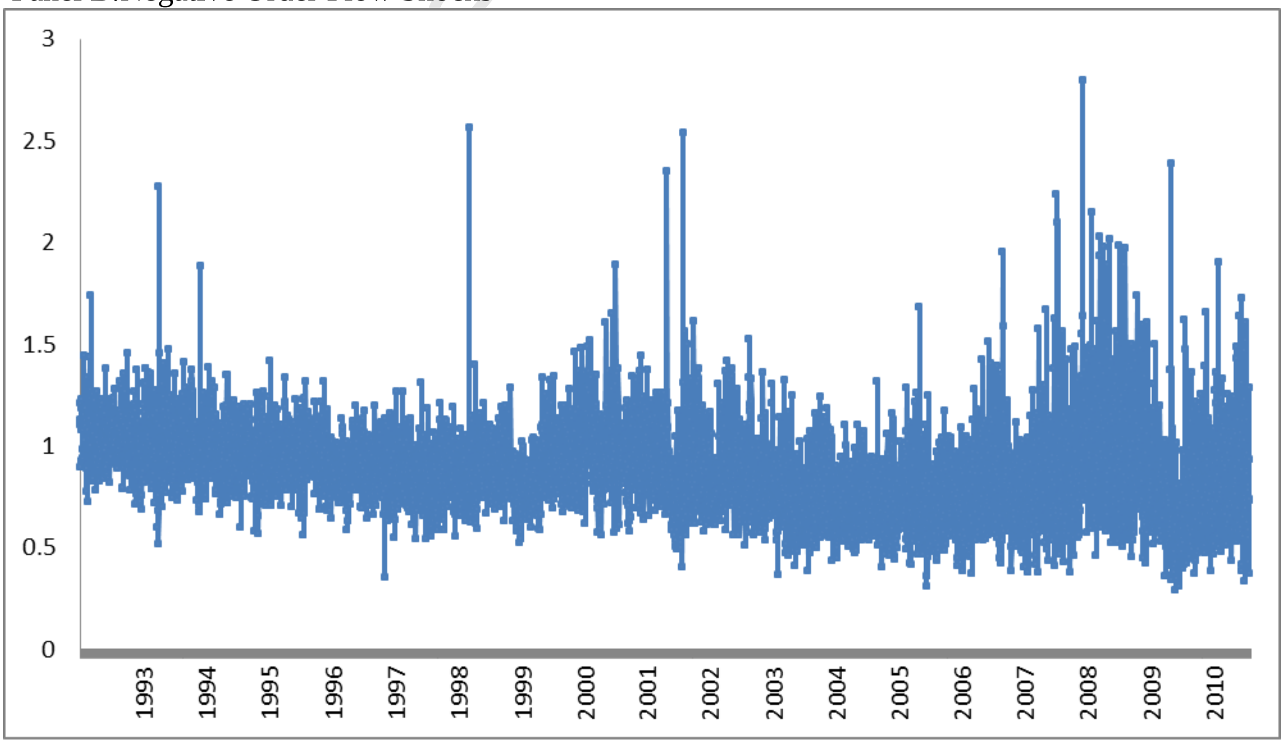
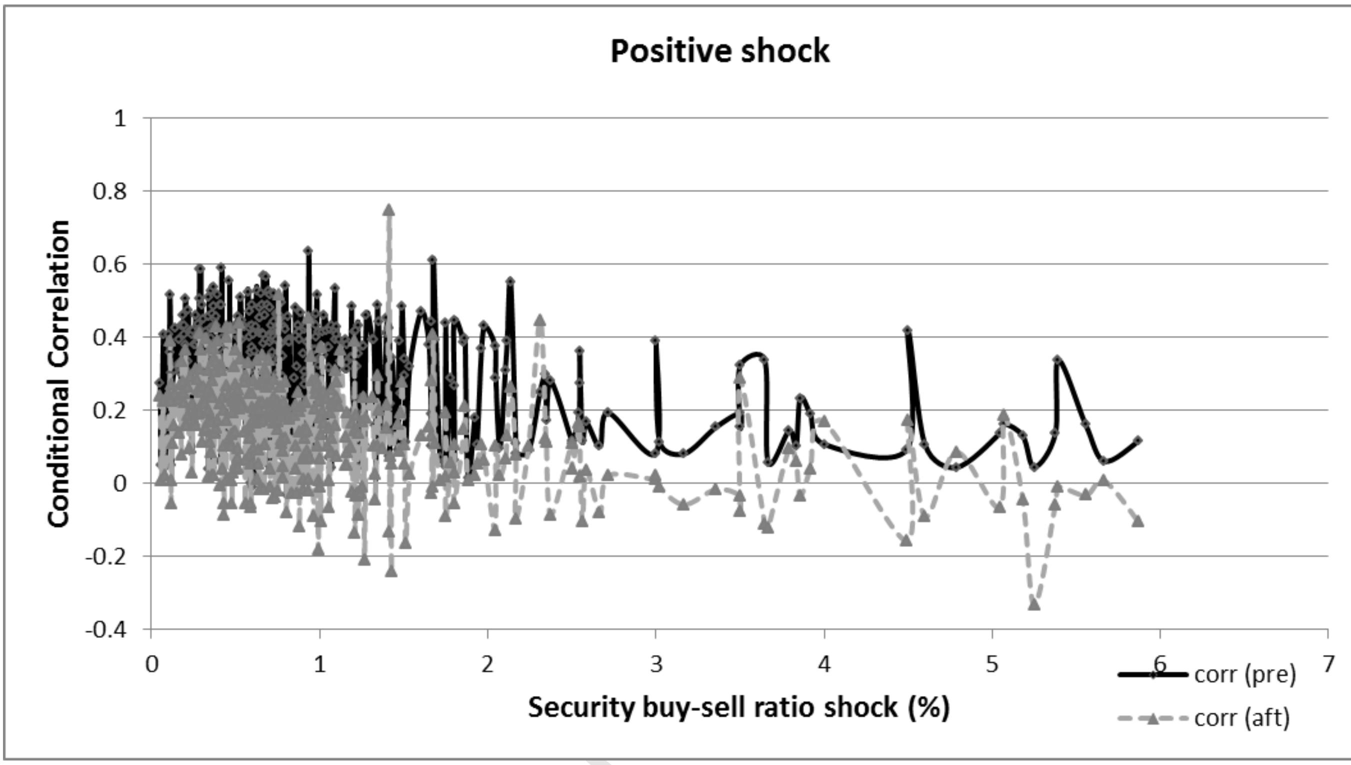


Figure 2: Conditional Correlation and Security Buy-Sell Ratio Shock

Panel A



Panel B

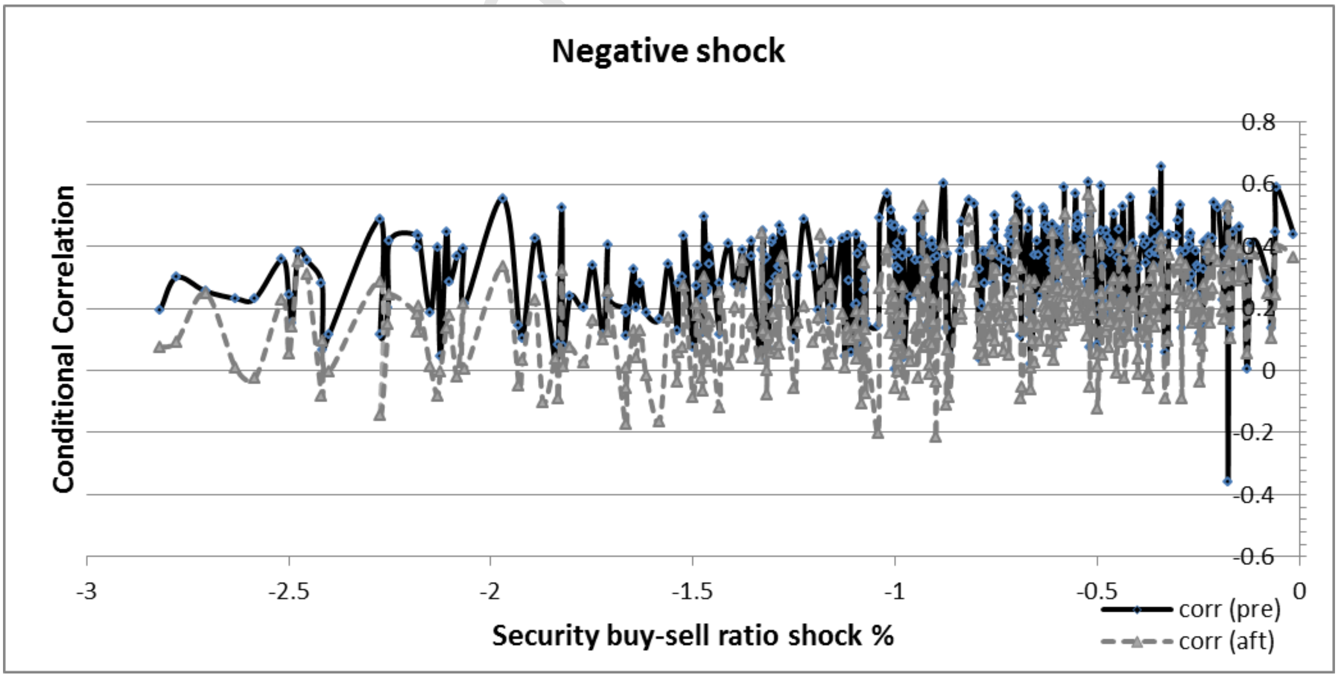
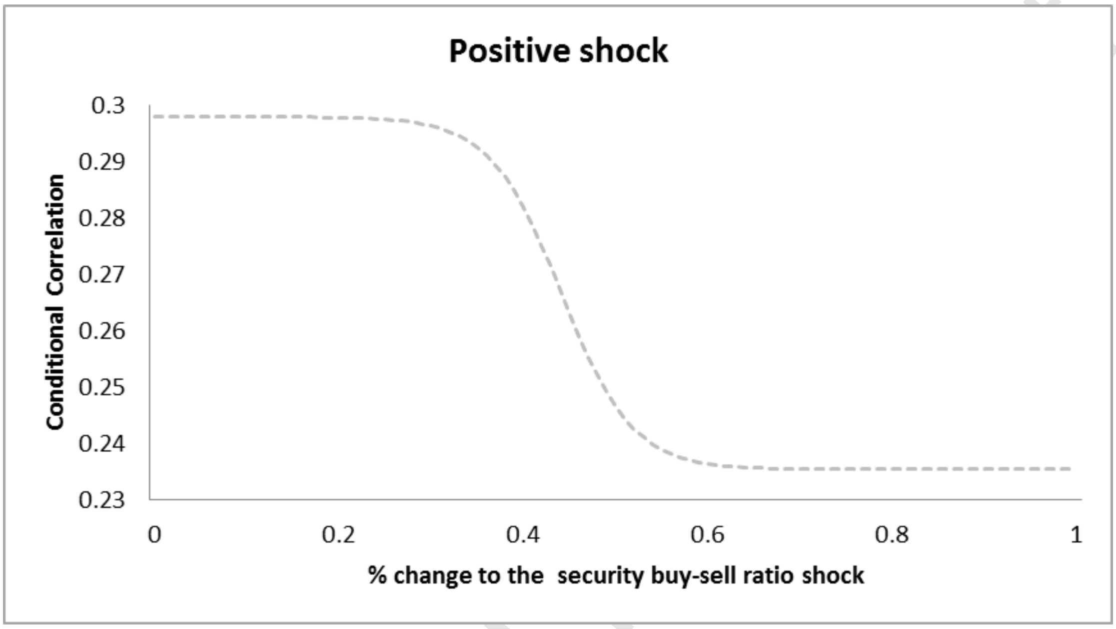


Figure 3: Conditional Correlation Plots and Security Order Flow Threshold

This figure presents the relationship between average conditional correlation and percentage changes to the buy-sell ratio. The solid line of Panel A represents the relationship between average conditional correlation and the percentage change in the buy-sell ratio when firms experience a positive security order flow shock. The dashed line represents the relationship between conditional correlation and the change to the buy-sell ratio when firms experience a negative security order flow shock.

Panel A



Panel B

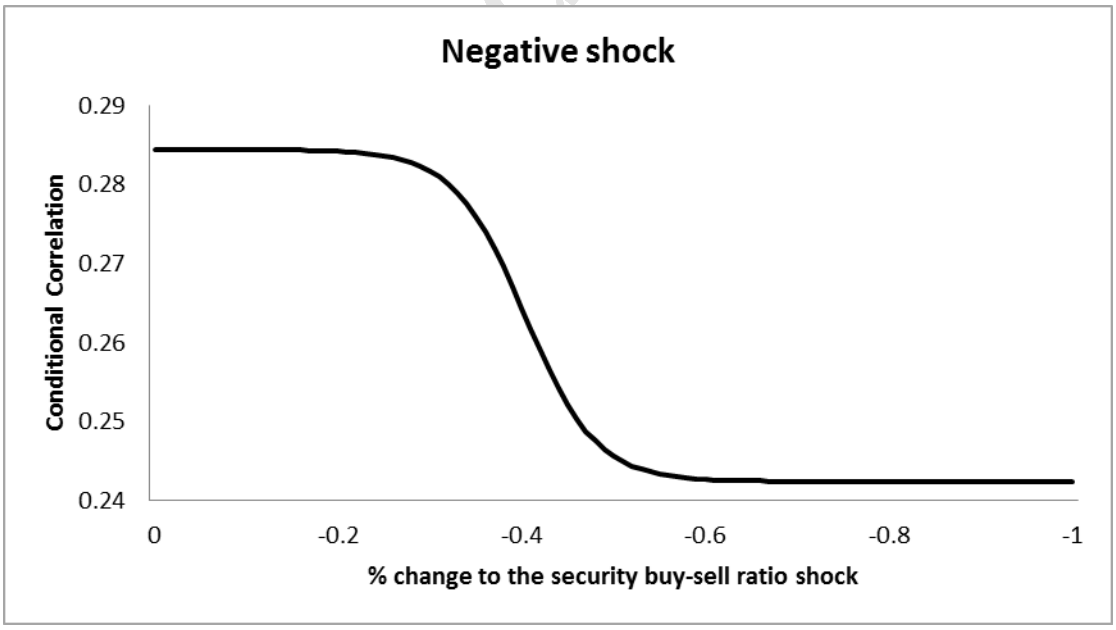
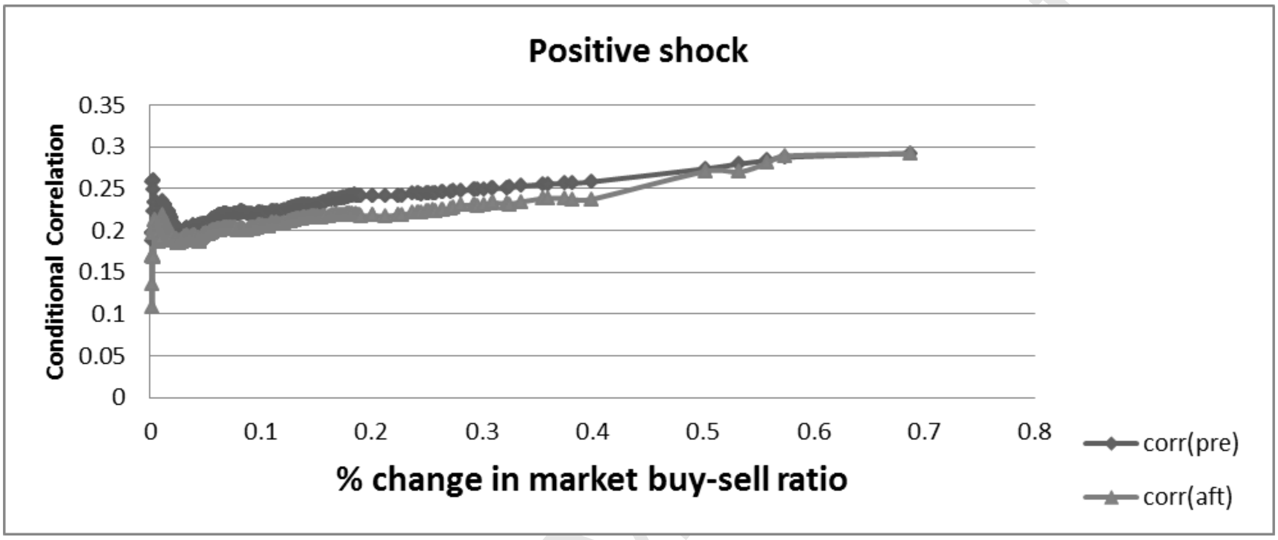


Figure 4: Conditional Correlation and Market Buy-Sell Ratio Shock

This figure plots the pre shock and post shock conditional correlation plotted against the percentage shock to the buy-sell ratio on a firm by firm basis. The darker line represents the pre-shock conditional correlation of firm *i* associated with its pre-shock buy-sell ratio and the lighter line plots the post-shock conditional correlation coefficient with its buy-sell ratio change. Panel A refers to stocks with positive market buy-sell ratio shocks. Panel B refers to results for negative firms with negative market order flow shocks.

Panel A



Panel B

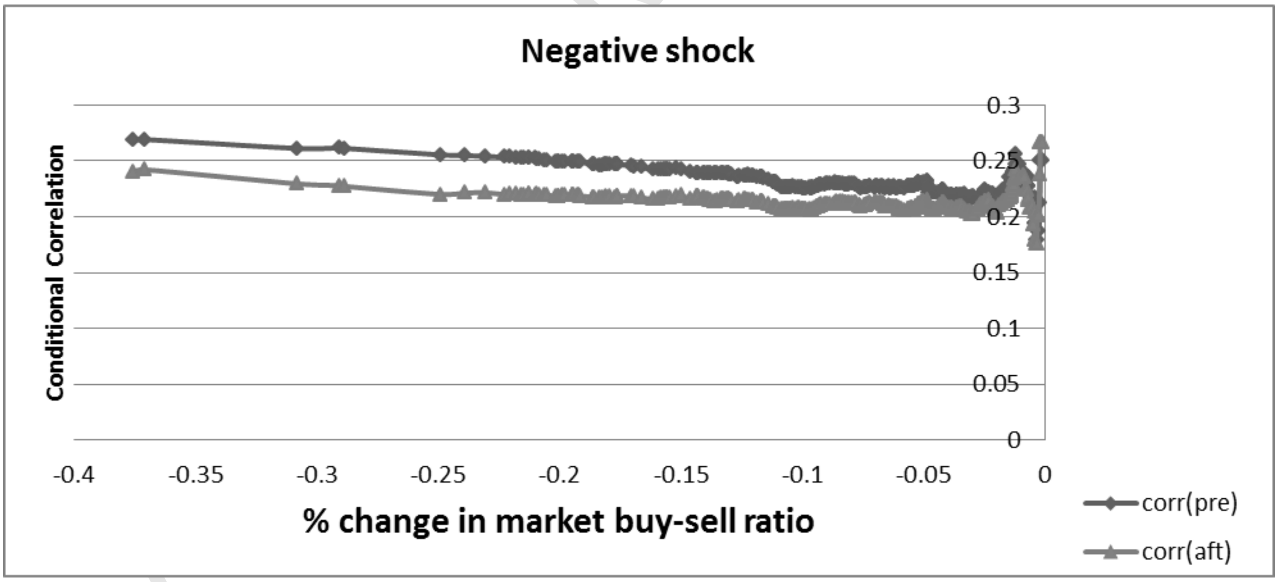
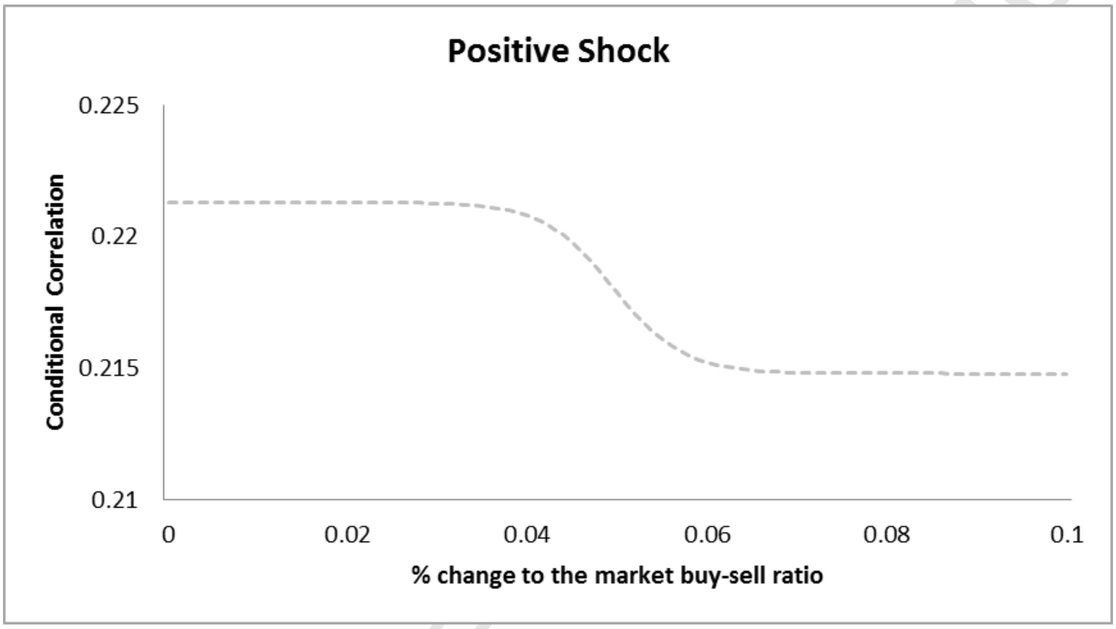


Figure 5 : Conditional Correlation Plots and Market Order Flow Threshold

This figure presents the relationship between average conditional correlation and percentage changes to the buy-sell ratio. The solid line of Panel A represents the relationship between average conditional correlation and the percentage change in the buy-sell ratio when firms experience a positive market order flow shock. The dashed line represents the relationship between conditional correlation and the change to the buy-sell ratio when firms experience a negative market order flow shock.

Panel A



Panel B