Asymmetric relationship between order imbalance and realized volatility: Evidence from the Australian market

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Abstract:

This paper examines the relationship between order imbalance and realized volatility in the Australian stock market for the period starting August 2007 to May 2016. We analyse the issue in four dimensions by decomposing order imbalance into buyer and seller initiated trades as well as realized volatility into good and bad volatility. We find that overall order imbalance has an impact on realized volatility in Australia, but as we consider good and bad volatility, order imbalance impacts on good volatility but not on bad volatility. We equally find that the effect of seller/buyer initiated trade on bad/good volatility is asymmetric, that is effect of seller initiated trade on bad volatility is consistently larger than that of buyer initiated trade on good volatility. Besides, while seller initiated trade has no significant effect on good volatility, buyer initiated trade has significantly reduced the bad volatility. We equally conclude that the number of trades and trade volume have an impact on realized volatility irrespective of the components of realized volatility.

Keywords: Order Imbalance, Realized Volatility, Good and Bad Volatility, Buyer versus Seller initiated trades, ASX50

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1. Introduction

The relationship between trading activity and volatility has been widely documented in finance literature. One of the key proxies that has been used to capture trading activity is trading volume. A number of studies have examined the relationship between absolute returns and volume to assess this important relationship, see for example, Benston and Hagerman (1974), Gallant et al. (1992), Jones et al. (1994), Lo and Wang (2000) among others. The seminal work of Karpoff (1987) identifies a number of reasons as to why the study of the price-volume relationship is important. In this paper, we consider order imbalance as our key measure to proxy volume. Our main objective is to assess the impact of order imbalance and realized volatility (RV) for the Australian stock market, namely ASX 50, for the period starting from August 2007 to May 2016. Particularly, we differentiate our study from previous literature substantially in that (1) we disaggregate order imbalance into buyer versus seller initiated trade and assess their impact on realized volatility separately and (2) we decompose realized volatility into good and bad volatility. Giot et al. (2010) define the "good" and the "bad" volatility as the persistent and the jump component of realized volatility, while Segal et al. (2015) considers "good" volatility as variation due to positive movements in asset prices (i.e., positive semivariance), while "bad" volatility is the uncertainty associated with negative changes in the prices (i.e., negative semivariance). In our study we follow, Segal et al. (2015) and decompose realized volatility into the positive and negative realized semivariance to represent the good and the bad volatility respectively.

Our motivation to consider order imbalance, flows from the literature in particular, from Chordia, Roll and Subrahmanyam (2002) and Chordia and Subramanyam (2004) who find a positive relationship between order imbalance and daily returns on a sample of stocks from the New York Stock Exchange. Order imbalance is important as it provides a signal as to the direction and sentiment to the market. Microstructure theories, see for example, Kyle's (1985) theory of price information, and Admati and Pfleiderer (1988) assumes that the price will be adjusted upwards/downwards when there is excess buy/sell orders. Other studies that relates to the importance of order imbalance include Kraus and Stoll (1972) and Sias (1997) who examine institutional order imbalances. Lee (1992) consider order imbalances around earnings announcements and Blume et al. (1989) consider order imbalances around the October 87 crash. Most of these studies around order imbalance are based on short time frames and are mainly in the US context. Chordia et al. (2002) consider a longer time frame, and also analyse the stocks listed on the New York Stock Exchange. This, hence brings us to our first key contribution, that is to provide a longer-term analysis of order imbalances and realized volatility (RV), covering a sample period of August 2007 to May 2016 in the Australian stock market. There is however some mixed results in the literature analysing order imbalance. While Chan and Fong (2000) conclude that it is order imbalance, rather than number of trades, that drives the volatility-volume relation, Chan and Fong (2006) and Giot et al. (2010) find that that absolute order imbalance does not provide significant explanatory power regarding realized volatility. In the Australian context, Shahzad et al. (2014) study the volatility-volume relation by considering volume into number of trades and average trade size, and split realized volatility into continuous and jump components. While their analyses mainly focus on the number of trades and average trade size at individual and institutional level, they conclude that order imbalance does not have an impact in the Australian context. Given the mixed results in the literature, our study aims to answer why the mixed results have been established in the literature. We assess whether a decomposition of order imbalance into buyer versus seller initiated trade or that of realized volatility into good and bad volatility will explain the mixed results. Essentially, we aim to assess if there an asymmetric relationship between buyer versus seller initiated trades and between good or bad volatility.

In our study, we focus on a smaller sample than Shazad et al (2014), namely the ASX50, using more recent data from August 2007 to May 2016. We include the ASX50 in our analysis to capture the most actively traded stocks on the Australian Stock Exchange. We focus our analysis on the top 50 most traded stocks as a very well-known feature of the Australian market is the problem of thin trading. In the Australian context, thin trading has been found in a range of applications including volatility modelling, see for example, Brooks, Faff and Fry (2001). The movement of value weighted indices are in fact driven by trading of the larger stocks in the market and hence we focus our analysis on the high volume individual stocks. Another reason why we consider the Australian market is that the growth in both direct and indirect investment in the equity market has been remarkable over the past decade in Australia. In 2016, the Australian equity market generally outperformed other developed equity markets globally (RBA, 2017). Data to March 2017 indicate that trading volumes have increased by 23% over the 12 months from 2016, and continue to grow (ASX, 2017a). The domestic equity market capitalisation is at a historic high, reaching $1.8 trillion in March 2017 (ASX, 2017b). Further, indirect ownership in equity markets has equally been in the highest in the world with the OECD highlighting that indirect investment held in Australia accounts for more than 50 percent in equity markets (OECD, 2016). As such, we significantly extend the literature on order imbalance and realized volatility in the Australian market. Further, we consider a sample period which covers the Global Financial Crisis (GFC) and the European Sovereign Debt Crisis (SDC). This period has been very volatile for the Australian stock market in that we had spillover effect from international crises, see for example, Yilmaz(2010).

Our second contribution is that we disaggregate order imbalance by analysing whether the trade is buyer imitated or seller initiated. Chordia, Goyal and Jegadeesh (2016) extend their analysis on net flows as they highlight that it is important to know the difference between buyer and seller initiated trades and this will enable understanding the relationship between volume and returns better and they explain this relationship by using a number of behavioural hypotheses. While they argue that there are a number of hypothesis that motivates the buyer and seller pattern of trade, they focus on the “when aspect” of buyers or sellers initiated trades. They find that on average both buyer and seller initiated trade increase with past returns. They find this relationship to be more negative over the short term returns and positive for the longer term returns. While studies in the volume-volatility relationship has considered the net flow that is order imbalance, we extend the literature by considering the difference between buyer and seller initiated trade. Hence our second contribution in this study is that, we assess the impact of buyer initiated and seller initiated trades on realized volatility separately.

Our third contribution is we consider the impact of order imbalance on realized volatility instead of absolute returns as in previous studies and consider further decomposing realized volatility in sub-components including good and bad volatility. Andersen and Bollerslev (1998) and Andersen et al. (2001), highlight that as high-frequency data becomes available, realized volatility can help estimate the true volatility by being more informative and closer to the underlying integrated volatility since it uses all the trading prices during the day. Chan and Fong (2006) examine the impact of number of trades, trade size and order imbalance on daily stock return volatility. They differ their study from their previous study in Chan and Fong (2000) and use realized volatility instead of absolute return as the measure of daily stock return volatility. In general, they confirm the conclusion of Jones et al. (1994) that the number of trades is the dominant factor in the volatility-volume relation. Neither trade size nor absolute order imbalance provides additional significant explanatory power regarding realized volatility. While we focus on realized volatility and order imbalance in the Australian context, our study makes further contributions to the realized volatility literature in two ways: (1) in terms of modelling, our study is improved by capturing the long-memory behaviour of realized volatility, which have not been considered in previous relevant studies. We capture long-memory behaviour using the HAR-(log) RV model and (2) we extend our analysis of realized volatility into good and bad volatility. The analysis of the volume and return relationship has indicated some weak relationship between these two variables, see for example, Karpoff (1987). Other studies highlight the negative relationship between volume and returns, for example, Campbell, Grossman and Wang (1993), Conrad, Hameed and Niden (1994) and Wang and Chin (2004). This negative relationship is explained by the market structure and the behavioural argument. The market structure explanation is that market makers are expected to act following high volume which signals that liquidity traders are active in the market and hence price is adjusted. The behavioural argument is that momentum is consistent with low volume, see Barberis, Shleifer and Vishny (1998), Hong and Stein (1999). Most of these studies consider absolute returns or squared returns which therefore eliminates the sign of the returns. Market participants perceive good and bad news in different ways and hence we should expect that the impact on volatility will be different. Bekeart and Wu (2000) show that firm returns are correlated with downside markets and the aggregate volatility in the market increases as covariance rises. Avramov, Chordia and Goyal (2006) argue that a positive return is accompanied by sell orders, which is mainly from informed traders who will reduce volatility, while a negative return will be associated by sellers who are mostly uninformed traders and hence volatility will increase. While Chan and Fong (2006) assess the impact of order imbalance and realized volatility, they do not consider the split in RV into good and bad volatility. Hence in our study, we try to assess if we have any asymmetric response from good or bad news from the market and decompose realized volatility in good and bad volatility. Segal, Shaliastovic and Yaron (2015) consider good versus bad uncertainties to assess if macroeconomic volatility increases or decreases aggregate growth and asset prices. Following their approach, we define good volatility as the volatility associated with positive return, while the bad volatility is the volatility associated with negative return. We provide further details in the next section.

The key findings of our study can be summarised as follows: (1) overall order imbalance has an impact on RV in the Australian market. Order imbalance increases RV in the good volatility sample but not in bad volatility sample; (2) when we assess whether the order is buyer or seller initiated, we find that seller initiated orders have an impact on bad volatility that is when returns are negative highlighting the losers and buyer initiated orders overall have an impact on both good and bad volatility, but more pronounced in good volatility. Our results here are consistent with the momentum strategy that is buyers initiate trades for winners and sellers initiate trade for losers ; (3) our results also indicate that the effect of seller/buyer-initiated trade on bad/good volatility is asymmetric, specifically, (i) the effect of seller initiated trade on bad volatility is consistently larger than that of buyer-initiated trade on good volatility and (ii) while seller initiated trade has no significant effect on good volatility, buyer-initiated trade significantly reduce the bad volatility. Finally, consistent with the previous literature we have a significant relationship between trading volume/ number of trades and realized volatility and this is consistent no matter which volatility component is considered that is, in both good and bad volatility.

The remainder of the paper is organised as follows. Section 2 details the data, section 3 presents the modelling framework. The results are discussed in section 4 and section 5 concludes the paper.

2. Data

We extract 5-minutes intraday data for component stocks of the S&P/ASX 50 index from Thompson Reuter via the Securities Industry Research Centre of Asia-Pacific (SIRCA). The index comprises the 50 largest stocks listed in the Australian Stock Exchange (ASX) with the cut-off market capitalization of approximately AUD 5 billion. As of March 2017, these top

50 ASX stocks accounted for about 62% of the capitalization of the Australian stock market.[2] Our full sample covers from 07th August 2007 to 31st May 2016. This sample period exhibits an interesting feature for robustness checks as it includes the Global Financial Crisis (GFC, from 07th August 2007 to 29th May 2009),[3] the European Sovereign Debt Crisis (SDC, from 5th November 2009 to 23rd January 2013) and a stable period (from 1st January 2014 to 31st May 2016). Besides the full sample analysis, therefore, we also perform our investigation on these three sub-samples for a comparison.[4] We summarize the definition of the three sub-sample periods as well as their remarkable events and relevant references in Table 1. We exclude data on weekends and holidays. We exclude the following stocks:Medibank Private Ltd, Scentre Group, South32 Ltd, Treasury Wine Estate Ltd, Vicinity Centres Stapled and Westfield Corporation Stapled from the analysis.

In addition, we facilitate our focus on the order imbalance – volatility relationship as advocated in the introduction by collecting information of seller and buyer initiated trades from SIRCA. The information helps to identify whether a particular trade is initiated by the buyer or the seller. We then compute the daily absolute order imbalance as the absolute value of the difference between daily buyer initiated trades and daily seller initiated trades. The daily buyer/seller initiated trades are aggregated from intraday buyer/seller initiated trades during that trading day.

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[2] See https://www.asx50list.com

[3] As the GFC originated continuously from the U.S. Sub-prime Mortgage crisis, we combine the two crisis periods as the GFC for convenience.

[4] We consider the SDC analysis since the EU was ranked as the third-largest trading partner of Australia in 2016. Further information about trading relationship between Australia and the EU can be found at http://ec.europa.eu/trade/policy/countries-and-regions/countries/australia/.

We summarize the cross-sectional mean of the descriptive statistics of the main variables in Table 2. We avoid the non-negativity condition of modelling volatility and scale of variables by taking the natural logarithm of all variables. This transformation also aims to satisfy the Heterogeneous Autoregressive Model of the realized volatility (HAR-RV), which is discussed in more detail in the next section. As we expect, the mean and the median of the realized volatility and its components, realized semivariances, in the crisis periods are consistently higher than in the stable period. The level of risk in the Australian stock market seems to be higher during the GFC period than the SDC period, supported by the higher average volatility in the former period. We observe that the mean and the median of all variables are close to each other, indicating the distributions of all variables are approximately symmetric. This supports our natural logarithm transformation of the variables.

We confirm the slow decaying pattern in realized volatility and realized semivariances in Table 3 by showing the cross-sectional mean of their autocorrelation at lag 1, 10, 20 and 50, respectively. This stylised fact is widely agreed in the literature and is referred to as the long-range-dependent or long memory behavior of the realized volatility (e.g., Andersen et al, 2001, 2003; Barndorff-Nielsen, 2002; Barndorff-Nielsen and Shephard, 2004; Fleming and Kirby, 2011; Do et al., 2016). While the literature in volatility spillover has recognized this long memory behavior of the realized volatility and incorporates this feature in the empirical modelling frameworks, it is rarely found in the volume-volatility literature. An exception, Do et al. (2014), who employ the fractional integrated process to accommodate the long memory behavior in examining the relationship between trading volume and higher moments of the return distribution.

3. Econometric modelling

3.1 Good versus Bad Volatility

Together with an increasing availability of high frequency data, Andersen et al. (2001, 2003) and Barndorff-Nielsen (2002) proposed to construct the realized volatility (or realized variance) in a non-parametric fashion as the sum of squared intra-day returns. This development facilitated an introduction of a new volatility measure,the realized semivariance, which distinguishes the downside and upside variation (see Barndorff-Nielsen et al., 2010). More specifically, the realized semivariance describes the volatilities due to negative and positive changes in asset prices, which are respectively called the negative and positive semivariance.

Previous studies in the volume – volatility literature have defined the "good" and the "bad" volatility as the persistent and the jump component of realized volatility, respectively (see Giot et al., 2010). This definition has been revised with the use of realized semivariance. Segal et al. (2015) considers "good" volatility as variation due to positive movements in asset prices (i.e., positive semivariance), while "bad" volatility is the uncertainty associated with negative changes in the prices (i.e., negative semivariance). Results emerging from Patton and Sheppard (2015) support the latter rather than the former definition. They show that the future variance is more strongly related to the past negative semivariance than the past positive semivariance. In addition, the effect of jumps on future variance is asymmetric, such that negative (positive) jumps cause higher (lower) future variance.

Similar to Segal et al. (2015) and Patton and Sheppard (2015), we decompose realized volatility into the positive and negative realized semivariance to represent the good and the bad volatility respectively. Firstly, we follow Andersen et al. (2001, 2003) and Barndorf-Nielsen (2002) to construct the realized volatility of stock i in day t from intra-day return as,

$$RV_{i,t} = \sum_{n=1}^{N} r_{n,i,t}^2 \tag{1}$$

where $r_{n,i,t}$ is the nth intra-day return of stock i in day t, calculated as the difference between intraday log prices, $r_{n,t} = \log(P_{n,i,t}) - \log(P_{n-1,i,t})$. N denotes the number of intra-day returns during any trading day.

We subsequently estimate the positive and negative realized semivariance ($RV_{i,t}^{+}$ and $RV_{i,t}^{-}$) as follows,

$$RV_{i,t}^{+} = \sum_{n=1}^{N} \mathbf{1}_{(r_{n,i,t} \geq 0)} r_{n,i,t}^{2} \tag{2}$$

$$RV_{i,t}^{-} = \sum_{n=1}^{N} \mathbf{1}_{(r_{n,i,t} < 0)} r_{n,i,t}^{2} \tag{3}$$

where $\mathbf{1}_{(.)}$ is an indicator function, receiving value of 1 if the logical function is true and 0 otherwise. The sum of positive and negative realized semivariance forms realized volatility in any trading day *t*, $RV_{i,t} = RV_{i,t}^{+} + RV_{i,t.}^{-}$ Essentially, we can respectively refer the $RV_{i,t}^{+}$ and $RV_{i,t}^{-}$ the upside and downside risk, which correspond to the right- and the left-tail of the return distribution. Segal et al. (2015), therefore, links the $RV_{i,t}^{+}$ to the good state of the return or good volatility, whereas, $RV_{i,t}^{-}$ is associated with the bad state of the return or bad volatility.

3.2 Modelling Framework

We capture the long-memory behavior of the realized volatility and realized semivariances using a simple, yet efficient representation of the HAR-RV model proposed by Corsi (2009). Andersen et al. (2007) shows that the HAR-RV has delivered remarkably good performance in modelling and forecasting the long-range dependency, which is comparable to a much more sophisticated Autoregressive Fractionally Integrated Moving Average (ARFIMA) model. The HAR-RV model has been widely employed in the literature (e.g., Corsi et al., 2010; Haugom et al., 2014; Patton and Sheppard, 2015; Vortelinos, 2016). The HAR-RV model for panel data can be specified as follows:

$$RV_{i,t} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + \varepsilon_{i,t} \tag{4}$$

where $RV_{i,t}^{w}$ and $RV_{i,t}^{m}$ are respectively defined as weekly and monthly realized volatility, which can be constructed as:

$$RV_{i,t}^{w} = \frac{1}{5}\sum_{j=1}^{5} RV_{i,t-j} \tag{5}$$

$$RV_{i,t}^{m} = \frac{1}{22}\sum_{j=1}^{22} RV_{i,t-j} \tag{6}$$

We investigate the volume-volatility relationship by extending the HAR-RV model to accommodate additional explanatory variables. We consider two main extensions to analyze the relationship between order imbalance and volatility, together with two additional versions for robustness checking the effect of number of trades and trading volume on volatility. These extensions are specified as follows,

HAR-RV-OB: $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + \theta|OB|_{it} + \varepsilon_{it}$

HAR-RV-SB: $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + w_s Si_{it} + w_b Bi_{it} + \varepsilon_{it}$

HAR-RV-NT: $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + \alpha NTrades_{it} + \varepsilon_{it}$

HAR-RV-TV: $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + \beta Volume_{it} + \varepsilon_{it}$

where $|OB|$ is the absolute order imbalance, Si and Bi respectively denotes seller and buyer initiated trades, $NTrades$ is the number of trades and $Volume$ is the number of shares traded.

Besides the total realized volatility (RV), we also apply the four extensions to model the negative realized semivariance (RV^{-}, proxies the bad volatility) and positive realized semivariance (RV^{+}, proxies the good volatility). We obtain the estimates using the Fama-MacBeth method with their Newey-West *t*-statistics. The standard errors are adjusted using the Newey-West method to overcome the heteroskedasticity and autocorrelation problems experienced in the Fama-MacBeth method.

4. Results and discussion

4.1 Total Volatility

We assess the impact of order imbalance on total volatility as well as to differentiate between the impact of buyer and seller initiated trades on total volatility and report the results in Table 4. Table 4 shows the impact of absolute order imbalance, which is calculated as the absolute value of difference between buyer initiated trades and seller initiated trades on the daily realized volatility across the four different samples. Panel A shows the results of the impact of order imbalance and RV, while panel B shows the results of buyer and seller initiated trades and RV. We estimate our model across four sub-samples which include the full sample, the GFC from August 2007 to May 2009, the sovereign debt crisis from November 2009 to January 2013 and we include a stable period from January 2014 to May 2016. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics. Panel A shows that, except for the European sovereign debt crisis, order imbalance seems to have a positive and significant impact on total volatility in the top 50 Australian stocks. The positive sign indicates that excess buy (sell) orders will move price up (down). The independent variables also include average weekly and average monthly RV, where only the weekly RV has an impact on realized volatility. This highlights that the market corrects itself in the short time frame and hence the average monthly RV does not seem to have an impact on RV. Across the four samples, we have a strong positive impact of order imbalance on RV in the full sample, the GFC (which is of a slightly higher magnitude, indicating the period of instability and higher volatility in the market) and the stable period. The European sovereign debt crisis does not seem to have affected trading in the Australian market to a large extent.

Although our results in Panel A are inconsistent with Shazad et al. (2014), who find that order imbalance has minimal impact on the Australian market, we support the main theory that explains this positive relationship, namely the price theory in market microstructure by Kyle(1985). Our finding here is equally consistent with Chordia et al. (2002). Chordia et al.

(2002) flags that there is strong reason to believe that large trade induces temporary price changes and hence order imbalances should exert pressure on market returns. Further explanation of our results is supported by Chordia et al. (2004) who explain why order imbalances can have an impact on the returns; namely (1) based on the inventory paradigm, that is market makers find it hard to re-adjust their inventories and (2) they argue that order imbalances indicate that there is excessive interest in a stock and if this is auto-correlated then order imbalance should impact on the returns. Another key explanation for the impact of order imbalance and realized volatility has been provided by Chan and Fong (2000). They argue that market makers cannot differentiate between the informed and uninformed traders transactions. They will consider the order imbalance and then revise their quotation and therefore prices will be adjusted accordingly. Hence Chan and Fong (2000) argue that order imbalance plays an important role in the volume-volatility relationship.

Panel B reports the impact of buyer and seller initiated trades on realized volatility. Across the four sub-samples, seller initiated trade has a significant and positive impact on the realized volatility. For buyer initiated trade while having a positive and significant impact across the 3 samples, except the GFC, the magnitude of the coefficients are smaller than the seller initiated trades. While our idea of testing the impact of buyer versus seller initiated trades on realized volatility is novel, our results are backed by a number of hypothesis that explain the motivations of buyers and sellers in the market which is the basis of the hypothesis in Chordia at al. (2016). Some of the seller motivation hypothesis include the disposition hypothesis, where it is expected that investors are quick to sell their winners but reluctant to sell their losers, see for example, Shefrin and Statman (1985). Constatinides (1984) tax-motivated trading model makes the opposite prediction that is sellers are likely to initiate trades for losers than for winners. Based on the tax induced trading, the argument is that investors should sell stocks with losses so as to gain on their taxes, and hence they will not sell the winners in the market, which is in contrast to the disposition effect. On the buyer side, the typical strategies used include the momentum strategy, see for example, Jeegadesh and Titman (1983) where typically the buyer who is most probably an uninformed trader will trade for the winners rather than the losers. We also have the contrarian hypothesis where the expectation will be that the buyers will initiate trade for the losers and the sellers will be more likely to initiate trade for the winners. Given all these trading strategies and motivation to initiate trade in the market, we should expect that buyer and seller initiated trade should impact on RV as shown by our results. If we consider panel B, the results of the subsample of the GFC period indicates that only the seller initiated trades had an impact on RV while buyer initiated trade did not have any effect on RV. This reflects the flight to quality that the market typically had during the GFC, see for example, Mustafaa et al. (2015). As the level of market risk increases in the market, during the GFC, investors, in particular buyers moved to more conservative investment like bonds, while seller initiated more trades as the level of market risk increased, reflecting the asymmetric response to market conditions between buyers and sellers.

4.2 Good versus Bad Volatility

In our study, following Segal et al. (2015), we decompose total volatility into good and bad volatility and assess the impact of order imbalance on good versus bad volatility as well as the impact of buyer versus seller initiated trade on good and bad volatility. We decompose realized volatility into the positive and negative realized semivariance to represent the good and the bad volatility respectively, hence good volatility represents periods of positive returns and bad volatility highlights periods of negative returns. We run our model and report the results of bad volatility in Table 5 and results of good volatility in Table 6. Similar to table 4, panel A focuses on order imbalance, while panel B reports the results of buyer versus seller imitated trade. Similar to the total imbalance model, our independent variables include weekly and monthly realized volatility. While weekly RV matters, monthly RV does not impact on good volatility, but has a significant impact on bad volatility. This indicates the persistence in negative return which can lead to fear in the market and hence the monthly RV matters.

Focusing on panel A of these two tables, it is clear that order imbalance have an impact on good volatility rather than on bad volatility. This further highlights that the results obtained in Table 4 are mainly driven by the results of good volatility rather than bad volatility and hence we argue that we can have an asymmetric response between good and bad volatility. To have a better understanding of this differential impact of the net flow, that is order imbalance, on good and bad volatility, we consider the separate effect of buyer versus seller initiated trade on good and bad volatility which is reported in panel B of table 5 and table 6.

Panel B of table 5 and table 6 reports the results of the impact of seller and buyer initiated trade on bad and good volatility. Panel B of Table 5 shows that in bad volatility periods, both buyer and seller initiated trade have an impact. The seller initiated trade has a positive and significant impact across the four samples while buyer initiated trade is significant across all samples except the stable sample period. The results of the seller initiated trade is in line with the momentum strategy, that is the sellers will initiate trade for the losers, captured by the negative return that is in bad volatility. In contrast, the buyer initiated trades are in line with the contrarian strategy that is the buyers will initiate trade for the losers. Interestingly, the seller initiated trade has a larger impact on bad volatility, given the estimated coefficients are larger than the buyer initiated trade and buyer initiated trade seem to reduce bad volatility. Panel B of table 6, shows the results for the good volatility that is when returns are positive. In contrast to the results obtained from table 5, seller initiated trade does not impact on good volatility. This implies that the disposition hypothesis does not hold in this case as we will expect that the seller to initiate trade for the winners in general. In contrast, the buyer initiated trade are consistent with the momentum strategy given that buyer initiated trades have a positive and significant impact on good volatility across the four different sub-samples. When returns are positive, the buyers, being the uninformed trader are expected to initiated trade for the winners and hence have a significant impact on good volatility. Overall our results highlight that while order imbalance order does have an impact on total volatility in the Australian market, it is mainly on good volatility rather than bad volatility. Further, we conclude that the effect of seller/buyer initiated trade on bad/good volatility is actually asymmetric, that is, if we consider the magnitude of the estimated coefficients, the effect of seller initiated trade on bad volatility is consistently larger than that of buyer initiated trade on good volatility and while seller-initiated trade has no significant effect on good volatility, buyer initiated trade has significantly reduced the bad volatility.

4.3 Trading Volume/Frequency and Realized Volatility (Total, Good and Bad)

We further analyse the relationship of volume on realized volatility, in particular by assessing both the impact of number of trades and trading volume on realized volatility. Jones et al. (1994), Chan and Fong(2006) and Giot et al. (2010) consider different measures of volume in that they consider the number of trades and trading volume as being key component to explain the volume-volatility relationship. As such in our study, we assess the impact of both the number of trades capturing the trading frequency and trading volume that is number of shares traded, on volatility in the Australian market by decomposing the total volatility into good and bad volatility. It should be noted that while Shazad et al. (2014) consider the number of trades and volatility relationship in the Australian context, we further extend this literature by considering (1) good and bad volatility and (2) we employ a different modelling framework as highlighted in the previous section. The results of the analysis of the relationship between number of trades and volatility are reported in table 7. Table 7 shows the impact of the number of trades (captured by α) on the daily realized volatility (RV) and its two components (bad volatility, RV^{-}) and good volatility, RV^{+}) across the four different samples. Similar to our previous model, we include weekly and monthly volatility in the analysis. Overall our results show that the number of trades that is trading frequency has a positive and significant impact on realized volatility. These results hold, no matter which way we decompose volatility, we have strong significant results for both good and bad volatility. Our results is well supported by the literature in that Jones et al. (1994) find that in the US context, the number of trades provides all the explanation of daily volatility in NASDAQ stock. These results are further confirmed by Chan and Fong (2006) that number of trades is the dominant factor in the volatility-volume relation. The results obtained of the decomposition of the total volatility into good and bad volatility is consistent with the conclusion drawn by Giot et al. (2010). In their analysis, they decompose realized volatility relations into a continuously varying component and a discontinuous jump component. Their results confirm that number of trades is the dominant factor in the volatility-volume relation, whatever the volatility component considered. Their analysis is based on the top 100 largest stocks on the New York Stock Exchange. Hence we equally confirm that the number of trades largely explains the volatility in the top 50 Australian stocks, no matter how we decompose total volatility, which is in good and bad volatility.

We present the results of the relationship between trading volume that is the number of shares traded and realized volatility in table 8. Table 8 shows the impact of trading volume (captured by β) on the daily realized volatility (RV) and its two components (bad volatility, RV^{-} and good volatility, RV^{+}) across the four sub-samples. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics. Similar to the results of the number of trades, the daily number of shares traded have a very significant and positive impact on realized volatility. These results are consistent across the four samples, whether it is a crisis or stable sample period. These results are equally similar to the results of the number of trades in that even if we decompose realized volatility into good and bad volatility the trading volume does have a positive and significant impact. Our results are similar to the US based literature of Chan and Fong (2006) and Giot (2010). In the Australian context, Shahzad et al (2014) analyze volume by considering number of trades and average trade size. They find that while number of trades is the most important variable, the average trade size does not have the same explanatory power. However, our results is similar to what Giot et al. (2010) concludes that of the volume proxies used, average trade size explains less of the RV. Giot et al (2010) highlights that the trading volume and trading frequency have a significant impact of realized volatility. Similarly, we conclude that in the Australian context, both trading frequency and trading volume have significant explanatory power in explaining realized volatility, no matter if we decompose between good or bad volatility.

5. Conclusion

We study the impact of order imbalance on realized volatility on the ASX 50 for a period starting August 2007 to May 2016. We decompose order imbalance in buyer versus seller initiated trade and decompose realized volatility in good and bad volatility. We therefore make a contribution to the literature by our analysis in numerous ways, in particular for the Australian market. Our key objective is to assess the impact of order imbalance (including buyer versus seller initiated trade) on total, good and bad volatility. We equally consider the volume and volatility relationship by considering trade frequency (number of trades) and trading volume (number of shares traded) and assessing the impact on both good and bad volatility.

Our key findings can be summarised as follows: (1) overall order imbalance has a significant impact on realized volatility in the Australian top 50 stocks; (2) as we decompose realized volatility into good and bad, order imbalance has a significant impact on good volatility but not on bad volatility; (3) we find that seller initiated trades have an impact on bad volatility whereas buyer initiated trades overall have an impact on both good and bad volatility, but more pronounced in good volatility;(4) our results also indicate that the effect of seller/buyer initiated trade on bad/good volatility actually asymmetric, that is, (i) the effect of seller initiated trade on bad volatility is consistently larger than that of buyer initiated trade on good volatility and (ii) while seller initiated trade has no significant effect on good volatility, buyer initiated trade has significantly reduced the bad volatility. Finally, we establish that both the trade volume and frequency of trades have a significant impact on realized volatility and these results hold, even if we decompose realized volatility into good and bad volatility.

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Table 1: Definition of sub-samples

Sample	Date	Description
Global Financial Crisis	07th Aug 2007 – 29th May 2009	We follow Lane (2012) and Bekaert et al. (2014) to define the starting date of the GFC period as 07th Aug 2007, when stock markets initially fell and central bank put its first intervention to support liquidity in financial markets. We select 29th May 2009 as the end date of the GFC, which is consistent with the conclusion of the National Bureau of Economic Research (NBER) and Dungey and Gajured (2014).
Sovereign Debt Crisis	5th Nov 2009 – 23rd Jan 2013	Consistent with Lane (2012), we define the starting date of the SDC period as 5th Nov 2009, when the market experienced an announcement of Greek budget deficit at 12.7% of GDP in 2009. We choose 23rd Jan 2013 and the end date of the SDC period, which remarked successful sovereign debt auctions across Eurozone (see Barley, 2013).
Stable	01st Jan 2014 – 31st May 2016	We avoid potential aftermath effect of the crises by selecting the starting date of the stable period as 01st Jan 2014.

Table 2: Descriptive statistics

This table reports the cross-sectional mean of summary statistics of realized volatility (RV), bad volatility that is negative semivariance (RV^{-}), good volatility that is positive semivariance (RV^{+}), order imbalance and its components (including seller initiated trade and buyer initiated trades). All variables are in their natural logarithm.

Sample	Variable	Mean	Median	Std.Dev	P5	P95	Min	Max
	RV	-8.37	-8.47	0.84	-9.55	-6.77	-10.68	-4.82
	RV^{-}	-9.10	-9.17	0.85	-10.36	-7.58	-11.52	-5.50
Full	RV^{+}	-9.09	-9.19	0.88	-10.34	-7.43	-11.52	-5.34
	Order Imbalance	5.58	5.79	1.17	3.35	7.09	0.02	8.25
	Sellier initiated trade	7.55	7.58	0.49	6.70	8.30	5.40	9.04
	Buyer initiated trade	7.55	7.58	0.49	6.71	8.30	5.47	9.09
	RV	-7.45	-7.50	0.86	-8.82	-6.05	-9.72	-4.83
	RV^{-}	-8.23	-8.22	0.84	-9.61	-6.83	-10.56	-5.51
GFC	RV^{+}	-8.17	-8.23	0.91	-9.61	-6.69	-10.55	-5.34
	Order Imbalance	5.21	5.41	1.14	3.00	6.68	0.30	7.56
	Seller initiated trade	7.17	7.19	0.41	6.47	7.81	5.58	8.37
	Buyer initiated trade	7.21	7.23	0.42	6.50	7.88	5.73	8.49
	RV	-8.53	-8.54	0.58	-9.46	-7.58	-10.37	-6.10
	RV^{-}	-9.25	-9.25	0.63	-10.27	-8.22	-11.20	-6.84
SDC	RV^{+}	-9.26	-9.27	0.62	-10.26	-8.23	-11.24	-6.55
	Order Imbalance	5.54	5.75	1.15	3.36	7.00	0.17	7.98
	Seller initiated trade	7.45	7.46	0.37	6.83	8.04	5.85	8.67
	Buyer initiated trade	7.45	7.46	0.38	6.84	8.04	5.81	8.71
	RV	-8.78	-8.79	0.59	-9.70	-7.79	-10.52	-6.47
	RV^{-}	-9.50	-9.52	0.65	-10.55	-8.42	-11.39	-7.12
Stable	RV^{+}	-9.51	-9.53	0.64	-10.51	-8.44	-11.39	-6.96
	Order Imbalance	5.83	6.06	1.14	3.62	7.25	0.32	8.05
	Seller initiated trade	7.91	7.92	0.35	7.34	8.47	6.61	8.99
	Buyer initiated trade	7.89	7.90	0.35	7.30	8.45	6.56	9.02

Table 3: Autocorrelations of realized volatilities

This table reports the cross-sectional mean of autocorrelation of realized volatility (RV), bad volatility that is negative semivariance (RV^{-}) and good volatility that is positive semivariance (RV^{+}) at different lags. ACF(n) denotes the autocorrelation value at lag n.

Sample	Variable	ACF(1)	ACF(10)	ACF(20)	ACF(50)
Full	RV	0.75	0.63	0.58	0.50
	RV^{-}	0.68	0.57	0.53	0.46
	RV^{+}	0.68	0.57	0.53	0.46
GFC	RV	0.67	0.49	0.40	0.17
	RV^{-}	0.60	0.43	0.35	0.15
	RV^{+}	0.60	0.44	0.35	0.16
SDC	RV	0.56	0.35	0.26	0.16
	RV^{-}	0.49	0.31	0.23	0.14
	RV^{+}	0.49	0.30	0.22	0.14
Stable	RV	0.55	0.36	0.30	0.23
	RV^{-}	0.45	0.30	0.25	0.19
	RV^{+}	0.47	0.31	0.25	0.19

Table 4: Impact of Order Imbalance, Buyer or Seller Initiated trade on Total Volatility

This table shows the impact of absolute order imbalance (calculated as absolute value of difference between Buyer Initiated trade and Seller Initiated trade) on the daily realized volatility (RV) across 4 different samples. Panel A shows the results of the impact of order imbalance, while panel B shows the results of buyer and seller initiated trades. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics in brackets. ***, ** and * denotes that the estimated coefficients are statistically significant at 1%, 5% and 10% level, respectively. The output for panel A is obtained from the following HAR-RV-OB models:$RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + \theta|OB|_{it} + \varepsilon_{it}$, where $RV_{i,t}^{w}$: Realized volatility over weekly horizon and $RV_{i,t}^{m}$: Realized volatility over monthly horizon. The output for panel B is obtained from the following HAR-RV-SB models, $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + w_s Si_{it} + w_b Bi_{it} + \varepsilon_{it}$.

	Total Volatility			
Sample	**Full**	**GFC**	**SDC**	**Stable**
Panel A: Order Imbalance				
φ_0	-0.064***	-0.079*	-0.037	-0.078*
	(-2.97)	(-1.74)	(-1.14)	(-1.67)
φ_1	-0.150***	-0.132***	-0.152***	-0.154***
	(-35.04)	(-13.64)	(-22.72)	(-18.10)
φ_w	1.157***	1.136***	1.162***	1.155***
	(119.73)	(56.54)	(72.73)	(60.22)
φ_m	-0.012	-0.009	-0.014	-0.006
	(-1.64)	(-0.57)	(-1.13)	(-0.45)
Order Imbalance	0.003**	0.007**	0.000	0.004**
	(2.24)	(2.26)	(0.19)	(2.11)
Adj- R^2	0.797***	0.798***	0.830***	0.770***
	(262.45)	(94.46)	(251.45)	(158.90)
Panel B: Buyer and Seller Initiated trades				
φ_0	-0.137***	-0.302***	-0.033	-0.169***
	(-5.73)	(-5.29)	(-0.96)	(-3.40)
φ_1	-0.151***	-0.132***	-0.155***	-0.152***
	(-34.90)	(-13.88)	(-23.22)	(-17.30)
φ_w	1.136***	1.122***	1.139***	1.132***
	(115.27)	(55.32)	(68.43)	(59.68)
φ_m	0.057***	0.030*	0.080***	0.050***
	(7.03)	(1.71)	(5.96)	(3.40)
Seller-initiated trades	0.044***	0.062***	0.048***	0.033***
	(8.12)	(4.23)	(6.51)	(3.10)
Buyer-initiated trades	0.023***	0.001	0.030***	0.024**
	(4.28)	(0.09)	(4.31)	(2.34)
Adj- R^2	0.802***	0.802***	0.835***	0.776***
	(271.44)	(95.54)	(261.39)	(167.72)
Number of Obs	95,999	18,686	35,355	26,757

Table 5: Impact of Order Imbalance, Buyer or Seller Initiated trade on Bad Volatility

This table shows the impact of absolute order imbalance (calculated as absolute value of difference between Buyer Initiated trade and Seller Initiated trade) on **bad volatility** that is negative semivariance (RV^{-}) across 4 different samples. Panel A shows the results of the impact of order imbalance, while panel B shows the results of buyer and seller initiated trades. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics in brackets. ***, ** and * denotes that the estimated coefficients are statistically significant at 1%, 5% and 10% level, respectively. The output for panel A is obtained from the following HAR-RV-OB models: $RV_{it}^{-} = \varphi_0 + \varphi_1 RV_{i,t-1}^{-} + \varphi_w RV_{i,t}^{-,w} + \varphi_m RV_{i,t}^{-,m} + \theta|OB|_{it} + \varepsilon_{it}$, where $RV_{i,t}^{-,w}$: negative semivariance over weekly horizon and $RV_{i,t}^{-,m}$: negative semivariance over monthly horizon. The output for panel B is obtained from the following HAR-RV-SB models, $RV_{it}^{-} = \varphi_0 + \varphi_1 RV_{i,t-1}^{-} + \varphi_w RV_{i,t}^{-,w} + \varphi_m RV_{i,t}^{-,m} + w_s Si_{it} + w_b Bi_{it} + \varepsilon_{it}$.

	Bad Volatility			
Sample	**Full**	**GFC**	**SDC**	**Stable**
Panel A: Order Imbalance				
φ_0	-0.064**	-0.067	-0.037	-0.096
	(-2.29)	(-0.97)	(-0.97)	(-1.64)
φ_1	-0.184***	-0.166***	-0.187***	-0.188***
	(-45.86)	(-18.14)	(-29.83)	(-23.14)
φ_w	1.199***	1.161***	1.212***	1.199***
	(124.54)	(56.05)	(79.94)	(62.54)
φ_m	-0.021***	-0.001	-0.028**	-0.019
	(-2.60)	(-0.05)	(-2.26)	(-1.21)
Order Imbalance	0.001	0.003	-0.000	0.003
	(0.74)	(0.86)	(-0.17)	(1.23)
Adj- R^2	0.737***	0.666***	0.797***	0.720***
	(194.85)	(69.62)	(218.98)	(137.56)
Panel B: Buyer and Seller Initiated trades				
φ_0	-0.077***	-0.172**	0.022	-0.151**
	(-2.64)	(-2.41)	(0.54)	(-2.46)
φ_1	-0.186***	-0.168***	-0.189***	-0.190***
	(-46.13)	(-18.67)	(-29.71)	(-23.19)
φ_w	1.182***	1.151***	1.188***	1.186***
	(119.76)	(55.31)	(74.51)	(61.26)
φ_m	0.046***	0.052***	0.062***	0.032*
	(5.32)	(2.74)	(4.33)	(1.93)
Seller-initiated trades	0.089***	0.111***	0.110***	0.050***
	(14.37)	(6.69)	(12.91)	(4.30)
Buyer-initiated trades	-0.026***	-0.046**	-0.037***	0.005
	(-4.24)	(-2.54)	(-4.71)	(0.41)
Adj- R^2	0.744***	0.671***	0.803***	0.727***
	(199.72)	(70.71)	(226.78)	(141.61)
Number of Obs	95,999	18,686	35,355	26,757

Table 6: Impact of Order Imbalance, Buyer or Seller Initiated trade on Good Volatility

This table shows the impact of absolute order imbalance (calculated as absolute value of difference between Buyer Initiated trade and Seller Initiated trade) on **good volatility** that is positive semivariance (RV^+) across 4 different samples. Panel A shows the results of the impact of order imbalance, while panel B shows the results of buyer and seller initiated trades. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics in brackets. ***, ** and * denotes that the estimated coefficients are statistically significant at 1%, 5% and 10% level, respectively. The output for panel A is obtained from the following HAR-RV-OB models: $RV_{it}^{+} = \varphi_0 + \varphi_1 RV_{i,t-1}^{+} + \varphi_w RV_{i,t}^{+,w} + \varphi_m RV_{i,t}^{+,m} + \theta|OB|_{it} + \varepsilon_{it}$, where $RV_{i,t}^{+,w}$: positive semivariance over weekly horizon and $RV_{i,t}^{+,m}$: positive semivariance over monthly horizon. The output for panel B is obtained from the following HAR-RV-SB models, $RV_{it}^{+} = \varphi_0 + \varphi_1 RV_{i,t-1}^{+} + \varphi_w RV_{i,t}^{+,w} + \varphi_m RV_{i,t}^{+,m} + w_s Si_{it} + w_b Bi_{it} + \varepsilon_{it}$.

	Good Volatility			
Sample	**Full**	**GFC**	**SDC**	**Stable**
Panel A: Order Imbalance				
φ_0	-0.071***	-0.082*	-0.036	-0.079
	(-2.78)	(-1.65)	(-0.93)	(-1.39)
φ_1	-0.178***	-0.158***	-0.181***	-0.190***
	(-45.10)	(-17.33)	(-28.31)	(-26.19)
φ_w	1.186***	1.168***	1.187***	1.200***
	(128.30)	(62.05)	(74.33)	(67.50)
φ_m	-0.013*	-0.014	-0.010	-0.015
	(-1.72)	(-0.88)	(-0.76)	(-1.02)
Order Imbalance	0.003**	0.010***	-0.000	0.006**
	(2.42)	(2.76)	(-0.21)	(2.39)
Adj- R^2	0.779***	0.788***	0.812***	0.750***
φ_0	(240.38)	(85.83)	(214.99)	(159.03)
	0.756***	0.766***	0.792***	0.724***
	(211.55)	(75.43)	(190.40)	(139.18)
Panel B: Buyer and Seller Initiated trades				
φ_0	-0.107***	-0.272***	0.013	-0.133**
	(-3.86)	(-4.35)	(0.33)	(-2.27)
φ_1	-0.179***	-0.159***	-0.183***	-0.189***
	(-45.42)	(-17.74)	(-28.94)	(-25.69)
φ_w	1.169***	1.156***	1.166***	1.184***
	(124.26)	(59.37)	(70.81)	(66.63)
φ_m	0.052***	0.024	0.081***	0.036**
	(6.43)	(1.38)	(5.91)	(2.39)
Seller-initiated trades	-0.003	0.012	-0.015*	0.013
	(-0.42)	(0.69)	(-1.80)	(1.06)
Buyer-initiated trades	0.068***	0.050***	0.092***	0.041***
	(10.95)	(2.78)	(11.05)	(3.45)
Adj- R^2	0.790***	0.799***	0.821***	0.761***
	(254.73)	(89.83)	(233.45)	(172.77)
	0.762***	0.771***	0.798***	0.730***
	(217.04)	(76.39)	(200.45)	(146.22)
Number of Obs	95,999	18,686	35,355	26,757

Table 7: Number of Trades and Realized Volatility (Total, Good and Bad)

This table shows the impact of number of trades (captured by α) on the daily realized volatility (RV) and its two components (bad volatility (RV^-) and good volatility (RV^+)) across 4 different samples. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics in brackets. ***, ** and * denotes that the estimated coefficients are statistically significant at 1%, 5% and 10% level, respectively. The output is obtained from the following HAR-RV-NT models: $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^w + \varphi_m RV_{i,t}^m + \alpha NTrades_{it} + \varepsilon_{it}$

	Total Volatility				**Bad Volatility**				**Good Volatility**			
Sample	**Full**	**GFC**	**SDC**	**Stable**	**Full**	**GFC**	**SDC**	**Stable**	**Full**	**GFC**	**SDC**	**Stable**
φ_0	-0.256***	-0.376***	-0.199***	-0.270***	-0.202***	-0.257***	-0.154***	-0.256***	-0.228***	-0.345***	-0.166***	-0.227***
	(-9.95)	(-6.24)	(-5.24)	(-5.00)	(-6.58)	(-3.45)	(-3.54)	(-3.98)	(-7.78)	(-5.23)	(-3.84)	(-3.62)
φ_1	-0.151***	-0.132***	-0.156***	-0.152***	-0.185***	-0.165***	-0.190***	-0.190***	-0.179***	-0.158***	-0.183***	-0.190***
	(-35.17)	(-13.78)	(-23.17)	(-17.73)	(-46.28)	(-18.37)	(-29.94)	(-23.47)	(-45.79)	(-18.00)	(-29.02)	(-25.85)
φ_w	1.140***	1.124***	1.145***	1.135***	1.187***	1.153***	1.197***	1.188***	1.173***	1.158***	1.173***	1.186***
	(117.30)	(55.63)	(70.13)	(60.19)	(121.43)	(55.38)	(76.56)	(61.80)	(126.82)	(60.93)	(72.77)	(67.29)
φ_m	0.045***	0.026	0.055***	0.047***	0.032***	0.047**	0.034**	0.028*	0.039***	0.019	0.054***	0.032**
	(5.74)	(1.48)	(4.31)	(3.21)	(3.84)	(2.47)	(2.50)	(1.72)	(5.01)	(1.12)	(4.14)	(2.12)
No of Trades	0.065***	0.064***	0.070***	0.061***	0.061***	0.068***	0.064***	0.059***	0.063***	0.062***	0.069***	0.057***
	(18.01)	(8.29)	(10.93)	(9.35)	(15.29)	(7.80)	(9.07)	(7.95)	(15.66)	(7.04)	(9.84)	(7.51)
Adj- R^2	0.802***	0.802***	0.834***	0.775***	0.743***	0.670***	0.801***	0.727***	0.761***	0.770***	0.796***	0.730***
	(270.78)	(95.09)	(260.40)	(168.58)	(199.32)	(70.34)	(225.87)	(142.73)	(217.40)	(76.28)	(198.62)	(147.07)
Number of Obs	95,999	18,686	35,355	26,757	95,999	18,686	35,355	26,757	95,999	18,686	35,355	26,757

Table 8: Volume and Realized Volatility (Total, Good and Bad)

Table shows the impact of trading volume (captured by β) on the daily realized volatility (RV) and its two components (bad volatility (RV^{-}) and good volatility (RV^{+})) across 4 different samples. We report the Fama-MacBeth regression coefficients with their Newey-West t-statistics in brackets. ***, ** and * denotes that the estimated coefficients are statistically significant at 1%, 5% and 10% level, respectively. The output is obtained from the following HAR-RV-TV models: $RV_{it} = \varphi_0 + \varphi_1 RV_{i,t-1} + \varphi_w RV_{i,t}^{w} + \varphi_m RV_{i,t}^{m} + \beta Volume_{it} + \varepsilon_{it}$

	Total Volatility				**Bad Volatility**				**Good Volatility**			
Sample	**Full**	**GFC**	**SDC**	**Stable**	**Full**	**GFC**	**SDC**	**Stable**	**Full**	**GFC**	**SDC**	**Stable**
φ_0	-0.477***	-0.334***	-0.447***	-0.618***	-0.423***	-0.299***	-0.374***	-0.602***	-0.510***	-0.335***	-0.493***	-0.627***
	(-12.89)	(-4.22)	(-7.69)	(-8.16)	(-9.69)	(-3.30)	(-5.41)	(-6.72)	(-12.02)	(-3.85)	(-7.65)	(-7.02)
φ_1	-0.152***	-0.133***	-0.155***	-0.155***	-0.184***	-0.166***	-0.189***	-0.187***	-0.180***	-0.160***	-0.182***	-0.190***
	(-35.65)	(-13.70)	(-23.58)	(-18.35)	(-45.89)	(-17.91)	(-30.35)	(-23.33)	(-46.07)	(-17.74)	(-29.11)	(-26.05)
φ_w	1.153***	1.138***	1.157***	1.146***	1.195***	1.165***	1.206***	1.191***	1.185***	1.172***	1.184***	1.193***
	(119.97)	(56.42)	(73.96)	(60.06)	(123.81)	(54.93)	(80.34)	(62.14)	(129.56)	(62.87)	(76.60)	(65.97)
φ_m	-0.019**	-0.018	-0.017	-0.014	-0.027***	-0.010	-0.030**	-0.027*	-0.023***	-0.023	-0.017	-0.026*
	(-2.58)	(-1.11)	(-1.43)	(-0.98)	(-3.36)	(-0.54)	(-2.42)	(-1.73)	(-2.99)	(-1.44)	(-1.41)	(-1.68)
Volume	0.022***	0.016***	0.021***	0.027***	0.018***	0.013***	0.017***	0.025***	0.023***	0.016***	0.023***	0.027***
	(14.38)	(4.04)	(9.04)	(9.99)	(11.37)	(3.66)	(6.51)	(8.44)	(13.24)	(3.70)	(8.85)	(8.28)
Adj- R^2	0.799***	0.799***	0.832***	0.771***	0.739***	0.666***	0.799***	0.722***	0.758***	0.768***	0.795***	0.725***
	(265.01)	(94.92)	(250.00)	(161.49)	(195.44)	(68.93)	(217.45)	(140.76)	(213.17)	(75.60)	(190.78)	(141.06)
Number of Obs	95,999	18,686	35,355	26,757	95,999	18,686	35,355	26,757	95,999	18,686	35,355	26,757