Common trends in volatility and news in the global equity market

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Abstract

This paper extends the long standing literature on the news volatility relationship. It proposes a fractionally cointegrated vector autoregression model to reveal a long-run equilibrium relation between news and volatility in the global equity market. The coherence between news from different countries is strongest at low frequencies, which establishes the existence of a global news stream. Such a global news stream is approximated well by news flow from the United States. Both volatility and news spillovers are significant implying strong integration between equity markets in Australia, Europe, and the United States.

Keywords
Volatility, news arrival, long memory, fractional cointegration
JEL Classification Numbers
C22, C32, G12

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1 Introduction

A fundamental postulate of financial economics is that asset prices change because of unexpected information. Due to seminal results of Ross (1989) it is widely accepted that the variance of the price equals the variance of the information flow in the absence of arbitrage. However, since the provocative finding of Roll (1988) that showed little relation between stock prices and news, there has been limited success in reliably identifying a news volatility relationship. This paper revisits this puzzle in a novel way. A unified framework for modeling the dynamic interconnection between realized volatility and news flow in the global equity market is proposed. Within this framework, recently available news data allows news flow to be treated as an observable, allowing both time and frequency domain techniques to be used to focus on specific patterns in the data. A model setup is based on the cofractional vector autoregression (VAR) of Johansen and Nielsen (2010, 2012), which may reveal the longer-run dependencies inherent in the data. It is shown that both volatility spilloveres and news from other countries are important for explaining the dynamic nature of volatility, which makes multiple country setting crucial. An important result is a one-to-one relation between volatility and news in the global equity market, which unequivocally supports findings of Ross (1989). Moreover, the global news flow can be approximated by news from the United States.

An enormous literature has been devoted to investigating dependance of asset prices and fundamental information. Early research (e.g. Shiller, 1981) found little correspondence between price changes and news items. However, more recent studies reveal significant explanatory power of macroeconomic factors in relation to stock returns. Flannery and Protopapadakis (2002) found that stock market returns are significantly correlated with inflation and money growth. Engle, Ghysels and Sohn (2013) show importance of distinguishing between short-run and long-run movements in macroeconomic activity for explaining volatility. The main finding of Engle, Ghysels and Sohn (2013) is that inflation and industrial production are significant explanatory factors of volatility. However, the long-run component driven by the economic factors accounts for less than half of the variation in volatility.

Another strand of literature suggests once news is correctly identified there is more evidence of a strong relationship between stock price changes and news flow. Tetlock's (2008) findings suggest that linguistic analysis of media content captures hard-to-quantify aspects of firm fundamentals, which investors quickly incorporate into stock prices. This paper extends this idea taking into consideration the tone and relevance of news items[1]. Having the news items related to the specific

[1] Engle and Ng (1993) emphasize the asymmetry of the volatility response to news, while Riordan, Storkenmaier, Wagener and Zhang (2013) point a particular significance of negative news messages which induce stronger market reactions.

equity market (Australia, Europe or the United States) identified the information volatility can be estimated. The basic idea is to extract the news component from the stock price to measure the contribution of public information to volatility. As evident from the empirical part of this paper, the information volatility has better explanatory power of price volatility than the number of news items. This result supports the asymmetric reaction of volatility to news as reported in Nelson (1991).

The fact of co-integration between volatility and news series, which is confirmed here, implies misspecification of fractionally integrated ARMA (ARFIMA) models. Since Andersen, Bollerslev, Diebold and Labys (2003) the ARFIMA models became a benchmark in the literature. The main advantage of this class of models is an ability to capture high persistence (long memory) in volatility by a fractionally integrated process (Ding, Granger and Engle, 1993; Ding and Granger, 1996; Andersen and Bollerslev, 1997). Baillie and Bollerslev (1989) found evidence of one common stochastic trend among the set of foreign exchange rates implying these series to be integrated of the first order, I(1). However, the near unit root property of volatility does not allow to use the idea of Baillie and Bollerslev (1989) directly and requires to treat volatility and news as fractionally integrated series. Moreover, the specific structure of the global trading day requires structural restrictions identifying linkages between different zones of the global equity market (see Engle, Ito and Lin, 1990). The co-fractional structural VAR for the realized volatilities and news in Australia, Europe, and the United States developed here allows to capture long memory in volatility and news and the calender structure of a trading day. Moreover, such model is able to take into account both short-run and long-run interconnections between volatility and news.

The rest of the paper proceeds as follows. Section 2 describes the structure of the global trading day, the high-frequency data set used in the paper and how jump-robust measures of realized volatility used in the empirical analysis are constructed. Section 3 discusses the presence of long memory in news and realized volatility. In Section 4 a fractionally cointegrated volatility model with news is proposed. Section 5 addresses the issue of the transmission of volatility and news within the Australian, European, and the United States equity markets. This is the simplest case implies links between volatility and news in every zone separately. Section 6 explores news-volatility patterns between trading zones in the global equity market. The analysis is now complicated by the calendar structure of the global trading day which allows intra day influences between zones. Structural co-fractional vector autoregressive models are used to account for the natural calendar restrictions, i.e. the global trading day. Section 7 extends the model from the previous section to adopt asymmetric effects from news to volatilities. Section 8 identifies the global news stream as news from the United States. Section 9 concludes.

2 Data and volatility estimates

The central purpose of this research is to deepen understanding of news-volatility linkages in a number of financial hubs in the global equity market, namely, Australia, Europe, and the United States. To achieve this, it is necessary to construct a comprehensive dataset capturing the volatility of this asset market within each trading zone. Consequently, a dataset was collected comprising high frequency (10 minute) data for the equity market in each of the three regions. The data was gathered from the Thomson Reuters Tick History database and covers the period from 4 January 2005 to 28 September 2012. Days where one market is closed are eliminated, as are public holidays or other occasions when trading is significantly curtailed. This high frequency data is used to construct daily estimates of volatility for 1696 full trading days.

Before setting out the exact specification of the data that was collected it is necessary to define the global trading day which is integral to this research. Each calendar day is split into three trading zones, namely Australia (AU), Europe (EU) and the United States (US). The Australia trading zone is defined as 9am to 4pm (Sydney time), the European trading zone 9am to 2:30pm (Central European Time) and the United States zone 6:30am to 3pm (Central Eastern Time), where all times are taken to be Local Time[2]. This setup may be illustrated as follows:

$$\underbrace{\overbrace{9\text{am}\cdots 4\text{pm}}^{\text{Australia}}\quad \overbrace{9\text{am}\cdots 2:30\text{pm}}^{\text{Europe}}\quad \overbrace{6:30\text{am}\cdots 3\text{pm}}^{\text{U.S.}}}_{\text{One Trading Day}}$$

The equity data in each of the three trading zones consists of closing prices for 10 minute intervals[3] for ASX 200 (AU), DAX 30 (EU) and S&P 500 futures contracts.

The high-frequency returns data is now used to construct time series of realized volatility estimates (Anderson, Bollerslev, Diebold and Labys, 2001, 2003) for each of the zones. For the purposes of estimating volatility and its associated components, define a jump-diffusion process for the logarithm of price,

$$dp(t) = \vartheta(t)dt + \sigma(t)dW(t) + \zeta(t)dq(t), \tag{1}$$

in which $\vartheta(t)$ is a drift process, $\sigma(t)$ is a positive stochastic volatility process, $dW(t)$ is the increment of a Wiener process and $q(t)$ is a counting process with intensity $\lambda(t)$, $t = 1, ..., T$. $P[dq(t) = 1] = \lambda(t)$ and $\zeta(t)$ reflects the size of discrete price jumps. It is well known that

[2]The period denoted as Asian trading (2 hours prior to Japan opening) by Engle, Ito and Lin (1990), is excluded here.

[3]The 10-minute frequency is chosen on the basis of volatility signature plots.

realized variation (commonly known as realized volatility) is defined as

$$RV_t(\Delta) \equiv \sum_{j=1}^{1/\Delta} r_{j,t}^2, \tag{2}$$

which is the sum of intraday squared returns and converges to the quadratic variation

$$QV_t = \int_{t-1}^{t} \sigma^2(s)ds + \sum_{t-1<s\leq t} \zeta_{j,t}^2. \tag{3}$$

The proxy for volatility in equation (3) includes contributions from both the continuous and jump components of price. Anderson, Bollerslev and Diebold (2007), however, demonstrate that information pertaining to future volatility is best captured by the persistent diffusive component of volatility. Using the diffusive component realized volatility therefore, is likely to provide more reliable estimates of volatility linkages. As these linkages are the primary focus of this research, a necessary prerequisite is a reliable method for estimating a continuous diffusive process.

A number of methods exist to effect this calculation and provide volatility estimates that are robust to jumps, the earliest of which is the bi-power variation (Barndorff-Nielsen and Shephard, 2004, 2002), given by

$$BV_t(\Delta) \equiv \frac{\pi}{2}\left(\frac{1}{1-\Delta}\right)\sum_{j=2}^{1/\Delta} |r_{j-1,t}||r_{j,t}|. \tag{4}$$

As this measure converges to integrated volatility, it is possible to decompose the total volatility into the contribution from jumps,

$$RV_t(\Delta) - BV_t(\Delta) \to \sum_{t-1<s\leq t} \zeta_{j,t}^2. \tag{5}$$

An important result that follows from equations (4) and (5) is that by construction, the bi-power variation can be used as an estimator of quadratic variance robust to jumps. Ait-Sahalia, Jacod and Li (2012) and Mancini (2009) propose two such estimators. These are truncated realized volatility, given by

$$TRV_t(\Delta, u_n) \equiv \sum_{j=1}^{1/\Delta} r_{j,t}^2 \cdot 1_{\{|r_{j,t} \leq u_n\}}, \tag{6}$$

and truncated power variation

$$TPV_t(\Delta, u_n, p) \equiv \sum_{j=1}^{1/\Delta} |r_{j,t}|^p \cdot 1_{\{|r_{j,t}| \leq u_n\}}, \tag{7}$$

in which $u_n = \iota\Delta^{\varpi}$ is a suitable sequence going to 0, $\iota > 0$, ϖ is an arbitrary constant, and $p \geq 2$ is a positive integer.

Of course, in practice suitable choices for α and ϖ must be provided. Todorov, Tauchen and Grynkiv (2011) argue for $\iota = 3\sqrt{BV_t}$ and $\varpi \in (0, 1/2)$ and these conditions are supported by an empirical example of Todorov, Tauchen and Grynkiv (2011). However, it is necessary to note that in choosing these parameters there is a risk of throwing away many Brownian increments, which makes it difficult to use this method in practice.

Andersen, Dobrev and Schaumburg (2012) introduce an alternative jump robust estimator known as minimum realized volatility

$$\mathrm{MinRV}_t(\Delta) \equiv \frac{\pi}{\pi-2}\left(\frac{1}{1-\Delta}\right)\sum_{j=2}^{1/\Delta}\min(|r_{j-1,t}|,|r_{j,t}|)^2. \tag{8}$$

Andersen, Dobrev and Schaumburg (2012) justify that minimum realized volatility measure provides better finite sample properties than bi-power variation. Due to this fact, and taking into account the arbitrary choice of the threshold ϖ in truncated power variation (even though it is more asymptotically efficient than bi-power variation and minimum realized volatility), the MinRV measure of integrated volatility robust to jumps is used.

The three series for realized volatility, calculated using equation (8) applied to each trading zone[4], are plotted in Figure 1. To the naked eye it appears that the estimates of realized volatility in Europe and the United States have similar patterns. The volatility in the United States is perhaps a little more pronounced during the Global Financial Crises period of 2007 - 2009. Figure 1 indicates that realized volatility in the Australian zone appears to experience more volatility events (appears more spiked) than the other zones.

To capture news flow, pre-processed news data from the Thomson Reuters News Analytics database is used. The text of news items broadcast over the Reuters network are analysed using linguistic pattern recognition algorithms. The analysis produces a number of characteristics relating to each news item including relevance to the specific firm, sentiment and novelty. Sentiment for each news item is coded +1, 0, -1 for positive, neutral and negative tones respectively. Here we take all news articles denoted as articles, representing fresh stories consisting of a headline and body text. Appends to previous articles, and alerts with no text body are ignored. News items relating to all constituents of the S&P 500, ASX 200 and DAX 30 indices are collected for each day during the sample period with a number of measurements relating to news flow taken. The total number of news items across all stocks are recorded reflecting volume of information flow. The final daily time series represent the number of articles[5] with relevance 1 for each of the three zones, namely Australia, Europe and the United States. Figure 2 shows the number of news per day for each of the zones normalized by the factor of $\sqrt{\widetilde{T}_i\xi_i}$, where $\widetilde{T}_i$ is the length of the trading day in the zone i and ξ_i is the number of stocks in the $i^{\text{th.}}$ index.

[4]Each volatility series is divided by the square root of the trading time in respective zone measured in hours.

[5]Such filtering of data was used by Gross-Klussmann and Hautsch (2011) who found that the articles with relevance 1 are the most frequent in the data.

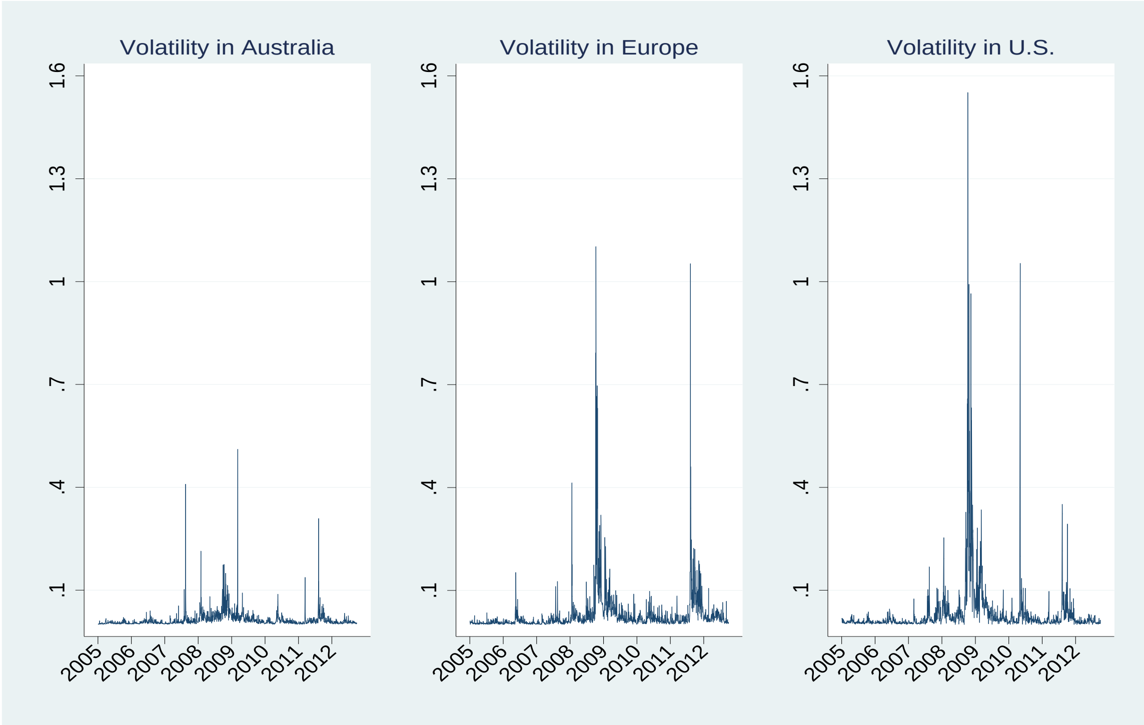

Figure 1: Minimum realized volatility estimates for the equity market in Australia, Europe and United States, respectively. The daily estimate of realized volatility for the period 4 January 2005 to 28 September 2012 is computed using (8), normalized by the factor of $\sqrt{\widetilde{T}_i}$, where $\widetilde{T}_i$ is the length of the trading day in the zone i and then scaled by 1000 before plotting.

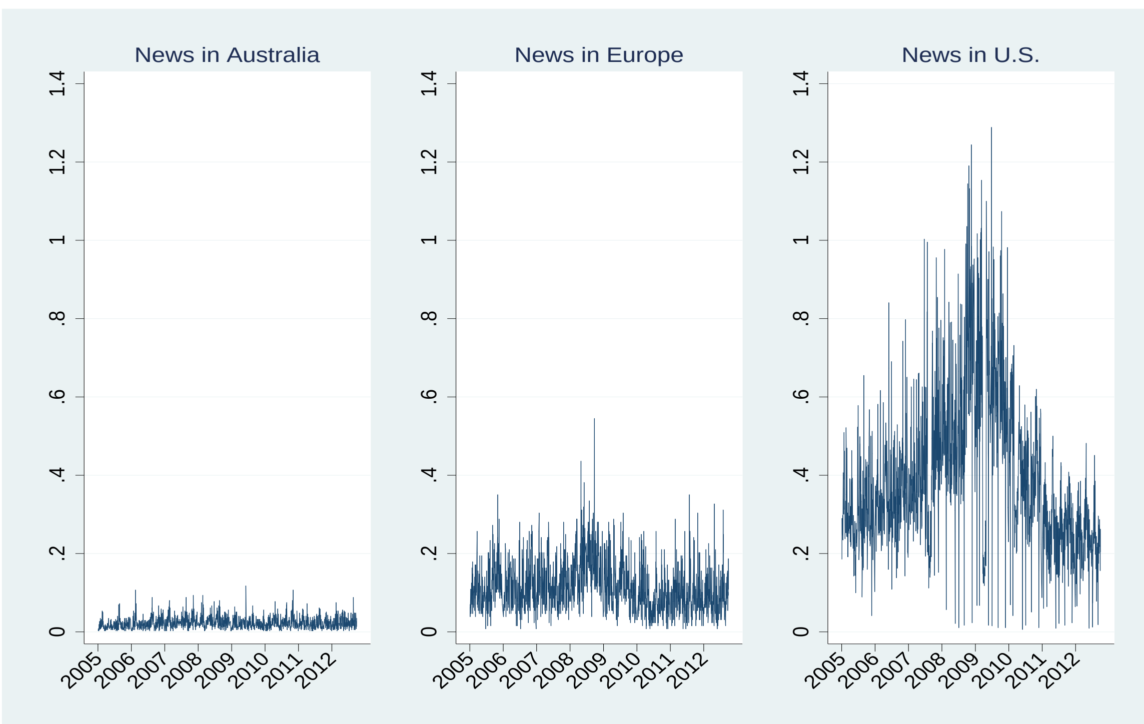

Figure 2: The number of news per day for the Australian, European and the United States equity markets normalized by the factor of $\sqrt{\widetilde{T}_i \xi_i}$, where $\widetilde{T}_i$ is the length of the trading day in the zone i and ξ_i is the number of stocks in the $i^{\text{th.}}$ index. The daily estimate of news are for the period 4 January 2005 to 28 September 2012.

As can be seen from the Figure 2 the number of news items in Europe and the United States is larger during the global financial crisis of 2007-2009. However, this pattern seems not to be pronounced in Australia which is conformed with the finding that the equity volatility series in Australia is more flat than in Europe or the United States (Figure 1).

Table 1:

Descriptive statistics.

Descriptive statistics for daily estimates of realized volatility and number of news in the equity market in Australia, Europe and the United States for the period 4 January 2005 to 28 September 2012. Time series are scaled by 1000.

		Mean	St.dev.	Min.	Max.	Skew.	Kurt.
	Australia	0.0139	0.0242	0.0004	0.5108	10.274	167.27
Volatility	Europe	0.0293	0.0658	0.0009	1.1022	8.7993	110.38
	U.S.	0.0330	0.0860	0.0003	1.5513	8.5367	104.25
	Australia	0.0238	0.0151	0.0027	0.1176	1.3636	6.1395
News	Europe	0.1143	0.0628	0.0078	0.5449	1.0336	4.9368
	U.S.	0.3962	0.1928	0.0061	1.2885	1.0210	4.3417

Table 1 reports summary statistics for the minimum realized volatility and news series. As can be seen from the Table 1 the mean level of volatility in the United States is greater that in Europe which in turn is greater that the mean volatility in Australia. Engle, Ito and Lin (1990) find volatility in the foreign exchange market is substantially higher during the New York trading hours than during Tokyo or London trading hours. Their view is that much of this volatility seems to originate from macroeconomic announcements released during New York trading hours. The results in Table 1 do support the notion that U.S. volatility is uniformly higher. The average number of news across the sample show similar to volatility patterns with the highest number in the United States. Such similarity lays the basis for analysing interaction between news and volatility which will be considered in later sections.

3 Fractional Integration in Realized Volatility and News

To explore whether or not there is a *prima facie* case for modelling commonality between realized volatility and news using fractional cointegration, the series must first be examined for the order of fractional integration. Bollerslev and Mikkelsen (1996) and Baillie, Bollerslev and Mikkelsen (1996) describe volatility as a long memory process with a fractional parameter d. Following Diebold and Innoue (2001) long memory can be defined by the rate of growth variances of partial sums as $\text{var}(S_T) = O(T^{2d+1})$, in which $S_T = \sum_{t=1}^{T} y_t$, y_t is a financial series of interest and T is the sample size.

A commonly used test for existence of long memory is the R/S statistic discussed by Lo (1991) that is defined as

$$Q_T = \frac{1}{\hat{\sigma}_T(q)}\Big[\max_{1\le k\le T}\sum_{t=1}^{k}(y_t-\bar{y}) - \min_{1\le k\le T}\sum_{t=1}^{k}(y_t-\bar{y})\Big], \tag{9}$$

in which $\bar{y}_t = (1/T)\sum_{t=1}^{T} y_t$, and $\hat{\sigma}_T(q)$ is the standard deviation of the Newey-West estimate of the long run variance with bandwidth q. Lo (1991) found that if there is short memory but no long memory in the series y_t, Q_T statistic should converge to the range of a Brownian bridge on the unit interval.

To quantify long memory, a semiparametric estimator of d was proposed by Geweke and Porter-Hudak (1983). This estimator implies that for a long memory time series y_t the spectral density $f(\omega)$ has a power-law decay $f(\omega)\sim c\omega^{-2d}$ when $\omega\to 0$. The GPH estimator $\hat{d}$ is represented by an ordinary least squares regression of the log periodogram $\{\log I(\omega_j)\}_{j=1}^{m}$ on $\{\log\omega_j\}_{j=1}^{m}$, where $\omega_j = 2\pi j/T$, $j=0,...,T-1$ are the Fourier frequencies,

$$I(\omega_j) = \frac{1}{2\pi n}\Big|\sum_{t=1}^{T} y_t \exp(-i\omega_j t)\Big|^2, \tag{10}$$

is the periodogram and m is a positive integer. Then the GPH estimator is given by -0.5 times the least-square slope estimate in the ordinary least squares regression. To specify m the automatic procedure of Hurvich and Deo (1999) or visual inspection of log-log periodogram plots can be used. When $|d|>0.5$, y_t is non-stationary; if $0<d<0.5$, y_t is stationary and has long memory; and when $-0.5<d<0$, y_t is stationary and has short memory.

Table 2:

Sample autocorrelations of volatility.

Sample autocorrelations of the realized volatility in the equity market of Australia, Europe, and United States, respectively.

	Volatility		
Lag	AU	EU	US
1	0.3845	0.5478	0.6330
2	0.3372	0.5837	0.6146
3	0.2866	0.5100	0.5379
4	0.2740	0.4509	0.5166
5	0.2491	0.4274	0.4827
6	0.2631	0.4332	0.4645
7	0.2434	0.3910	0.4230
8	0.2317	0.3861	0.5148
9	0.2392	0.3971	0.4946
10	0.2824	0.3350	0.4629

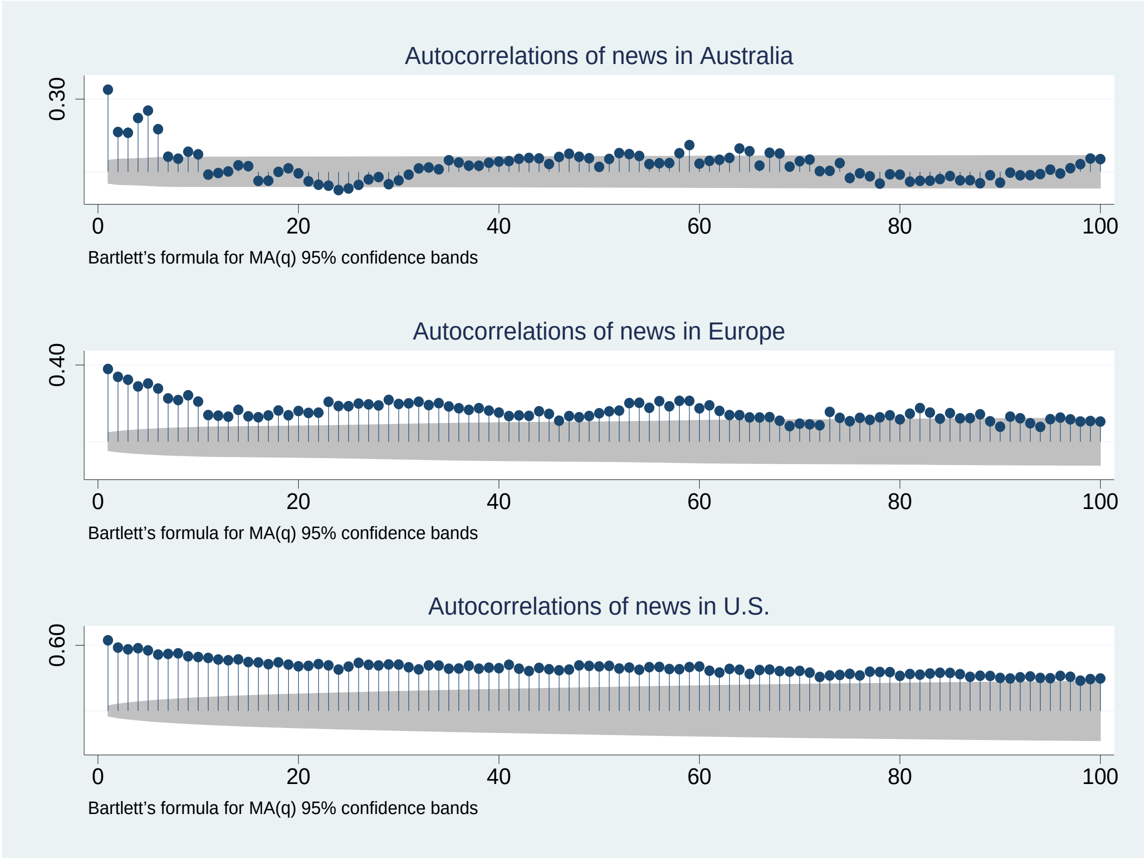

Figure 3: Sample autocorrelations of the news series in the equity market of Australia, Europe, and United States, respectively.

The definition of the long memory discussed earlier implies that the time series has a slowly decaying autocorrelation function. The autocorrelations out to ten lags for each of realized volatility series are reported in Table 2. All series indicate a fair amount of persistence, which is statistically significant. This is to be expected for volatility given that autorcorrelation in the squares of financial returns is a well-known and well-documented phenomenon[6] (Pagan, 1996). It appears the volatility in the United States is more persistent than volatility in Europe which in turn is more persistent than Australian volatility.

In the case of news (see Figure 3), the only European and the United States series have significant correlations at 100 lags. The news series in Australia experienced significant persistence only at the first 10 lags. Overall, the autocorrelation patterns are similar to that of volatility.

To check for the existence of long memory in the volatility and news series formally, the R/S test defined by equation (9) can be used. The test clearly rejects the short memory hypothesis for all time series.

[6]Similar findings were reported by Andersen, Bollerslev, Diebold and Labys (2003) and Deo, Hurvich and Lu (2006) for realized volatility.

Table 3:

The estimates of the parameter d.

The GPH estimates of fractional differencing parameter d from equation (10) with t-statistics for Australia, Europe, and the United States. The power $m = [T^{0.6}]$.

		$\hat{d}$	t-statistic
	Australia	0.4318	4.7183
Volatility	Europe	0.5273	8.8130
	U.S.	0.6921	12.870
	Australia	0.1998	2.5479
News	Europe	0.3265	3.2070
	U.S.	0.4806	5.2402

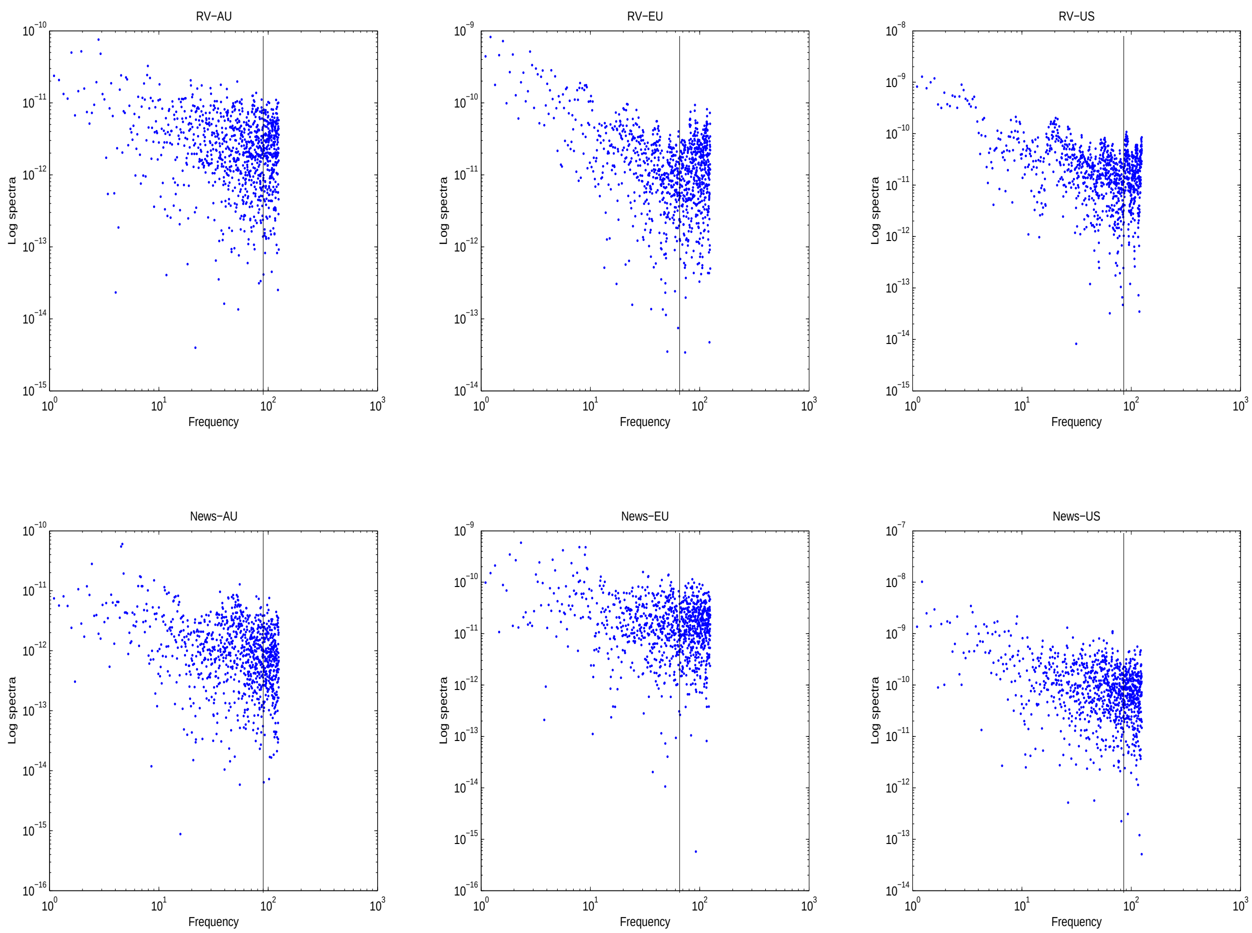

Figure 4: Log spectra of the volatility and news series in Australia, Europe, and the United States. The periodograms are plotted on a double logarithmic scale. The daily estimate of the series are for the period 4 January 2005 to 28 September 2012. The vertical line in each plot is the visually chosen $m = [T^{0.6}]$. The maximum number of frequencies used for the estimation is $m = [T^{0.65}] = 125$.

For estimating the fractional difference parameter d the number of Fourier frequencies m needs to be chosen. Hosking (1981) recommends $m = [T^{0.5}]$ while Shimotsu (2007) argued that $m = [T^{0.65}]$. As far as a value of m depends on specific empirical application, it is preferable to chose m by inspecting the log-log periodogram plots presented in Figure 4. An approximate linearity of the series is pronounced for $m = [T^{0.6}]$, which is separated by vertical lines and related to 87 Fourier frequencies. It is important to note that the GPH estimator is asymptotically unaffected by seasonality in volatility or news series as it uses only Fourier frequencies in a neighborhood of zero.

The estimates of the parameter d, using the GPH estimator from (10) with $m = [T^{0.6}]$ frequencies, are reported in Table 3. The United States and European volatility is non-stationary, a fact perhaps related to the strong influence of the global financial crisis on these zones. Australia is the most stable zone which is supported by $d = 0.4318$. The news series are stationary in all three zones.

4 Fractional Cointegration

Since all the volatility and news series have long memory or non-stationary, it is natural to conjecture if these series share a common stochastic trend(s), that can explain their behavior. Such conjecture about a presence of the stochastic trend can be formulated using the concept of cointegration (Engle and Granger, 1987). The existence of cointegration among sets of non-stationary time series implies that both long-run and short-run dynamics can be captured by a vector error correction model (VECM).

For a nonstationary n dimensional series the cointegrated vector autoregression (VAR) is

$$\Delta y_t = \alpha(\beta^{'} y_{t-1} + \rho^{'}) + \sum_{j=1}^{k} \Gamma_j \Delta y_{t-j} + \epsilon_t, \tag{11}$$

where $\Delta y_{t-j} = y_{t-j} - y_{t-j-1}$ and $\alpha, \beta, \rho, \Gamma$ are the parameters of the model. The long run dynamics are captured by the stationary combinations $\beta^{'} y_t$, while the short-term dynamics is determined by Γ_j. The representation theorem of Engle and Granger (1987) allows to test for cointegration by estimating the rank of the matrix $\Pi = \alpha\beta^{'}$.

Supposing that matrix Π is rank deficient and suppressing the constant term ρ for simplicity the model (11) can be rewritten in a structural form as

$$A\Delta y_t = \alpha^{*}\beta^{'} y_{t-1} - \sum_{j=1}^{k} B_j \Delta y_{t-j} + \varepsilon_t, \tag{12}$$

in which A and B_j are matrices of structural coefficients and $\alpha^{*} = A\alpha$. The main task in structural VECM (12) is to estimate coefficients of the matrix A. Note that the structural models proposed in this paper are identified by construction from the calender structure of the trading day. However, different identification schemes can be easily used within the proposed framework.

Both of the models defined in (11) and (12) imply that data are I(1) processes. However, such assumption is denied by the previous section where two series are non-stationary and other four series are stationary with long memory. In order to work the VECM representation into a form suitable for use with fractionally integrated series it can be incorporated into a time series model using the idea of Hosking (1981). Given an estimate of the fractional differencing parameter d is available, define the lag operator L as

$$(1-L)^d = \sum_{k=0}^{\infty} \delta_k(d) L^k, \tag{13}$$

where $\delta_k(d) = \delta_{k-1}(d)(k-1-d)/k$, $\delta_0(d) = 1$. Kunsch (1986) proposed to truncate the infinite process in (13) at $\sqrt{T}$. In this case the VECM defined in (11) can be rewritten (suppressing the constant term) to allow y_t to be fractional of order d (Johansen; 2008 and Johansen and Nielsen; 2010) as

$$\Delta^d y_t = \Delta^{d-b} L_b \alpha \beta^{'} y_t + \sum_{j=1}^{k} \Gamma_j \Delta^d L_b^j y_t + \epsilon_t, \tag{14}$$

where $L_b = 1 - \Delta^b$, $\Delta^b = (1-L)^b$, ϵ_t is an n-dimensional i.i.d process with a positive definite covariance matrix V, α and β are $n \times r$ parameter matrices, d and b are fractional differencing parameters. The model $VAR_{d,b}(k)$ defined in (14) accommodates classical VARFIMA if $b = 1$. The special case of the model with $d = b$ is

$$\Delta^d y_t = \alpha L_d \beta^{'} y_t + \sum_{j=1}^{k} \Gamma_j \Delta^d L_d^j y_t + \epsilon_t. \tag{15}$$

The structural analogue of the model (15) can be presented as

$$A\Delta^d y_t = \alpha^* L_d \beta^{'} y_t - \sum_{j=1}^{k} B_j \Delta^d L_d^j y_t + \varepsilon_t. \tag{16}$$

Note that the model (16) is a special case of the system (14) with the additional calender structure represented by matrix A. In the empirical study the system (16) is always identified. The time series y_t from equation (14) is cofractional of order $d - b$ when there exist vectors β for which $\beta^{'} y_t$ has a unique fractional order $d - b$.

The model (14) can be estimated by maximum likelihood (Johansen and Nielsen; 2012) using the function

$$\log L_T(\theta) = -\frac{T}{2} \log(\det(T^{-1} \sum_{t=1}^{T} \epsilon_t \epsilon_t^{'})), \tag{17}$$

where θ represent model parameters and

$$\epsilon_t = \Delta^d y_t - \Delta^{d-b} L_b \alpha \beta' y_t - \sum_{j=1}^{k} \Gamma_j \Delta^d L_b^j y_t, \tag{18}$$

$$\epsilon_t = \Delta^d y_t - \alpha L_d(\beta' y_t + \rho') - \sum_{j=1}^{k} \Gamma_j \Delta^d L_d^j y_t, \tag{19}$$

are residuals from the models (14) and (15) respectively. Johansen and Nielsen (2012) showed that the parameters $\alpha, \beta, \rho, \Gamma$ can be concentrated out of the likelihood function and numerical optimization is only required for the fractional parameters d and b. Moreover, under i.i.d. errors the maximum likelihood parameter estimates $(\hat{d}, \hat{b}, \hat{\alpha}, \widehat{\Gamma}_j)$ are asymptotically Gaussian, while ρ and β are asymptotically mixed normal. Such results allow using standard inference for all parameters of the model.

Since the parameters of the reduced model are estimated the residuals $\hat{\epsilon}_t$ can be used to receive parameter estimates of the structural model (16). Assuming normality of the residuals ε_t the full information maximum likelihood estimates of A and the structural covariance matrix D are obtained by maximizing

$$\log l_T(\theta^s) = -\frac{n}{2}\log 2\pi - \frac{1}{2}\log\det(V) - \frac{1}{2(T-p)} \sum_{t=p+1}^{T} \hat{\epsilon}_t' V^{-1} \hat{\epsilon}_t, \quad \theta^s = (A, D), \tag{20}$$

in which p is a number of initial observations, $V = SS'$ and $S = A^{-1}D^{1/2}$. This maximization problem is equivalent to solving the nonlinear system of equations $\widehat{V} = SS'$. Since A is estimated, the structural parameters B_j can be obtained from $B_j = \hat{A}\widehat{\Gamma}_j$, where the $\widehat{\Gamma}_j$ are computed from the reduced form model.

A key ingredient for investigating commonality between news and volatility is a cointegration test for rank r. When $0 < r < n$ (Johansen and Nielsen; 2012), y_t is fractional of order d and $\beta' y_t$ is fractional of order $d - b$. More specifically, the hypothesis of interest is $rank(\Pi) \leq r$ against $rank(\Pi) \leq n$. To test these hypotheses the profile likelihood function (17) should be maximized which gives the values $L(\hat{d}_n, \hat{b}_n, n)$ and $L(\hat{d}_r, \hat{b}_r, r)$ under the two alternatives. The likelihood ratio test statistic for the model (14) is then $LR(n-r) = 2\log(L(\hat{d}_r, \hat{b}_r, r)/L(\hat{d}_n, \hat{b}_n, n))$. Theorem 11 from Johansen and Nielsen (2012) presents the limit distributions for the likelihood ratio test. In the case of "weak cointegration" that is $0 < b < 0.5$ the likelihood ratio (LR) statistic has a standard asymptotic distribution $\chi^2(n-r)^2$. When it comes to "strong cointegration", which means that $0.5 < b \leq d$, asymptotic theory is nonstandard and the LR statistic is

$$LR(n-r) \xrightarrow{D} tr\Big(\int_0^1 (dW) W_{b-1}' \Big(\int_0^1 W_{b-1} W_{b-1}' du \Big)^{-1} \int_0^1 W_{b-1} (dW)' \Big), \tag{21}$$

where dW is the vector of increments of standard Brownian motion and W_{b-1} is the correspondent vector fractional Brownian motion. The distribution (21) is continuous in b and can be computed using the numerical algorithm of MacKinnon and Nielsen (2014).

This framework can be used to investigate volatility and news interaction across the global equity market. In particular, the realized volatility and news series are expected to be $I(d)$ but fractionally cointegrate to an $I(0)$ process. In this case the parameters β naturally govern the long term relationship between the series. To check the absence of fractional cointegration the linear hypothesis $\beta_{ij} = 0$ can be tested.

Now the commonality between news and volatility and the news-volatility dissimilarity hypotheses can be formulated in terms of cointegration. Within the model (15) the commonality hypothesis is represented by inequality $r > 0$, which means that there exists at least one cointegration vector. If volatility series are not cofractional the commonality is rejected and the dissimilarity hypothesis is accepted. In this case the dynamics of volatility can be modelled using a simple fractional (S)VAR. Moreover, if the cointegration rank r of the model (15) is equal to $n-1$ there is a single $I(d)$ component (long-run equilibrium relationship) usually referred to as a common trend. In this case interaction between volatility and news can be explained by a single common factor. This situation coincides with the world wide meteor shower case of Engle, Ito and Lin (1990). If the commonality between news and volatility is found the (S)VECM model can be used to capture both the long and the short run dynamics. The main advantages of the proposed (S)VECM: the model is more parsimonious which suggests a less complicated lag structure, long memory and non-stationarity of volatility and news series can be captured.

5 Volatility and news within Australia, Europe and the United States

Early results of Mandelker (1974), Aharony and Swary (1980) and Asquith and Mullins (1986) confirm that asset prices change due to unexpected fundamental information. However, the controversial results of Roll (1988) showed little relation between stock prices and public announcements. Extending findings of Roll (1988), Shiller (1981), Berry and Howe (1994) and Mitchell and Mulherin (1994) explained price movements by irrational noise trading or the transmission of private information. This section revisits the volatility-news relation hypothesis for the global equity market. It is assumed that there is no interaction between markets, which means that volatility in every zone can be explained by the news flow from the same zone[7].

A conventional framework of Campbell and Shiller (1988) states that

$$r_t - E_{t-1}(r_t) = (1-\varrho)\sum_{j=0}^{\infty}\varrho^j(E_t - E_{t-1})(\vartheta_{t+j+1}) - \sum_{j=0}^{\infty}\varrho^j(E_t - E_{t-1})(r_{t+j+1}), \qquad (22)$$

where r_t is the log return from time $t-1$ to t, ϑ_t is the corespondent log dividend, and $E_t(\cdot)$ is the

[7]This simplifying assumption will be relaxed in the following sections.

conditional expectation given information at the time t. The unexpected returns represented by the left-hand side of equation (22) can be naturally modeled using the GARCH(1,1) framework[8] of Engle (1982), which implies

$$r_t - E_{t-1}(r_t) = \epsilon_t, \tag{23}$$

$$h_t = \kappa + \mu h_{t-1} + \phi r_{t-1}^2, \tag{24}$$

in which ϵ_t is the innovation term with mean 0 and conditional variance h_t and κ, μ and ϕ are parameters.

In order to explain volatility in terms of news announcements an additional term, representing news process, can be included in equation (24). Due to the strong persistence of news (see Section 3) the filtered series are chosen to be included into the model. Now the model defined in (23) and (24) can be adapted to the case of three zones as

$$r_t = \omega + \epsilon_t,$$

$$h_t = K + M\, h_{t-1} + \Phi\, r_{t-1}^2 + \Lambda\, \Delta^d \epsilon_{news,t}^2 \tag{25}$$

where $h_t = [h_{\mathrm{au},t}\ h_{\mathrm{eu},t}\ h_{\mathrm{us},t}]'$, $r_t^2 = [r_{\mathrm{au},t}^2\ r_{\mathrm{eu},t}^2\ r_{\mathrm{us},t}^2]'$, $\Delta^d = diag[\Delta^{d_{au}}, \Delta^{d_{eu}}, \Delta^{d_{us}}]'$ and the subscripts are self evident. The parameter matrices of interest are

$$M = \begin{bmatrix} \mu_{11} & 0 & 0 \\ 0 & \mu_{22} & 0 \\ 0 & 0 & \mu_{33} \end{bmatrix}, \quad \Phi = \begin{bmatrix} \phi_{11} & 0 & 0 \\ 0 & \phi_{22} & 0 \\ 0 & 0 & \phi_{33} \end{bmatrix}, \quad \Lambda = \begin{bmatrix} \lambda_{11} & 0 & 0 \\ 0 & \lambda_{22} & 0 \\ 0 & 0 & \lambda_{33} \end{bmatrix}.$$

The main difference of the model (25) from the conventional GARCH is that news variables are observable. Engle Ito and Lin (1990) used a similar model to explain volatility spillovers between Asia, Europe, and the United States interpreting news as an ARCH term. However, their model does not allow for contemporaneous effects between news and volatility[9]. Moreover an empirical relation between news and volatility (see e.g. Kalev, Liu, Pham and Jarnecic (2004) for Australian stock market and Hautsch, Hess and Veredas (2011) for German bond market) is normally confirmed only for the high (minute) frequency data, while such relation is poorly identified on a daily level.

The estimation results[10] of the model (25) are presented in Table 4. Before discussing results note that the model (25) was estimated in two steps. On the first step a semiparametric estimate of d was received applying Geweke and Porter-Hudak (1983) regression. The second step estimates the GARCH-X model with filtered news series by maximizing likelihood function with normal

[8]A similar representation of unexpected returns was used by Engle and Rangel (2008) to analyse an impact of GDP, inflation indices, exchange rates, and short-term interest rates on volatility in the global equity market.

[9]Alternatively volatility can be linked to macroeconomic activity as in Engle, Ghysels and Sohn (2013) who found that the higher inflation causes higher volatility.

[10]The constant term is suppressed for simplicity.

Table 4:

The estimates of the GARCH model with news.

The table reports estimates of the GARCH-X model,

$$r_t = \omega + \epsilon_t,$$

$$h_t = K + M\,h_{t-1} + \Phi\,r_{t-1}^2 + \Lambda\,\Delta^d \epsilon_{news,t}^2$$

from equation (25) based on daily observations from January 4, 2005 to September 28,2012. The fractional difference parameters d are significant according to asymptotic standard errors. The reported robust standard errors are calculated using numerical Gradient and Hessian with (***) denotes significance at the 1% level.

	Australia	Europe	United States
$\Delta^{0.2268}\epsilon^2_{\text{news},t}$	0.0000 (0.0010)	-	-
$\Delta^{0.3450}\epsilon^2_{\text{news},t}$	-	0.0161*** (0.0060)	-
$\Delta^{0.4278}\epsilon^2_{\text{news},t}$	-	-	0.0153*** (0.0047)
K	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)
$r^2_{i,t-1}$	0.1370*** (0.0159)	0.0726*** (0.0072)	0.1233*** (0.0111)
$h_{i,t-1}$	0.8385*** (0.0100)	0.9108*** (0.0060)	0.8392*** (0.0098)

residuals. The results reported in Table 4 reveals significant lagged effects in all three zones. Contemporaneous effects are significant in Europe and the United States which provides further support that days with more news are more likely to be associated with high volatility. However Australian news has no impact on volatility on the same day. Bhattacharya, Daouk, Jorgenson, and Kehr (2000) found that Mexican stock market does not react to company news, while volatility of returns, volume of trade or bid-ask spreads follow usual patterns. They suggest that unrestricted insider trading causes prices to fully incorporate the information before its public release. Another explanation of independence of news and volatility can be related to a slow response of investors to valid information, which is supported by Chan (2003). The speed of the response can be rooted in the time varying sensitivity of the price to the information (see Berger, Chaboud and Hjalmarsson; 2009).

This paper points toward a different explanation of this phenomena relying on market integrity. In particular, volatility and news in any zone are driven by the same process, which attributes conditional heteroscedasticity of stock returns to time-dependence in the global news arrival process. Such conjecture is consistent with the Mixture Distribution Hypothesis of Clark (1973). To investigate a news-volatility puzzle in more details long term trends in volatility should be taken into consideration. Such trends can be naturally captured using the cointegration methodology of Johansen (1991 , 2008), which is discussed in the following section.

6 Can common trends in volatility be explained by news?

The results of the previous section imply that volatility in Europe and the United States are contemporaneously related to the news flows from these countries, while such effect is not present in Australian stock market. Taking another view this section investigates commonality between volatility and news in the long run, permitting volatility spillovers between zones within the same trading day. The previous literature studies the impact of news announcements on volatility only within a single country (Ederington and Lee; 1993). To the best of our knowledge Jiang, Konstantinidi and Skiadopoulos (2012) is the only study that examines the relation between news and stock market volatility spillovers. However, they do not allow for intra day volatility and news effects and restrict their analysis only to lagged effects from the previous day.

To motivate the importance of capturing the long-term interrelatedness of volatility and news flows the coherence measure of these variables can be considered. The coherence is similar to the square of correlation between two series, taking values from zero to one representing no relation and perfect correlation respectively. However, the coherence is a function of frequency, which allows investigating the absence of relation between series across different periodicities.

The estimates of coherence are based on the classic Welch's method (see, e.g. Granger and Hatanaka; 1964). As follows from Figure 5 the coherence between volatility and news is closer to one for the lowest frequencies and decrease to close to zero for the higher frequencies. Moreover, volatilities between Europe and the United States are stronger related in the long run than between Australia and the United States. News series have similar patterns in all three zones, which implies strong commonality between them. For this reason, the dynamic relation between news and volatility should be examined in the long run in more details.

Moreover, the natural calender structure of a trading day documented by Engle, Ito and Lin (1990) needs to be taken into account. For example, events in Australia can influence the volatility in both Europe and the United States on the same trading day. In fact there is a natural ordering in each calendar day which imposes the structure $\mathrm{AU}_t \rightarrow \mathrm{EU}_t \rightarrow \mathrm{US}_t$. Consequently the model discussed in this section must be represented in a structural form in which the calendar structure of the trading day imposes a recursive set of short-run restrictions on the intra day interactions of the variables.

The model is given by

$$A\Delta^d x_t = \alpha^* L_d \beta' x_t - \sum_{j=1}^{k} B_j \Delta^d L_d^j x_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{iid } N(0, D) \tag{26}$$

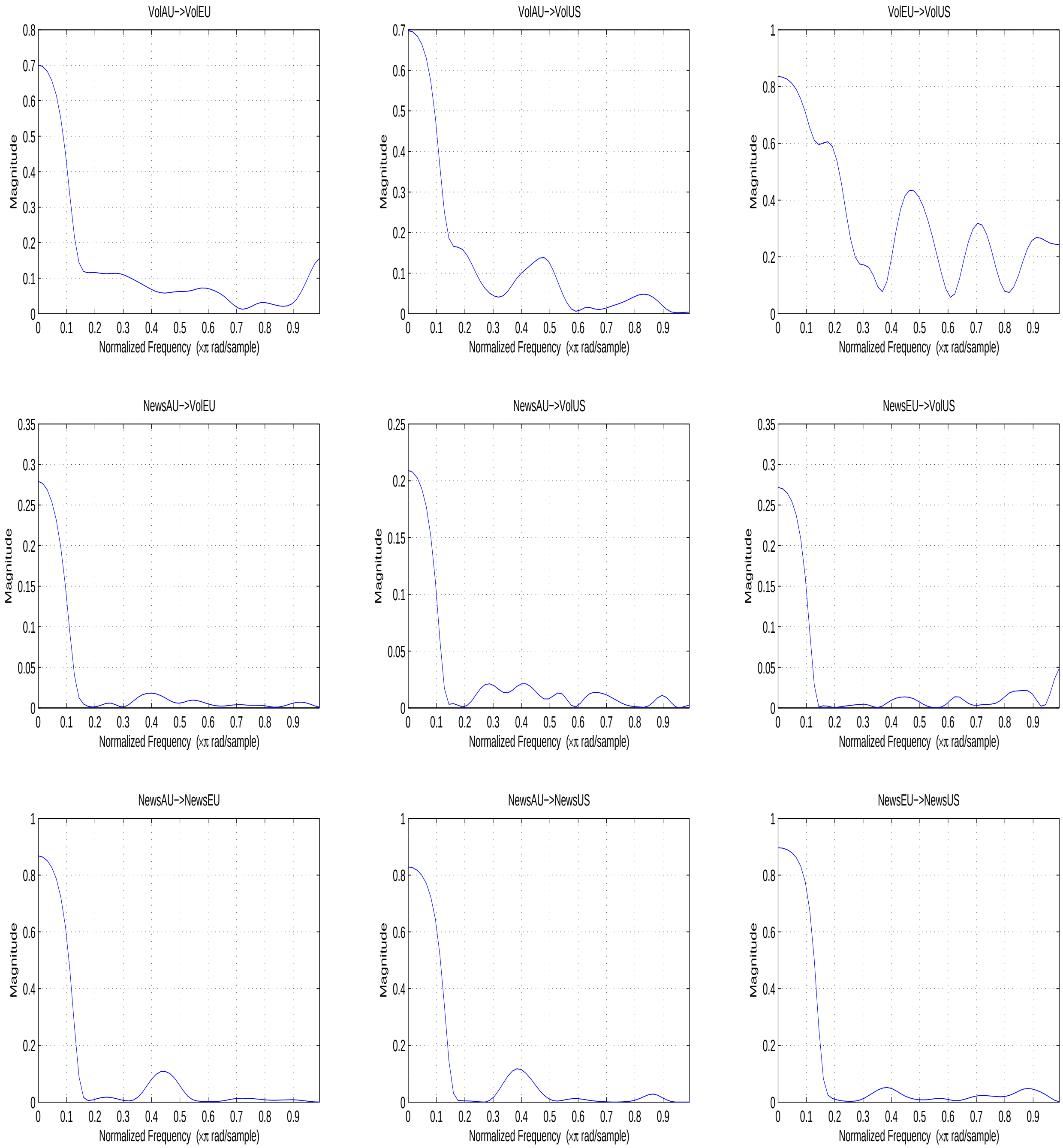

Figure 5: Coherence between volatility and news in Australia, Europe, and the United States across frequencies. The figure plots the coherence between volatility in different zones (upper panel), volatility and news (middle panel), and news flows (lower panel) imposing the natural calender structure of the trading day. The estimates are received using Welch's averaged modified periodogram method based on daily observations from January 4, 2005 to September 28, 2012.

in which

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ -\eta_{21} & 1 & 0 & -\eta_{24} & 0 & 0 \\ -\eta_{31} & -\eta_{32} & 1 & -\eta_{34} & -\eta_{35} & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & -\eta_{54} & 1 & 0 \\ 0 & 0 & 0 & -\eta_{64} & -\eta_{65} & 1 \end{bmatrix}, \quad x_t = \begin{bmatrix} \mathrm{au}_t^{\mathrm{vola}} \\ \mathrm{eu}_t^{\mathrm{vola}} \\ \mathrm{us}_t^{\mathrm{vola}} \\ \mathrm{au}_t^{\mathrm{news}} \\ \mathrm{eu}_t^{\mathrm{news}} \\ \mathrm{us}_t^{\mathrm{news}} \end{bmatrix}.$$

the matrices B_j are nuisance parameters for lag j, $\alpha^* = A\alpha$ and β are parameter matrices capturing long term dynamics, and ε_t is a vector of disturbances with $n \times n$ covariance matrix D. This is the co-fractional VAR of Johansen and Nielsen (2010; 2012) amended slightly to take into account the structure of trading day. Such model is a natural framework which allows distinguishing between long-run and short-run effects in a setting involving fractionally integrated variables. As a result, equation (26) defines an error correction model with fractionally cointegrated variables I(d). The upper left and lower right shaded blocks of the matrix A highlight coefficients describing the self-effects of intra day volatility and news in the equity markets. The structure of these matrices incorporate the calendar restrictions imposed by the definition of the global trading day. The feedback effects from volatility to news represented by the lower left block are restricted to be zero in the model. The triangular restrictions are imposed which require that the top block of β be the identity matrix (Phillips; 1991).

The absence of any common trend in realised volatilities and news flows will imply that the cointegrating rank of the system (26) is zero. In this instance, the volatility dynamics can be estimated by a simple fractional VAR without an error correction term. On the other hand, the hypothesis of commonality between news and volatility is represented by a non zero cointegration rank $r > 0$. In this case the global news-volatility pattern can be described by the full VECM (26). Moreover, in the case where the cointegration rank is $r = n - 1$, the realised volatilities and news flows share a single common trend, which is the driving factor behind the $I(d)$ features of x_t (Stock and Watson, 1988). In this case, there is only one fractionally integrated process describing the evolution of volatility in all zones. This situation is similar to the effect known as the meteor shower with world-wide news flows documented by Engle, Ito and Lin (1990).

The first practical issue at hand is the correct choice of optimal lag length, k. Given the rapid dissemination of news in financial markets, intuition would suggest that one week (5 trading days) would be enough to capture all the relevant information in lagged values of realized volatility and news. Moreover, as reported by Andersen, Bollerslev, Diebold and Labys (2003) long-memory VAR models of volatility requires less lags than classical VARs. Formally the choice may be guided by relying on well known information criterion (AIC and BIC) for lag length selection and checking if the included B_k, the coefficient matrices on the lag differences of the dependent variables, are statistically significant. As expected, the BIC favour a more parsimonious lag structure than the AIC. Overall, two lags were chosen as being sufficient for the model.

To estimate the cofractional rank r for the VECM (26) the test of Johansen and Nielsen (2012) is applied. The model contains $r = 4$ cofractional equations, which implies that volatility in every zone can be expressed as a function of a news flow, or equivalently that there is one driving factor for volatility in each of these regions. The main interest of this section lies in investigating the volatility-news relation in the short and the long run. The former relation is represented by the matrix A whose estimates are presented in Table 5.

Table 5:

The estimates of the cofractional vector error correction model (VECM).

The table reports maximum likelihood estimates of the cofractional VECM model,

$$A\Delta^d x_t = \alpha^* L_d \beta^{'} x_t - \sum_{j=1}^{2} B_j \Delta^d L_d^j x_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{iid } N(0, D)$$

from equation (26) with a structural restriction $\alpha^* = A\alpha$ based on daily observations from January 4, 2005 to September 28, 2012. The estimates of B are not presented here because of space limitation. The fractionally differencing parameter $d = 0.4887$ is significant according to QML standard errors. The reported standard errors are calculated using numerical Hessian with (***) denotes significance at the 1% level. To test significance of β_{ij} the hypotheses $H_0 : \beta_{ij} = 0$ were tested for each individual coefficient applying likelihood ratio test. CV and IV are assigned to cointegration and impact vectors respectively.

		RV			News		
		Australia	Europe	United States	Australia	Europe	United States
$A^{'}$	$\eta^{au}_{vola,t}$	1	-0.5979^{**} (0.2636)	-0.0475 (0.1461)	0	0	0
	$\eta^{eu}_{vola,t}$	0	1	-0.6278^{***} (0.1666)	0	0	0
	$\eta^{us}_{vola,t}$	0	0	1	0	0	0
	$\eta^{au}_{news,t}$	0	0.0795 (0.0844)	-0.0170 (0.0808)	1	-0.3704^{***} (0.0930)	-0.6067^{***} (0.2194)
	$\eta^{eu}_{news,t}$	0	0	0.0184 (0.0186)	0	1	-0.3011^{***} (0.0586)
	$\eta^{us}_{news,t}$	0	0	0	0	0	1
$\beta^{'}$	CV_1	1	0	0	0	-0.4314^{***}	0.0193
	CV_2	0	1	0	0	-1.3315^{***}	0.0856
	CV_3	0	0	1	0	-1.5316^{***}	0.0348
	CV_4	0	0	0	1	-0.3147^{***}	0.0154
$\alpha^{'}$	IV_1	-0.3642^{***} (0.0904)	0.5101^{**} (0.2257)	0.4892^{*} (0.2667)	0.0783 (0.0619)	-0.0871 (0.2390)	-0.4662 (0.5792)
	IV_2	-0.0601^{*} (0.0351)	-0.2861^{***} (0.0801)	-0.0993 (0.1018)	0.0075 (0.0239)	-0.0388 (0.0930)	-0.2861 (0.2282)
	IV_3	0.1102^{***} (0.0258)	0.0871 (0.0651)	-0.0269 (0.0756)	-0.0273 (0.0179)	-0.0193 (0.0696)	0.1983 (0.1687)
	IV_4	0.0269 (0.0757)	-0.1485 (0.1768)	-0.3791^{*} (0.2227)	-0.1268^{***} (0.0528)	0.6070^{***} (0.2054)	-0.4356 (0.5027)

All the coefficients in the lower highlighted block are significant at the 1% level, which means that news are strongly related with itself in the short run. The upper shaded block corresponds with volatility transmissions between Australia, Europe, and the United States within the same trading day. The spillovers from Australia to Europe and from Europe to the United States are significant, while there is no significant impact from Australia to the United States. Surprisingly, none of the $\eta_{news,t}$ coefficients are significant, suggesting that there is no cross-country links between news and volatility within the trading day. This phenomena can be explained by the long-term patterns represented by cointegrating vectors in matrix β and correspondent impact matrix α. In particular, volatility in all zones is significantly related to news from Europe in the long run. Moreover, contegration vector CV_4 reveals significant connection between Australian and European news.

Overall the news flows are strongly interrelated both in the long and short run, while significant ties between news and volatility are pronounced only in the long run. Such findings confirm the results of Jiang, Konstantinidi and Skiadopoulos (2012) that news announcements do not fully explain the volatility spillovers. However, to investigate the dynamics of interaction between volatility and news impulse response analysis is presented.

6.1 Impulse Responses

The solution of the model (26) is given by the properties of the polynomial (see Johansen and Nielsen; 2012, p.2674)

$$\Psi(L_d) = (1 - L_d)I_n - \alpha\beta' L_d - \sum_{j=1}^{k} \Gamma_i (1 - L_d) L^d, \tag{27}$$

in which $\Gamma_j = A^{-1}B_j$ and I_n is the unit matrix. Equation (27) defines the criteria for fractionality of order d and zero cofractionality, which means that impulse responses can be estimated from (27). Due to $\Psi(L_d)$ is invertible under mild assumptions (Johansen and Nielsen; 2012) equation (26) can be rewritten in the reduced form as

$$x_t = \Psi(L_d)^{-1}\epsilon_t. \tag{28}$$

By setting the unit shock δ as a one-standard deviation the implied impulse responses for period h can be obtained as

$$IIR(h, \delta, \Omega_{t-1}) = \Psi(L_d)^{-1}\Xi, \tag{29}$$

where Ξ is a matrix of standard deviations of ϵ_t and Ω_{t-1} is the information set available at time $t-1$. Note that IIR are different from conventional impulse responses received from moving average representation. Here the main interest in the long-term reaction of volatility and news

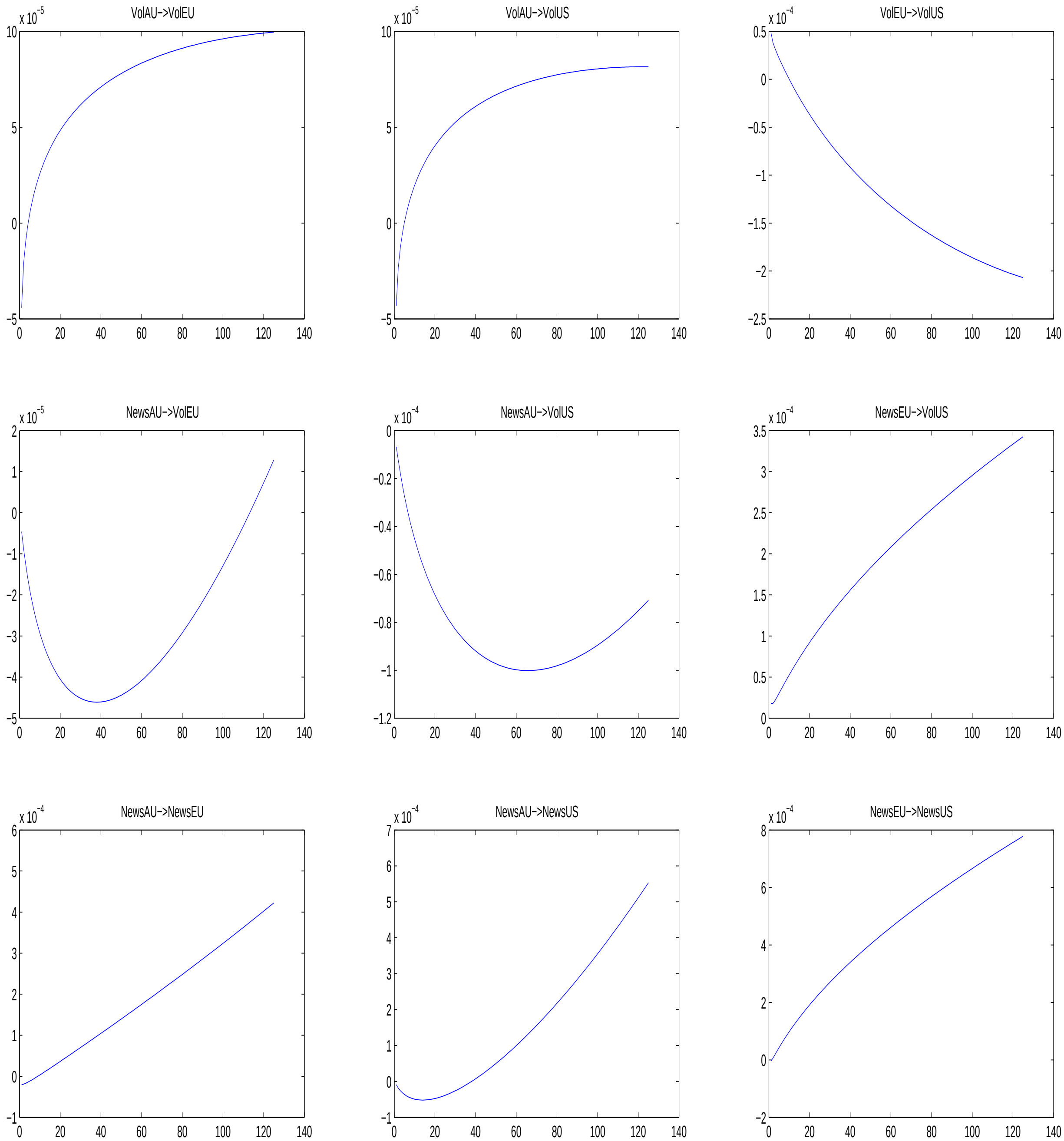

Figure 6: Impulse response functions for volatility and news. The figure plots the implied impulse response functions (IIR) defined in (29) from the model (26). The upper panel represents IIR for volatility, middle panel - impulse responses of volatility to news shocks, and lower panel - impulses of news. All of the estimates are based on daily observations for the period 4 January 2005 to 28 September 2012.

to shocks. For this reason the IIRs are estimated for a relatively long period of time (6 months), which is corespondent to a frequency analysis from Section 3.

As follows from Figure 6 volatility shocks from Australia have similar effects on Europe and the United States, which is positive in both cases. European shocks in volatility have a positive impact on the United States within two weeks, while after that this effect becomes negative. News-volatility implied impulse responses reveal positive effects from Europe to the United States and from Australia to Europe. All IIRs for news have a similar pattern, which implies a strong interconnectedness between news flows from each zone.

Summarizing results of the section, news from all three zones are interrelated both in the short and long run, which can be interpreted as an existence of a global news flow in the equity market. Volatility spillovers are significant, which supports the meteor shower hypothesis of Engle, Ito and Lin (1990). News have impact on volatility only in the long term. Such results are received assuming that both positive and negative news have similar impact on volatility. However, Engle and Ng (1993) argue that responses of volatility to news are asymmetric, which can be tested using sentiment scores and relevance of news items, which is the subject of the following analysis.

7 How news tone affects volatility?

According to Griffin, Hirschey and Kelly (2011) despite a large international literature, there is relatively little understanding of differences in the informational environment across countries[11]. One challenge in this literature is the transformation of news and media content to variables that can be studied in econometric models. To investigate if news items have different impact on the stock market volatility the tone of news should be taken into account.

The first task is to define news implied price, which can incorporates positive and negative tone of news. Following Harris and Raviv (1993) it is assumed that market participants share common prior beliefs and receive common public information in each of the trading zones. In this case each of the news implied price series in Australia, Europe and the United States should be a function of public news from the same zone. To measure a tone of news in each minute k the realized tone for each zone is introduced as

$$\mathrm{RT}_k = \mathrm{RT}_0 + N_k \frac{\delta_k}{2}, \tag{30}$$

in which N_k is a counter that counts the number of news events that have occurred up to and

[11] As documented by Riordan, Storkenmaier, Wagener and Zhang (2013) negative news messages are particularly informative and induce stronger market reaction. In particular, negative messages are associated with higher adverse selection costs than positive or neutral messages. Tetlock, Saar-Tsechansky, and Macskassy (2008) report that the United States equity market rapidly incorporates most of the information associated with the linguistic content of news articles.

including time k, and $\delta_k = \sum_j(\text{positive}_j - \text{negative}_j)\text{relevance}_j$. Equation (30) implies that every time when news occur the realized tone jumps by $\frac{\delta_k}{2}$ up if tone of news within the minute k is positive or down if it is negative.

Using the realized tone at minute t_k of the day t from equation (30) the news implied price can be represented as

$$\text{NIP}_t = \sqrt{\frac{1}{n-1}\sum_{t_k=1}^{\hat{n}}(\text{RT}_{t_k} - \overline{\text{RT}}_t)^2}, \tag{31}$$

where $\hat{n}$ is a number of minutes in a trading day, and $\overline{\text{RT}}_t$ is an average realized tone on day t. Despite its simplicity, the model of the news implied price captures the essential features of the price process. The news implied prices for each of the trading zones are presented in Figure 7. As can be seen from Figure 7 the news implied price in the United States quite closely mimics the corespondent futures price, while such pattern is not pronounced for Australia and Europe.

Now equation (31) can be used to define information volatility on day t for zone i as

$$\text{INV}_t^i = \frac{\lambda_t^i}{NIP_t^i}, \tag{32}$$

where $i \in \{au, eu, us\}$, and λ_t^i is the intensity of news in the zone i. Heuristically equation (32) allows news implied volatility to be explained by two factors: variance per news item and expected number of news per time unit. Engle and Russell (1998) used a similar idea to model ultrahigh frequency volatility of price. As follows from the previous section news series are strongly interrelated which allows to conjecture about the global information volatility, which can be calculated as

$$\text{INV}_t^g = \text{INV}_t^{au} + \text{INV}_t^{eu} + \text{INV}_t^{us}. \tag{33}$$

Having the estimates of information volatilities the commonality hypothesis between volatility and news conditioned on the tone of information flow can be tested. To do so the model (26) from the previous section is estimated with the global information volatility series instead of correspondent variables representing a number of news for Australia, Europe and the United States. As a result, the parameter matrix A and dependant variable x_t are represented as

$$A = \begin{bmatrix} 1 & 0 & 0 & 0 \\ -\eta_{21} & 1 & 0 & 0 \\ -\eta_{31} & -\eta_{32} & 1 & -\eta_{34} \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad x_t = \begin{bmatrix} \text{au}_t^{\text{vola}} \\ \text{eu}_t^{\text{vola}} \\ \text{us}_t^{\text{vola}} \\ \text{INV}_t^g \end{bmatrix}. \tag{34}$$

The highlighted block captures volatility spillovers while the coefficient η_{34} represents effects of news to the United States volatility. Once again, the absence of any common trend in realised volatilities will imply that the cointegrating rank of the system (26) is zero and the volatility dynamics can be estimated by a simple fractional SVAR without an error correction term. On

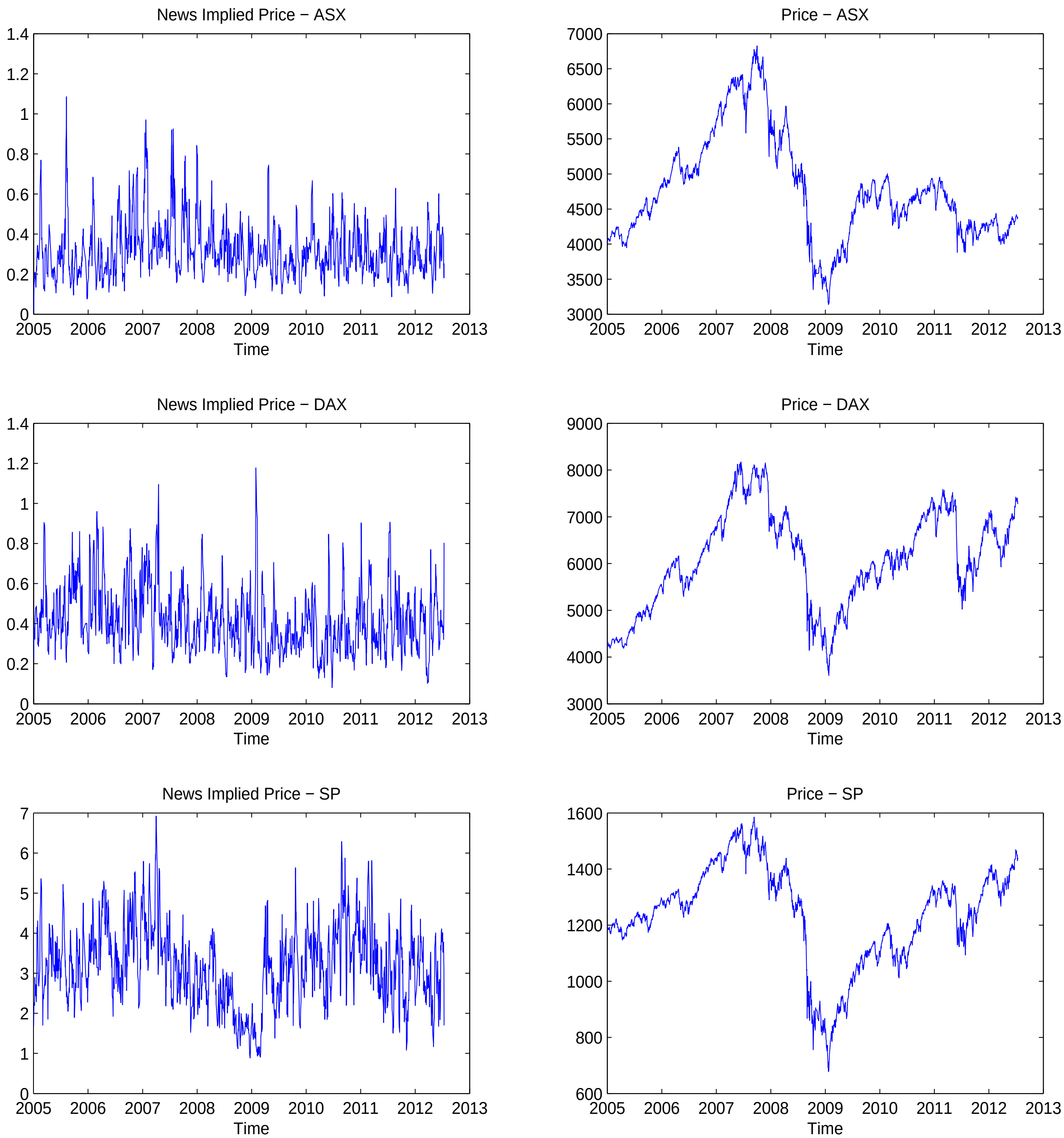

Figure 7: News implied and futures prices. The figure plots futures and news implied daily prices defined in equation (31). The news implied prices were smoothed using moving average filter with the span 5 for illustrative purposes. The time for futures prices is 12:00. The upper panel represents ASX 200 prices, middle panel - DAX 30 prices, and lower panel - S&P 500 prices.

the other hand, the hypothesis of a single underlying common trend which may be interpreted as the common global news flow, will be represented by a non-zero cointegration rank given by $r = n - 1$. In this case the impact of volatility is independent of the trading zone with one process, namely global news, describing the evolution of volatility in all zones. The respective estimates of the model with a global news flow are presented in Table 6. First of all, the rank of

Table 6:

The estimates of the cofractional vector error correction model (VECM).
The table reports maximum likelihood estimates of the cofractional VECM model,

$$A\Delta^d x_t = \alpha^* L_d \beta' x_t - \sum_{j=1}^{2} B_j \Delta^d L_d^j x_t + \varepsilon_t, \qquad \varepsilon_t \sim \text{iid } N(0, D)$$

with matrix A defined in (34) implying a structural restriction $\alpha^* = A\alpha$ based on daily observations from January 4, 2005 to September 28, 2012. The cointegration rank $r = 3$ is estimated using Johansen procedure discussed earlier. The number of lags is chosen according to AIC and BIC. The estimates of B are not presented here because of space limitation. The fractional difference parameters $d = 0.4318$ is significant according to QML standard errors. The reported standard errors are calculated using numerical Hessian with (***) denotes significance at the 1% level. To test significance of β_{ij} the hypotheses $H_0 : \beta_{ij} = 0$ were tested for each individual coefficient applying likelihood ratio test. CV and IV are assigned to cointegration and impact vectors respectively.

		RV			News volatility
		Australia	Europe	United States	Global market
A'	$\eta^{au}_{vola,t}$	1	-0.5982^{**} (0.2940)	-0.0542 (0.1436)	0
	$\eta^{eu}_{vola,t}$	0	1	-0.6207^{***} (0.1673)	0
	$\eta^{us}_{vola,t}$	0	0	1	0
	$\eta^{gl}_{news,t}$	0	0	-0.0091 (0.0109)	1
β'	CV_1	1	0	0	-0.2597^{*}
	CV_2	0	1	0	-0.6082^{**}
	CV_3	0	0	1	-1.6903^{***}
α'	IV_1	-0.3708^{***} (0.1155)	0.7594^{***} (0.2994)	0.4967 (0.3411)	0.6988 (0.9665)
	IV_2	-0.0500 (0.0331)	-0.2698^{***} (0.0797)	-0.1835^{*} (0.0968)	-0.3083 (0.2981)
	IV_3	0.0647^{***} (0.0160)	-0.0172 (0.0385)	-0.0106 (0.0469)	-0.0460 (0.1346)

the system $r = 3$, which implies that there is a global news flow which drives all three markets. The long run relations ties represented by cointegrating vectors confirms this finding. However, the effect of global news on volatility in Australia captured by CV_1 is weaker than in Europe or the United States. The intradaily effects represented by matrix A reveal a similar to Table 5 pattern in volatility, namely significant spillovers from Australia to Europe and from Europe to the United States. The global news have no significant impact on volatility in Australia within a trading day, which is supported by the insignificant coefficient $\eta = -0.0091$.

To investigate dynamics of interaction between the global news flow and volatility in each zone implied variance decomposition can be estimated as

$$\mathrm{IVD}_h = \sum_{i=1}^{h} IIR_i \odot IIR_i, \tag{35}$$

where $\odot$ is the Hadamard product and IIR_i are implied impulse responses from equation (29). Due to important results of Diebold and Yilmaz (2014) variance decomposition can be naturally interpreted as a measure of connectedness. In particular, if variance decomposition is high the variables of interest are strongly interrelated. A primary interest here is to investigate dynamics of connectedness between volatility and news, which is presented in Figure 8. When it comes to volatility, spillover patterns are similar for all three cases. Namely, there are three distinct regions in time: a short term burst of connectedness that happens during the first week is followed by the period where variance decomposition is relatively flat and a right region corresponding to the exponential growth of connectedness. The variance decompositions for global news show a clear pattern, the global news flow is strongly connected to volatility in all three zones. Such finding supports a frequency domain results of Figure 5.

This section confirmed a fairly strong *prima facie* case for the 'commonality in news-volatility' hypothesis in all three zones. Overall, these results lead to an important conclusion that it is not possible to regard each trading zone as being completely independent of all the others. A second interesting conclusion to emerge from this analysis is that there are strong linkages between realized volatility in all of the three trading zones in the long run. The existence of a single global news stream driving volatility is accepted. These findings confirm the important role of news in propagating the volatility around the global market, which was documented by Engle and Ng (1993).

8 Identifying the global news stream

The existence of a global news stream in the equity market raises the question of identifying this phenomenon, which is a main task of this section. To do so a model of the global equity market is considered. Within this model the calendar structure of a trading day is relaxed and volatility and news of the global equity market are considered on a daily basis. Such model allows a good explanation of why aggregate volatility changes over time, which is unsolved problem (see, e.g. Engle, Ghysels and Sohn, 2013; Fernandez-Villaverde and Rubio-Ramirez, 2013).

There are two main approaches in literature explaining the time varying nature of volatility. Both of them imply that volatility is driven by a latent factor, which is related to macroeconomic

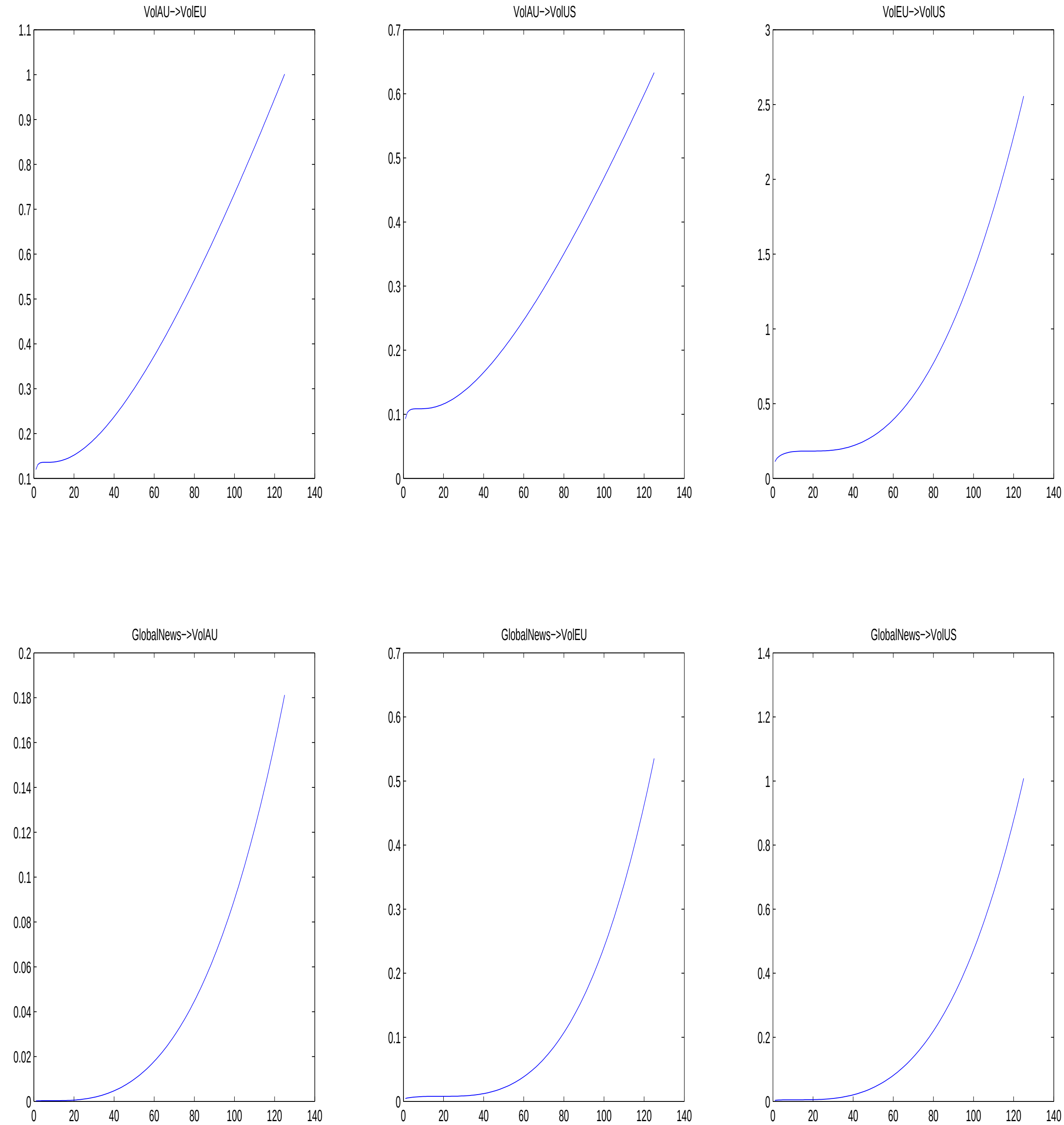

Figure 8: Implied variance decomposition for volatility and news. The figure plots the implied variance decompositions (IVD) defined in (35). The presented values are multiplied by 10^6 for illustrative purposes. The upper panel represents IVD for volatility and lower panel - IVD for the global news flow and respective volatilities. All of the estimates are based on daily observations for the period 4 January 2005 to 28 September 2012.

activity like in Flannery and Protopapadakis (2002) or to jump process approximating news flow as in Maheu and McCurdy (2004). In contrast to these approaches the global news stream is defined as an observable variable which can be included in the cofractional model discussed earlier. In this case relation between news and volatility can be interpreted and ambiguous assumptions about linkages between jumps and news are not required.

Consider the reduced form cofractional system

$$\Delta^d y_t = \alpha\beta' L_d y_t + \sum_{j=1}^{2} \Gamma_j \Delta^d L_d^j y_t + \epsilon_t, \tag{36}$$

in which d is a fractional differncing parameter, α and β are parameter matrices that define long term dynamic of the model, Γ_j are nuisance parameters, ϵ_t are disturbances of the model, and $y_t = [RV_t^g, INV_t^g]'$ contains volatility $RV_t^g = RV_t^{au} + RV_t^{eu} + RV_t^{us}$ and information volatility is defined in (33). The parameter matrix β defines long term ties between volatility and news in the global equity market. The estimates of the model (36) are presented in Table 7.

Table 7:

The estimates of the global cofractional vector error correction model (VECM).
The table reports maximum likelihood estimates of the cofractional VECM model defined as,

$$\Delta^d y_t = \alpha\beta' L_d y_t + \sum_{j=1}^{2} \Gamma_j \Delta^d L_d^j y_t + \epsilon_t. \qquad \epsilon_t \sim \text{iid } N(0, V)$$

The estimates are based on daily observations from January 4, 2005 to September 28, 2012. The cointegration rank $r = 1$ is estimated using Johansen procedure discussed earlier. The number of lags is chosen according to AIC and BIC. The estimates of Γ are not presented here because of space limitation. The fractional difference parameters $d = 0.4832$ is significant according to QML standard errors. The reported standard errors are calculated using numerical Hessian with (***) denotes significance at the 1% level. To test significance of β_{ij} the hypotheses $H_0 : \beta_{ij} = 0$ were tested for each individual coefficient applying likelihood ratio test. CV and IV are assigned to cointegration and impact vectors respectively.

		RV	Information volatility
		Global equity market	Global equity market
β'	CV_1	1	-1.2594^{***}
α'	IV_1	-0.0104 (0.0078)	-0.0517^{***} (0.0192)

The coefficient in CV_1 is significant at the 1% level with the correspondent impact coefficient $\alpha_{21} = -0.0517$. To test the hypothesis of commonality between volatility and news formally $H^1 : \beta' = [1, -1]$ should be tested. Using the likelihood ratio test with the standard χ^2 asymptotic values the p-value 0.802 strongly supports H^1, which means that news and volatility in the global equity market are fractionally cointegrated. Another important conclusion is existence of one-to-one relation between information and realized volatilities in the long run. Such finding unequivocally proves the seminal hypothesis of Ross (1989) for the global equity market.

Table 8:

The estimates of the cofractional vector error correction model with the United States news stream.

The table reports maximum likelihood estimates of the cofractional VECM model defined as,

$$\Delta^d y_t = \alpha\beta^{'} L_d y_t + \sum_{j=1}^{2} \Gamma_j \Delta^d L_d^j y_t + \epsilon_t. \qquad \epsilon_t \sim \text{iid } N(0, V)$$

The estimates are based on daily observations from January 4, 2005 to September 28, 2012. The cointegration rank $r = 1$ is estimated using Johansen procedure discussed earlier. The number of lags is chosen according to AIC and BIC. The estimates of Γ are not presented here because of space limitation. The fractional difference parameters $d = 0.5183$ is significant according to QML standard errors. The reported standard errors are calculated using numerical Hessian with (***) denotes significance at the 1% level. To test significance of β_{ij} the hypotheses $H_0 : \beta_{ij} = 0$ were tested for each individual coefficient applying likelihood ratio test. CV and IV are assigned to cointegration and impact vectors respectively.

		RV	Information volatility
		Global equity market	the United States market
$\beta^{'}$	CV_1	1	-0.6243^{***}
$\alpha^{'}$	IV_1	-0.0901^{**} (0.0400)	0.1769^{***} (0.0591)

As evident from the analysis of the previous section the United States news flow might be a main driving factor of the global equity market. Such conjecture can be investigated in more details replacing in equation (36) the global news flow by the United States news. The estimates of such model are presented in Table 8. The coefficient in CV_1 is significantly distinct from zero. Now the parameter $d = 0.5183$ is more than 0.5 which implies the non-standard asymptotics (see Section 4). The hypothesis $H^1 : \beta^{'} = [1, -1]$ is related to p-value 0.051, which means the validity of the hypothesis at the 5% level. This result allows approximating the world news in the equity market by the United States flow. Overall, these results suggest that both volatility spillovers and news from other zones are important in explaining the time varying nature of volatility.

9 Conclusion

This paper provides a detailed explanation of the elusive dependencies between volatility and news in Australia, Europe, and the United States. An innovative data set comprising volatility estimates and news streams is used to examine a relation between these variables across all three regions. The main hypothesis of this research is if volatility in the global equity market can be explained by the global news flow.

Both volatility and news are fractionally cointagrated which naturally motivates the cofractional VECM. The calendar structure of the trading day requires representing the cofractional model in a structural form. The news series are strongly interrelated which proves the existence of the global stream. Volatility in all three zones is mainly driven by the global news stream which can be approximated by news from the United States. Using a frequency domain representation that allows to focus on specific components of the spectra, a positive volatility-news relation is uncovered only in low frequencies. Such a one-to-one relation between volatility and news in the long run empirically supports the Mixture Distribution Hypothesis for the global equity market. Intra day volatility spillovers are significant from Australia to Europe and from Europe to the United States. As follows from the variance decomposition analysis all three zones are strongly interrelated in the long-run.

The major conclusion that emerges from this program of research is that in the context of the global equity market the volatility-news linkages can be characterized by the long-run equilibrium relation. Not only does this conclusion appear to be a robust one, but it is also consistent with previous work both theoretical and empirical.

References

Aharony, J., and Swary, I. 1980. Quarterly dividend and earnings announcements and stockholders' returns: An empirical analysis. *The Journal of Finance*, **35**, 1–12.

Ait-Sahalia, Y., Jacod, J., and Li, J. 2012. Testing for jumps in noisy high frequency data. *Journal of Econometrics*, **168**, 207–222.

Andersen, T., and Bollerslev, T. 1997. Heterogeneous information arrivals and return volatility dynamics: uncovering the long-run in high frequency returns. *Journal of Finance*, **52**, 975–1005.

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Labys, P. 2001. The distribution of realized exchange rate volatility. *Journal of the American Statistical Association*, **96**, 42–55.

Andersen, T.G., Bollerslev, T., Diebold, F.X., and Labys, P. 2003. Modeling and forecasting realized volatility. *Econometrica*, **71**, 579–625.

Andersen, T.G., Bollerslev, T., and Diebold, F.X. 2007. Roughing it up: including jump components in the measurement, modeling, and forecasting of return volatility. *Review of Economics and Statistics*, **89**, 701–720.

Andersen, T.G., Dobrev, D., and Schaumburg, E. 2012. Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics*, **169**, 75–93.

Asquith, P., and D.W., Mullins. 1986. Equity issues and offering dilution. *Journal of Financial Economics*, **15**, 61–89.

Baillie, R.T., and Bollerslev, T. 1989. Common stochastic trends in a system of exchange rates. *Journal of Finance*, **44**, 167–181.

Baillie, R.T., Bollerslev, T., and Mikkelsen, H.O. 1996. Fractionally integrated generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, **74**, 3–30.

Barndorff-Nielsen, O. E., and Shephard, N. 2004. Power and bi-power variation with stochastic volatility and jumps. *Journal of Financial Econometrics*, **2**, 1–37.

Barndorff-Nielsen, O.E., and Shephard, N. 2002. Econometric Analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of Royal Statisitcal Society, Series B*, **64**, 253–280.

Berger, D., Chaboud, A., and Hjalmarsson, E. 2009. What drives volatility persistence in the foreign exchnage market. *Journal of Financial Economics*, **94**, 192–213.

Berry, T.D., and Howe, K.M. 1994. Public information arrival. *The Journal of Finance*, **49**, 1331–1346.

Bhattacharya, U., Daouk, H., Jorgenson, B., and Kehr, C.H. 2000. When an event is not an event: the curious case of an emerging market. *Journal of Financial Economics*, **55**, 69–101.

Bollerslev, T., and Mikkelsen, H.O. 1996. Modeling and pricing long memory in stock market volatility. *Journal of Econometrics*, **73**, 151–184.

Campbell, J.Y., and Shiller, R.J. 1988. The dividend-price ratio and expectations of future dividends and discount factors. *Review of financial studies*, **1**, 195–228.

Chan, W.S. 2003. Stock price reaction to news and no-news: drift and reversal after headlines. *Journal of Financial Economics*, **70**, 223–260.

Clark, P.K. 1973. A subordinated stochastic process model with finite variance for speculative prices. *Econometrica*, **41**, 135–155.

Deo, R., Hurvich, C., and Lu, Y. 2006. Forecasting realized volatility using a long-memory stochastic volatility model: estimation, prediction and seasonal adjustment. *Journal of Econometrics*, **131**, 29–58.

Diebold, F.X., and Inoue, A. 2001. Long memory and structural change. *Journal of Econometrics*, **105**, 131–159.

Diebold, F.X., and Yılmaz, K. 2014. On the network topology of variance decompositions: measuring the connectedness of financial firms. *Journal of Econometrics*, **182**, 119–134.

Ding, Z., and Granger, C. 1996. Modellling volatility persistence of speculative returns: A new approach. *Journal of Econometrics*, **73**, 185–215.

Ding, Z., Granger, C.W.J., and Engle, R.F. 1993. A long memory property of stock market returns and a new model. *Journal of Empirical Finance*, **1**, 83–106.

Ederington, L., and Lee, J. 1993. How markets process information: news releases and volatility. *Journal of Finance*, **48**, 1161–1191.

Engle, R.F. 1982. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. *Econometrica*, **50**, 987–1008.

Engle, R.F., and Granger, C.W.J. 1987. Co-integration and error correction: representation, estimation, and testing. *Econometrica*, **55**, 251–276.

Engle, R.F., and Ng, V.K. 1993. Measuring and testing the impact of news on volatility. *Journal of Finance*, **48**, 1749–1778.

Engle, R.F., and Rangel, J.G. 2008. The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies*, **21**, 1187–1222.

Engle, R.F., and Russell, J.R. 1998. Autoregressive conditional duration: A new model for irregularly spaced transaction data. *Econometrica*, **66**, 1127–1162.

Engle, R.F., Ito, T., and Lin, W.L. 1990. Meteor showers or heat waves? Heteroskedastic intra-daily volatility in the foreign exchange market. *Econometrica*, **58**, 525–542.

Engle, R.F., Ghysels, E., and Sohn, B. 2013. Stock market volatility and macroeconomic fundamentals. *Review of Economics and Statistics*, **95**, 776–797.

Fernandez-Villaverde, I., and Rubio-Ramirez, I.F. 2013. Macroeconomics and Volatility: Data, Models, and Estimation. *Advances in Economics and Econometrics: Tenth World Congress*, **3**, 137–183.

Flannery, M.J., and Protopapadakis, A.A. 2002. Macroeconomic factors do influence aggregate stock returns. *Review of Financial Studies*, **15**, 751–782.

Geweke, J., and Porter-Hudak, S. 1983. The estimation and application of long memory time series models. *Journal of time series analysis*, **4**, 221–238.

Granger, C.W.J., and Hatanaka, M. 1964. Spectral analysis of economic time series. *Spectral analysis of economic time series.*

Griffin, J.M., Hirschey, N.H., and Kelly, P.J. 2011. How important is the financial media in global markets? *Review of Financial Studies*, **24**, 3941–3992.

Groß-Klußmann, A., and Hautsch, N. 2011. When machines read the news: using automated text analytics to quantify high frequency news-implied market reactions. *Journal of Empirical Finance*, **18**, 321–340.

Harris, M., and Raviv, A. 1993. Differences of opinion make a horse race. *Review of Financial studies*, **6**, 473–506.

Hautsch, N., Hess, D., and Veredas, D. 2011. The impact of macroeconomic news on quote adjustments, noise, and informational volatility. *Journal of Banking & Finance*, **35**, 2733–2746.

Hosking, J.R.M. 1981. Fractional differencing. *Biometrika*, **68**, 165–176.

Hurvich, C.M., and Deo, R.S. 1999. Plug-in Selection of the Number of Frequencies in Regression Estimates of the Memory Parameter of a Long-memory Time Series. *Journal of Time Series Analysis*, **20**, 331–341.

Jiang, G.J., Konstantinidi, E., and Skiadopoulos, G. 2012. Volatility spillovers and the effect of news announcements. *Journal of Banking & Finance*, **36**, 2260–2273.

Johansen, S. 1991. Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, **59**, 1551–1580.

Johansen, S. 2008. A representation theory for a class of vector autoregressive models for fractional processes. *Econometric Theory*, **24**, 651–676.

Johansen, S., and Nielsen, M.Ø. 2010. Likelihood inference for a nonstationary fractional autoregressive model. *Journal of Econometrics*, **158**, 51–66.

Johansen, S., and Nielsen, M.Ø. 2012. Likelihood inference for a fractionally cointegrated vector autoregressive model. *Econometrica*, **80**, 2667–2732.

Kalev, P.S., Liu, W.M., Pham, P.K., and Jarnecic, E. 2004. Public information arrival and volatility of intraday stock returns. *Journal of Banking & Finance*, **28**, 1441–1467.

Künsch, H. 1986. Discrimination between monotonic trends and long-range dependence. *Journal of Applied Probability*, **23**, 1025–1030.

Lo, A.W. 1991. Long-Term Memory in Stock Market Prices. *Econometrica*, **59**, 1279–1313.

MacKinnon, J.G., and Nielsen, M.Ø. 2014. Numerical distribution functions of fractional unit root and cointegration tests. *Journal of Applied Econometrics*, **29**, 161–171.

Maheu, J.M., and McCurdy, T.H. 2004. News arrival, jump dynamics, and volatility components for individual stock returns. *The Journal of Finance*, **59**, 755–793.

Mancini, C. 2009. Non-parametric threshold estimation for models with stochastic diffusion coefficient and jumps. *Scandinavian Journal of Statistics*, **36**, 270–296.

Mandelker, G. 1974. Risk and return: The case of merging firms. *Journal of Financial Economics*, **1**, 303–335.

Mitchell, M.L., and Mulherin, J.H. 1994. The impact of public information on the stock market. *The Journal of Finance*, **49**, 923–950.

Nelson, D.B. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica*, **59**(2), 347–70.

Pagan, A.R. 1996. The econometrics of financial markets. *Journal of Empirical Finance*, **3**, 15–102.

Phillips, P.C.B. 1991. Optimal inference in cointegrated systems. *Econometrica*, **59**, 283–306.

Riordan, R., Storkenmaier, A., Wagener, M., and Zhang, S. 2013. Public information arrival: price discovery and liquidity in electronic limit order markets. *Journal of Banking & Finance*, **37**, 1148–1159.

Roll, R. 1988. R2. *The Journal of Finance*, **43**, 541–566.

Ross, S.A. 1989. Information and volatility: The no-arbitrage martingale approach to timing and resolution irrelevancy. *The Journal of Finance*, **44**, 1–17.

Shiller, R.J. 1981. Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Economic Review*, **71**, 421–436.

Shimotsu, K. 2007. Gaussian semiparametric estimation of multivariate fractionally integrated processes. *Journal of Econometrics*, **137**, 277–310.

Stock, J.H., and Watson, M.W. 1988. Testing for common trends. *Journal of the American Statistical Association*, **83**, 1097–1107.

Tetlock, P.C., Saar-Tsechansky, M., and Macskassy, S. 2008. More than words: quantifying language to measure firms' fundamentals. *The Journal of Finance*, **63**, 1437–1467.

Todorov, V., Tauchen, G., and Grynkiv, I. 2011. Realized Laplace transforms for estimation of jump diffusive volatility models. *Journal of Econometrics*, **164**, 367–381.