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Abstract

This paper is the first to study volatility spillover effects emerging from international commodity markets to the Australian equity market. The analysis is based on a novel approach utilizing a multivariate HAR model where realized volatility is decomposed into jump and continuous elements. Accounting for synchronous and non-synchronous trading times in the individual markets, volatility transmission is analyzed for realized volatility as well as for its jump and diffusion components separately. The analysis is based on intraday data from 2008 to 2012 divided in two samples and controls for global equity risk as reflected in the MSCI World Index. The results provide evidence of spillover effects mainly from the LME copper futures market to the Australian equity market during the crisis period. This relationship holds also in the post-crisis time. In this period, the DJ-UBS commodity index appears to additionally contain relevant information for the elements of the future Australian equity market volatility. In contrast, less incremental information is inherent in aluminium futures series and no spillover effects can be observed emerging from a global benchmark of oil prices.

Keywords: Volatility transmission; HAR model; Intraday data; Realized volatility; Jumps; Commodity markets.

JEL Classification: C5, G1, G15.

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1 Introduction

Commodities, in particular aluminium and copper, iron ore and concentrates, coal and natural gas, play a leading role in Australia's exports (DFAT, 2012). Export earnings from mineral resources (excluding oil and gas) increased from AU$154 billion in 2010-11 to AU$165 billion in 2011-12. In 2010-11, mineral exports accounted for 60% of the total Australian goods and services exports signifying an increase from 41% in 2006-07 (MCA, 2012). Thus, Australia's economy exhibits a material exposure to global mineral commodity price levels and their volatility due its export activity. On the other hand, with only about 0.3% of the world's oil reserves, its crude oil resources are very limited. However, oil is second to coal in terms of shares in Australia's primary energy consumption. As it is estimated that the oil consumption will increase significantly over the two next decades while the domestic crude oil production is expected to decline further, Australia becomes more and more reliant on imports of transport fuels and dependent on the world's oil price level (ABARE, 2010).

Generally, commodity prices are subject to short-term price movements and long-term price trends. Short-term price movements relate to seasonal demand, the impact of supply disruptions, such as natural disasters, risk premiums associated with geopolitical tensions or economic shocks. In the longer term, major influential factors of commodities prices are marginal production cost, affecting the supply side, and a combination of long-term economic growth and demand-side efficiency improvements (ABARE, 2010). These factors cause volatility in global commodities markets, which itself may exert substantial spillover effects on the volatility of the Australian stock market.

The world-wide increasing financial market integration has generated sustained interest in examining volatility transmission across major markets (Malik and Hammoudeh, 2007). The major focus is on volatility transmission patterns, especially in equity and foreign exchange markets (Soriano and Climent, 2006). Australia has already been subject of analysis in a number of studies. Most attention has been dedicated to volatility spillover analysis among equity markets (Brailsford, 1996; Brooks and Henry, 2000; Gupta and Jithendranathan, 2011; Karunanayake and Valadkhani, 2011; Kim, 2005; Pan, Liu and Roth, 1999; Sakthivel, Bodkhe and Kamaiah, 2012; Susmel, 2000; Yilmaz, 2010). Other studies on volatility transmission involving Australian markets analyse linkages between the equity market and the index futures market (Bhar, 2001), between stock and bond markets (Fang, Lim and Lin, 2006), stock, bond and foreign exchange markets (Dean, Faff and Loudon, 2010; Hakim and McAleer, 2010), spillovers within the Australian regional electricity market (Worthington, Kay-Spratley and Higgs, 2005) and in the real estate market (Hoesli and Reka, 2010; Lee, 2009). Furthermore, Kearney and Daly (1997) study how monetary volatility is transmitted to the volatility of Australian financial asset prices and Kim and Nguyen (2008) focus on the impact of the Reserve Bank of Australia and the U.S. Feds target interest rate announcement news on the Australian financial market volatility.

It is apparent that no work has been devoted to volatility transmission between the Australian equity market and major commodity markets, although analyzing volatility spillovers between the Australian economy, which is heavily reliant on commodity exports and imports, and the global commodity markets may have important policy implications and be useful for hedging purposes and asset allocation. Furthermore, all aforementioned contributions use return data sampled at a daily or lower frequency to examine volatility transmission mechanisms. Only exceptions in this literature domain are the studies of Chng and Gannon (2003), Gannon (2010) and Sim and Zurbruegg (1999). Chng and Gannon (2003) address volatility transmission across Australian stock index futures, index futures options, and 90-day bank accepted bill futures markets from January to June 1994. Gannon (2010) use intraday data from the Australian cash index and index futures markets of 1992 nearest futures contracts. Sim and Zurbruegg (1999) study volatility co-movements between Australian and Japanese spot and futures markets covering the period from July 1997 to October 1997. Therefore, for the best of the authors' knowledge, there is no study on volatility spillovers with focus on the Australian equity market involving longer intraday time series and recent periods.

To uncover interrelationships between financial assets' second moments, a multivariate version of the heterogeneous autoregressive (HAR) model of Corsi (2009) is used. Motivated by the heterogeneous market hypothesis of Müller et al. (1997) and Dacorogna et al. (1998), Corsi (2009) proposes a simple autoregressive-type volatility model involving volatilities realized over different time periods. The default univariate version of the HAR model forecasts volatility as linear functions of the most recent historical daily, weekly, and monthly realized volatilities. Due to its easy application, this model enjoys a broad popularity in the plethora of modelling and forecasting techniques of financial markets volatility. In contrast, the literature using a multivariate HAR framework is rather scarce. Bauer and Vorkink (2011) propose a matrix-logarithm model of the realized covariance matrix of stock returns. Bubák, Kočenda, and Žikeš (2011) use a vector HAR to analyze realized volatility transmission between Central European currencies and the EUR/USD foreign exchange from 2003 to 2009. In particular, they extend the one-asset HAR by incorporating historical volatility of all considered exchange rates into one transmission model for the one-step ahead realized volatility. Soucek and Todorova (2013) adopt a similar approach and use an orthogonalized HAR model to study volatility spillovers between the stock index futures on S&P 500, Nikkei 225, FTSE 100 and the futures on the West Texas Intermediate crude oil. The main advantage of the multivariate HAR model is its ability to assign spillover effects to daily, weekly and monthly horizons, which cannot be done by means of the widely established multivariate GARCH framework.

The methodological contribution of this study is to investigate the potential volatility transmission patterns from international commodity markets to the Australian equity market by extending the multivariate framework of Bubák et al. (2011) and Soucek and Todorova (2013). More specifically, realized volatility is decomposed in its continuous and jump components in order to allow for in-depth insights into the following question: Are mainly jumps of international commodity markets transmitted or do the spillover effects arise due to both continuous and jump elements? Similar to the analysis of Busch, Christensen and Nielsen (2011) who study the incremental information content of implied volatility in the univariate case, the current study additionally considers separate modelling of both the continuous and jump components in order to understand whether the diffusion/jump component of the Australian market volatility is influenced by continuous/jump elements only or the pattern is more mixed and complex. Furthermore, we account for the non-synchronicity of the trading times in different markets by incorporating realized volatility, bipower variation and jumps for the overlapping trading time as well as for the non-overlapping time slots so that these are considered separately in the volatility models. This is an issue of high practical importance for volatility modelling which has not been addressed in the framework of the HAR model for realized volatility before.

In particular, we extend the univariate HAR model for realized volatility and its jump and continuous components of the Australian equity market by considering realized volatility of two export commodities (aluminium and copper futures from the London Metal Exchange), an indispensable import commodity proxied by the Western Texas Intermediate benchmark for oil prices and a broad commodity index (DJ UBS Commodity Index, UBSCI thereafter). The time period under consideration is divided into two subsamples comprising the most distressed months of the Global Financial Crisis and its aftermath.[1] Moreover, in order to allow for reliable conclusions about the incremental information content of commodity volatility series for forecasting Australian future equity market volatility, it is verified that they do not merely contain information already reflected in a global equity volatility benchmark. To this end, the realized volatility of the MSCI World Index is used as an indicator of equity market volatility. Being quoted 24 hours a day, it includes 24 developed stock

[1]Full-sample results are not presented in order to save space.

markets and is expected to promptly subsume all information arrivals in the international equity markets.

Putting the research question into the perspective of the chosen methodology, it is expected to uncover spillover effects mainly due to non-synchronous trading times arising from the MSCI World volatility series as they exhibit the highest informational content by nature. The major questions pursued in the following analysis are: Are there any additional transmission effects inherent in the commodity markets after controlling for a global equity markets uncertainty? If any, do the spillover effects emerge from jump or continuous volatility components? Which elements of the Australian equity market volatility are affected by the spillovers?

The study provides evidence that there are significant spillover effects originating from international commodity markets to the Australian stock market with pronounced differences in the transmission patterns during the crisis and post-crisis period. Even after controlling for global equity risk, these effects remain significant. In particular, during the crisis period spillovers can be observed mainly from the LME copper futures market to the Australian equity market probably due to the acknowledged responsiveness of copper to global economic cycles. This relationship holds also in the post-crisis time, during which the UBSCI commodity index appears to add relevant information for future volatility of the Australian market as well. The source of the documented spillover effects are non-synchronous trading hours, as well as both short- and longer-term continuous and jump components of realized volatility.

The remainder of the paper is structured as follows. Section 2 discusses the assets selected for the empirical analysis. Section 3 presents the methodology and the data processing procedure. Section 4 reports the empirical results. Section 5 provides some concluding remarks.

2 Data series selection and description

In total, the analysis concerns potential volatility transmission emerging from one import and two export commodities as well a commodity index, controlling for global equity volatility. Five-minute returns for the assets under consideration are obtained from the Thomson Reuters Tick History database at the Securities Industries Research Centre of Asia Pacific (SIRCA) and cover the period from January 2008 to December 2012 due to data availability. In the text which follows, the data series selection is justified, given the availability of sufficiently liquid assets in the database. Figure 1 provides a general view of the dynamics of the daily closing prices of the considered securities over the entire sample.

The volatility of the Australian stock market is proxied using the S&P/ASX200 index (hereafter ASX). ASX is regarded as a primary investable benchmark in Australia. Its constituents are the largest 200 listed companies at the Australian Stock Exchange in terms of market capitalization. The ASX spot quotations cover the time from 10:00 to 16:00 Eastern Standard Time. The spot index is chosen in order to avoid any staleness of index futures prices during non-trading times of the Australian Stock Exchange.

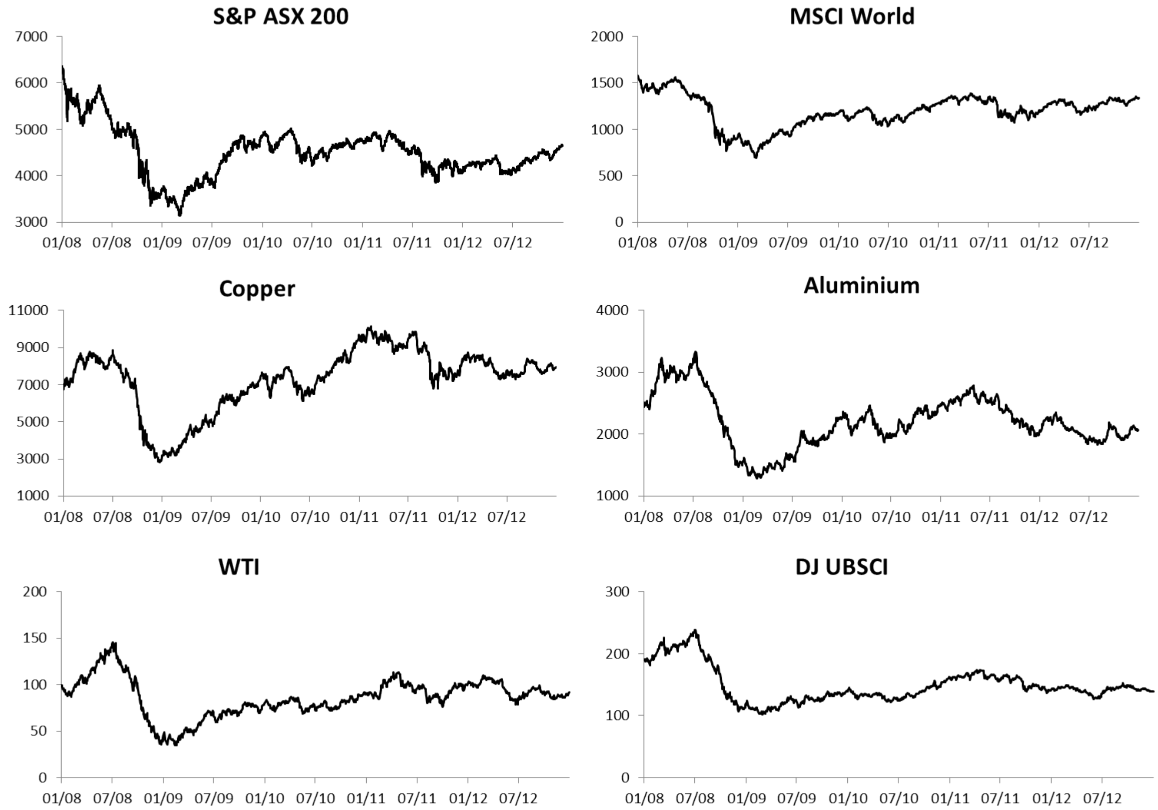

Figure 1: Closing prices of the assets under consideration

As crucial export commodities for Australia, LME futures contracts on aluminium and copper are taken into account. The two metals are very important in the industrial sense and have the highest trading volume among the base metals (Watkins and McAleer, 2008). Australia is one of the world's top six copper producers and the world's largest producer of bauxite and alumina. Of course, it is not argued that aluminium and copper have a most prevailing role in Australia's exports. However, it is believed that, due to its linkages to the overall economy, copper tracks the business cycles well and thus may have some predictability characteristics (Lahart, 2006; Choi and Hammoudeh, 2010). Aluminium is incorporated because already a simple plot of the price movements of aluminium and copper (Figure 1) reveals that while at end of the sample period, aluminium prices are almost below the price of its beginning, copper exceeds the high price level documented shortly before the financial crisis. This suggests that while the volatilities of both metals share periods of similar dynamics, at other times each market exhibits an idiosyncratic evolvement which cannot be observed in the remaining series. The futures prices are quoted in US dollars per ton. The data originate from the exchange operated electronic trading platform LMEselect and the daily transaction records span from 1:00 to 19:00 Greenwich Mean Time (GMT).

Crude oil is considered as a most prominent example of an import commodity for Australia. More specifically, the study utilizes CME futures on the Western Texas Intermediate (WTI) crude oil representing an international oil benchmark. Due to its high sensitivity to special events like natural disasters, and geopolitical events in oil-producing countries, oil prices have shown a greater speed of adjustment to equilibrium than other commodities (Hammoudeh and Yuan, 2008; Hammoudeh, Sari and Ewing, 2009). The oil futures are traded 24 hours a day in the Eastern Time (EST) zone and their prices are quoted in US dollars per barrel.

Next, to reflect the volatility of the overall commodity markets environment, the Dow Jones-UBS Commodity Index is included in the analysis. The UBSCI is composed of commodities traded on US exchanges, with the exception of aluminum, nickel and zinc, which are traded on the LME. The UBSCI is a broadly diversified index composed of futures contracts on physical commodities.[2] It is quoted between 8:00 and 15:00 EST.

Last, to allow conclusions about the incremental informational content of commodity volatility series, one needs to ensure that they do not merely incorporate information arrivals and volatility dynamics already reflected at a worldwide equity level. The MSCI World Index is chosen to control for a 'global' volatility factor. It is constructed to capture the evolvement of large and mid cap equity across 24 equity markets. Quotations are given in US dollars and around the clock on US trading days.

[2]The UBSCI is favored over the Goldman Sachs Commodity Index because the latter assigns substantially heavier weights to energy commodities.

3 Methodology

3.1 Decomposition of realized volatility in jump and continuous components

Following the approach of Andersen, Bollerslev, and Diebold (2007), it is assumed that the logarithm of the asset price follows the general stochastic volatility jump diffusion model,

$$dp(t) = \mu(t)dt + \sigma(t)d\omega(t) + \kappa(t)dq(t),\ t \geq 0,$$

where $\mu(t)$ is a continuous locally bounded variation process, $\sigma(t)$ is a strictly positive volatility process, $\omega(t)$ denotes a standard Brownian motion, $dq(t)$ is a counting process with $dq(t) = 1$ corresponding to a jump at time t and 0 otherwise, and $\kappa(t)$ refers to the size of the corresponding jumps.

To measure the daily quadratic variation using intraday data, a realized variance measure is employed. As proposed by Andersen and Bollerslev (1998), this is calculated on the basis of the intraday futures' prices $p_{t,i}$ with resulting continuous intraday returns

$$r_{t,i} = p_{t,i} - p_{t,i-1} \text{ for } i > 0, \tag{1}$$

where the first index t denotes the day of observation $t = 1, 2, \ldots, T$. The index i shows the time of observation on a particular day $i = 0, 1, 2, \ldots, M + 1$. The realized variance is then estimated by finding the total of squared intraday returns,

$$RV_t = \sum_{i=1}^{M} r_{t,i}^2. \tag{2}$$

When $M \to \infty$, RV_t converges to the true quadratic variation and squared jumps,

$$RV_t \to \int_{t-1}^{t} \sigma^2(s)ds + \sum_{t-1<s<t} \kappa^2(s). \tag{3}$$

Following Barndorff-Nielsen and Shephard (2004) and Barndorff-Nielsen and Shephard (2006), the nonparametric separation of the continuous sample path and jump components of quadratic variation can be done through the related bipower and tripower variation measures. The realized bipower variation is

$$BV_t = \left(\sqrt{2/\pi}\right)^{-2} \sum_{i=2}^{M} |r_{t,i}||r_{t,i-1}|,$$

where $\mu_1 = \sqrt{2/\pi}$ is based on the product of adjacent returns in absolute terms. In theory, a higher value of M improves the precision of the estimators, but in practice it also makes them more prone to market microstructure effects, such as bid-ask bounces and measurement errors. This may introduce artificial, often negative serial correlation in returns. For this reason, the analysis in this study follows the approach of Huang and Tauchen (2005) who propose a staggered bipower variation,

$$BV_t = \mu_1^{-2} \frac{M}{M-(k+1)} \sum_{i=k+2}^{M} |r_{t,i}||r_{t,i-k-1}|. \tag{4}$$

Since it avoids the multiplication of adjacent returns, staggering mitigates the resulting bias. BV_t then provides a consistent estimator of the integrated variance unaffected by jumps,

$$BV_t \rightarrow \int_{t-1}^{t} \sigma^2(s)ds \quad \text{for} \quad M \rightarrow \infty. \tag{5}$$

It follows that the difference $(RV_t - BV_t)$ converges to the sum of squared jumps that have occurred during the day t. However, this difference may occur to be non-zero due to some sampling variation, so that positive differences need to be classified as significant in order to be taken into account. Following Huang and Tauchen (2005) and Andersen, Bollerslev, and Diebold (2007), the test statistic

$$Z_t = \sqrt{M} \frac{(RV_t - BV_t)/RV_t}{\left((\mu_1^{-4} + 2\mu_1^{-2} - 5)\max(1, TQ_t BV_t^{-2})\right)^{1/2}} \tag{6}$$

is utilized where TQ_t is the staggered realized tripower quarticity

$$TQ_t = \mu_{4/3}^{-3} \frac{M^2}{M-2(k+1)} \sum_{i=2k+3}^{M} |r_{t,i}|^{4/3}|r_{t,i-k-1}|^{4/3}|r_{t,i-2k-2}|^{4/3} \tag{7}$$

with $\mu_{4/3} = 2^{2/3}\Gamma(7/6)/\Gamma(1/2)$. We follow Huang and Tauchen (2005) and use $k = 1$ in (4) and (7). A jump on day t is regarded as significant when $Z_t > \Phi_\alpha$ where Φ_α is the α quantile of the standard normal distribution,

$$J_t = I_{Z_t > \Phi_\alpha}(RV_t - BV_t, 0). \tag{8}$$

The continuous component of quadratic variation is estimated by the remainder of RV_t,

$$C_t = RV_t - J_t. \tag{9}$$

In other words, C_t is equal to RV_t if no significant jumps are observed during day t and equal to BV_t, otherwise. Results are reported for $\alpha = 0.001$, in line with existing literature.[3]

3.2 Stand-alone and multi-asset HAR-CJ models

As the incorporation of additional parameters may cause instability of the univariate HAR-CJ model, we first consider its stand-alone, one-asset version in order to examine whether the estimates of the augmented model change dramatically or remain in a reasonable range. Furthermore, a focus is set on the incremental explanatory power of bi- and multivariate models as compared to the univariate model in terms of the models' adjusted R^2.

The deployed univariate HAR model for one-step ahead realized volatility as well as its diffusion and jump elements as dependent variables reads

$$\begin{aligned} X_t^A &= \beta_0 + \beta_1 C_D^A + \beta_2 C_W^A + \beta_3 C_M^A + \beta_4 J_D^A + \beta_5 J_W^A + \beta_6 J_M^A + \sqrt{h_t}\epsilon_t \\ h_t &= \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1}, \quad \text{for} \quad X_t^A = RV_t^A, C_t^A, J_t^A. \end{aligned} \tag{10}$$

C_W^A (J_W^A) and C_M^A (J_M^A) denote historical normalized sums of C and J for the Australian equity market established over the last 5 and 22 trading days (up to day $t-1$). Following Corsi et al. (2008), the volatility of realized volatility is explicitly accounted for by fitting a GARCH(1,1) to the residuals of the HAR-CJ model. This extension takes into account that empirical observation that the volatility of volatility tends to increase when the volatility is high and provides a better empirical fit of the transmission models. All volatility elements are used in a logarithmic form ($\log(RV)$, $\log(C)$, $\log(J+1)$) because this transformation makes them closer to normal and also does not impose non-negativity constraints which is an essential aspect for estimation purposes.[4] In the following, the logarithmic function is omitted in the formulas for the sake of clarity. The models for realized volatility, the diffusion and jump components are abbreviated as HAR-RV-CJ, HAR-C-CJ and HAR-J-CJ, respectively.

[3] As robustness tests, the empirical results based on α =0.005 and 0.01 are examined as well. The results are quantitatively similar to those reported in this study.

[4] The logarithmic specifications of the jumps follows Andersen et al. (2007).

To study volatility spillovers from commodity markets to the Australian equity market, the next step employs bivariate models augmented by the volatility components of a second asset, referred to as S in the general case,

$$
\begin{aligned}
X_t^A &= \beta_0 + \beta_1 C_D^A + \beta_2 C_W^A + \beta_3 C_M^A + \beta_4 J_D^A + \beta_5 J_W^A + \beta_6 J_M^A + \\
&\quad \beta_7 C_{D,N}^S + \beta_8 C_{D,T}^S + \beta_9 C_W^S + \beta_{10} C_M^S + \beta_{11} J_{D,N}^S + \beta_{12} J_{D,T}^S + \beta_{13} J_W^S + \beta_{14} J_M^S + \\
&\quad \beta_{15} d_t + \sqrt{h_t}\epsilon_t \\
h_t &= \omega + \alpha_1 \epsilon_{t-1}^2 + \alpha_2 h_{t-1},
\end{aligned}
\tag{11}
$$

with C^A and J^A denoting the continuous and jump components of the Australian market whereas C^S and J^S are the corresponding terms of the second asset in the respective bivariate model. d_t is a dummy variable taking into account days where the second asset is not traded as discussed in the following section. Again, the one-step ahead realized volatility as well as its jump and continuous components are considered as dependent variables separately in order to gain a better understanding of the incremental explanatory power emerging from the inclusion of a second asset in a realized volatility model.

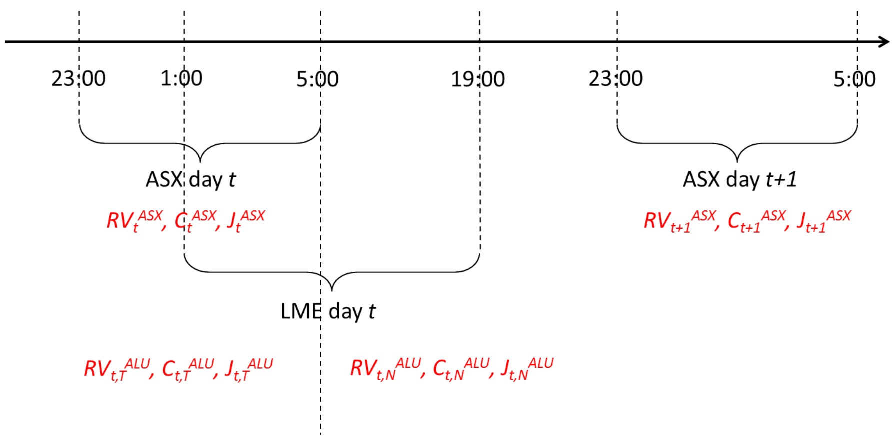

Figure 2: Accounting for overlapping and non-overlapping trading times in the case of aluminium

Special attention is dedicated to the deviating trading times of the assets under consideration. We illustrate our approach at the example of the Australian market and the LME market for aluminium. Following Andersen, Bollerslev, Diebold, and Labys (2003), we define a trading as the interval from 21:00 GMT to 20:59 GMT of the following day. The Australian trading day covers the time window between 23:00 to 5:00 while aluminium contracts are traded between 1:00 and 19:00.

If incorporated without any adjustment in the HAR model for Australian volatility, the aluminium volatility components of the previous day will include information of 14 additional hours which are not covered by the ASX elements. To discern whether potential spillover effects emerge from periods when both markets are open or from time slots when the Australian market is already closed, the following procedure is adopted. The LME trading day is split into two periods - from 1:00 to 5:00 (covering the ASX trading time) and 5:00 to 19:00 (non-overlapping with ASX). For each of these periods, realized volatility, bipower variation and jumps are established separately for every day and the test for significant jumps is run. The results in the volatility components denoted as $C^S_{D,T}$ and $J^S_{D,T}$ for the overlapping trading time and $C^S_{D,N}$ and $J^S_{D,N}$ for the non-overlapping time slots, respectively, in equation (11). This adjustment concerns the previous day's components of the second asset only. To ensure that the weekly and monthly components include solely information already available for the Australian market, the elements assigned to the non-overlapping period from 5:00 to 19:00 of the last day are excluded.

If a volatility component is denoted as X for generality, the normalized sums of the previous week's and month's realized volatility, continuous and jump elements are calculated as

$$X_W = \frac{1}{5}\left(\sum_{i=2}^{5} X_{t-i} + X^T_{t-1}\right), \text{ and } X_M = \frac{1}{22}\left(\sum_{i=2}^{22} X_{t-i} + X^T_{t-1}\right), \quad X = RV, C, J, \tag{12}$$

with X^T_{t-1} denoting the corresponding volatility element obtained for the previous day's overlapping market time. This approach is illustrated in Figure 2. Strictly seen, a certain bias arises from the fact that for example X_W covers four days and solely a certain portion of the fifth. The current analysis was also run by scaling all involved volatility components up to the length of the whole trading day in the corresponding market. The results are nearly the same as those obtained as the reported ones. More importantly, the volatility transmission patterns do not change and the relevant coefficients remain both quantitatively and qualitatively comparable to those obtained with the unscaled series.

In a next step, to identify the driving forces of the volatility spillovers, we incorporate all bivariate model parameters significant at least at the 5% level into multi-asset HAR-CJ models. In doing so, major question is whether the individual commodities contain identical information sets or whether a joint consideration may enhance the explanatory power of the bivariate models. Main indicators of interest are the adjusted R^2 of the different models and in case of a notable increase, the magnitude and sign of the statistically significant parameters.[5]

[5]Volatility transmission literature often accounts for the covariance of the series. Generally, the HAR model can be extended by considering the individual residuals series in a MGARCH framework in the sense of Bubák, Kočenda,

A vital concern regarding volatility transmission is whether commodity markets contain unique useful information for the one-step ahead volatility of the Australian market or the identified spillovers are reflecting merely the volatility of the global economy. To control for this, the volatility components of the MSCI World are included in the analysis as a proxy of the development of the global economy and treated equally to the commodities. First, its incremental impact is assessed within bivariate models for RV^A, C^A, J^A for comparison purposes. Subsequently, the insignificant right-hand side variables of the two-asset models are eliminated and the remaining terms are included in a multi-asset framework.

Similar to Thuraisamy, Sharma, and Ali Ahmed (2013) and Bubák, Kočenda, and Žikeš (2011), it is accounted for different market states by considering subsamples in order to link the observed spillover effect to the big picture of the international financial markets. More specifically, the sample period of 5 years is split into two subperiods ranging from 2008 to 2009 (crisis period) and the post-crisis period thereafter (2010-2012). Analysis of the realized volatility levels shows that while the volatility of the Australian equity market is relatively high in both periods (see subsequent section), realized volatility is much more volatile during the first period as opposed to during the post-crisis period. To determine where to split the whole sample into subsamples, recursive estimations are conducted by gradually extending the sample month by month, similarly to the approach of Bubák, Kočenda, and Žikeš (2011) The HAR-CJ parameter estimates for both jump and continuous volatility components behave in a stable manner from around the beginning of 2010 onwards. Extending the sample period further, however, leads to frequent changes in the estimated coefficients. For this reason, the estimations and tests are conducted and presented separately for the both subsamples.

The HAR-RV-CJ and HAR-C-CJ are estimated via Maximum Likelihood method. When the jump component of the Australian realized volatility is a dependent variable, the GARCH(1,1) extension for clustering effects is discarded as it yields to non-converging estimations or not plausible parameters of the variance equation confirming that jumps exhibit very different time series properties than realized volatility series. In this case, the estimations are conducted via OLS using Newey-West standard errors.

and Žikeš (2011). This approach allows for studying the conditional correlations between the volatility series under consideration. The analysis of the conditional correlations is beyond the scope of this study as the current approach focuses on unidirectional spillovers from commodity markets to the Australian market but omits the inverse direction since it is not plausible to hypothesize that ASX might cause the volatility of, for example, WTI US crude oil.

3.3 Data processing

In order to establish daily realized volatilities and their decomposition into continuous and jump components, weekend periods and public holidays are discarded in all data series. If an asset is not traded 24 hours a day, overnight returns are discarded as they are known to provide very noisy volatility estimates.

The raw data are time-stamped in GMT. Since the analysis involves assets traded in different time zones and misleading inference of volatility transmission may arise due to an unappropriate treatment of non-synchronous trading times, especially when using high-frequency data, special attention is given to the synchronization of the data series. The procedure utilized for considering overlapping and non-overlapping open market times of different assets on the same calendar day is addressed in the previous section. The only asset whose historical volatility components for the previous day are not split into terms attributable to time slots coinciding and not coinciding with the trading times of the Australian exchange results, is the UBSCI as it is quoted only during times when the ASX is not. For this reason, $C^S_{D,T}$ and $J^S_{D,T}$ in equation (11) are set equal to zero.

Furthermore, as the analysis also involves assets traded at different market places, days of deviating activity need to be taken into account. Because the focus is set on the unidirectional spillovers from commodity markets to the Australian equity market and the Australian volatility components are the dependent variables in the HAR-CJ models, solely days on which the Australian market is open are taken into consideration. If for example, it is Thursday, and the US market was open on the previous day (Wednesday) but Australian exchange was not, the equation for the Thursday's Australian volatility omits the Wednesday's US volatility and uses rather the Tuesday's US volatility as a previous day's volatility. On Friday, however, the US volatility on Thursday is included in the calculation of the weekly and monthly historical components. If, in turn, the Australian exchange is open on Thursday and the US market is closed (which happens only in very few cases), a dummy variable that represents the domestic holidays relevant for the independent variable is used. There are a total of 507 and 757 observations for the Australian market in Period 1 and Period 2, respectively.

Last, similar to the majority of the literature on volatility spillovers, there is no incorporation of foreign exchange rate effects when calculating returns denominated in a different currencies. Such an adjustment would result in additional volatility emerging from the forex markets that may be unrelated to volatility within the equity and commodity markets subject to interest (Sim and Zurbruegg, 1999).

Table 1 reports summary statistics for the logarithmic annualized variance series under consideration for each subsample separately. The series of realized volatility and its continuous component exhibit very similar characteristics, as expected, and have a distribution much closer to the normal than their counterparts without a logarithmic specification (not tabulated to save space). The jumps exhibit another magnitude and opposite signs due to the specific logarithmic transformation, $\log(J_t + 1)$. Note for example that an annualized daily volatility of 25% is equal to -2.77 as a log transformed variance, whereas a daily jump of annualized magnitude 25% is equal to 0.06. This discrepancy between the magnitudes of log jump and continuous volatility components will lead to partially unproportionate coefficients in the model estimations as presented below (Tables 3 to 8). Furthermore, consistent with previous literature, the jumps exhibit substantially higher skewness and kurtosis.

4 Results

4.1 Stand-alone models

The results of the stand-alone models for realized volatility of the Australian market as well as its continuous and jump components are reported in Table 2, together with regression diagnostics. Q represents the Ljung-Box Q statistics for the null hypothesis of no autocorrelation up to lag 20 in the residual series, LM shows the Lagrange Multiplier test for ARCH disturbances, with p-values given in parentheses. The models for RV and C include a GARCH(1,1) variance equation whereas, as mentioned above, the HAR-J-CJ omits this extension.

Forecasting the next day's C is very similar to forecasting RV itself, with the HAR-C-CJ model achieving consistently higher R^2 values. This has a straightforward intuition since the continuous components are more predictable than the realized volatility as the latter additionally includes less foreseeable jump effects. The volatility of volatility appears to be highly persistent for both sample periods. In both subsamples, the weekly continuous component exhibits the highest relevance. However, while in the HAR-RV-CJ model jumps are significant, along with individual continuous volatility components (weekly for Period 1 and monthly for Period 2), in the HAR-C-CJ models significant effects are assigned only to the historical continuous constituents. In contrast, in the jump models, both C and J prove to have a significant impact on the one-step-ahead jumps. The explanatory power of the jump models is much lower than the models for RV and C. Finally, the reported diagnostics suggest that most of the univariate specifications provide a reasonable fit to the corresponding underlying volatility process. ARCH effects remain in the residuals especially in the jump models where no variance equation is included in the estimation. This suggests the possiblity of further adjustments.

4.2 Bivariate models

Parameter estimates and diagnostics for the unrestricted bivariate transmission models according to equation (11) are presented in Tables 3 to 5. Columns 2–6 report estimates based on Period 1 (January 2008 to December 2009) and columns 7–11 the estimates based on Period 2 (January 2010 to December 2012). The corresponding t-statistics are given in parentheses. Additionally to the Ljung-Box Q-statistics and LM test, F-statistics of the Wald test for the joint null hypothesis that all coefficients related to the second asset are zero ($\beta_7 = .. = \beta_{14} = 0$) in (11) uncover potential Granger causalities. Again, for all tests, the p-values are given in parentheses.

To start with a number of general observations, it becomes obvious that augmenting a HAR-CJ model by a second asset's volatility components does not cause a notable instability. The coefficients of the own volatility components as well as of the GARCH(1,1) extension for RV and C which are significant in the univariate models remain for the most part significant and of similar magnitude in the multi-asset case. This indicates that the bivariate HAR models for realized volatility do not suffer notably from an overparameterization problem. Furthermore, the dummy variables accounting for differing trading days in the individual markets are found to be statistically insignificant across all cases.

Focusing on the HAR-RV-CJ models (Table 3), the Wald tests show that for the first period, solely copper and the MSCI index seem to carry statistically significant information about the future volatility of the Australian equity market, leading to a modest increase in $R^2_{Adj.}$ of 0.2% in the case of copper and more considerable one of 2.2% for MSCI World Index, as opposed to the univariate model. In both cases, both the daily continuous volatility component emerging after the close of the Australian market $C^S_{D,N}$ and the historical monthly element C^S_M appear to contain significant incremental information content for the one-step ahead volatility of ASX.

In contrast, in the after-crisis time, the Wald tests confirm that all commodity markets as well as the MSCI World Index Granger cause the realized volatility of the Australian market. Both jump and diffusion components from the ASX closed market time appear to be statistically significant in most cases, along with the historical monthly components of aluminium, copper and the commodity index. The two-asset HAR-RV-CJ document more pronounced increases in $R^2_{Adj.}$ ranging from 1.4%

(WTI) to 4.1% (MSCI).

Next, the predictability of the continuous components C of realized volatility is considered (Table 4). Similar to the results for RV, the first period is characterized by modest increases in $R^2_{Adj.}$ for commodity assets as compared to the stand-alone models. Highest gain is achieved in the case of MSCI (2.8%) with the Wald test indicating a Granger causality at the 5% level for aluminium and MSCI only. In the second period, all additional assets appear to Granger cause the continuous volatility component of ASX, even if augmenting the univariate HAR-CJ does not lead to a very pronounced improvement of explanatory power. Furthermore, in the second subperiod, daily continuous components from both trading and non-trading time appear to have a significant impact.

The HAR-J-CJ models reveal the stronger incremental explanatory power of a second asset's volatility components for the jumps observed in the Australian market (Table 5). Here, a strong increase in the $R^2_{Adj.}$ (up to 11.4%) corroborated by the Wald test results which confirm the existence of causality is documented in all cases but the bivariate model with UBSCI. In the crisis time, copper surprisingly leads to a stronger increase than MSCI. Furthermore, in this first sample period, only jump components of the second asset under consideration are statistically significant whereas in the post-crisis subsample both jump and continuous components of the second asset, especially emerging from the non-market time for ASX, play a significant role.

4.3 Full models

Given the estimation results for the bivariate models, it is subsequently to be identified whether any additional transmission effects are inherent in the commodity markets after controlling for a global equity markets uncertainty. Tables 6 to 8 show estimation results for the restricted, all-asset HAR-RV-CJ, HAR-C-CJ and HAR-J-CJ models involving the components of the assets in consideration which are identified as significant at least at the 5% level in the bivariate models (Tables 3 to 5). The tables contain two panels with the upper one reporting estimates based on Period 1 (2008 to 2009) and the lower one reporting estimates based on Period 2 (2010 to 2012), respectively. Diagnostics providing evidence of the goodness of the models' fit are omitted to save space, along with the parameters of the equation for the volatility of realized volatility.[6] Finally, the adjusted R^2 of all bivariate models are summarized and opposed to the stand-alone and full models in Table 9.

Firstly, considering observations valid for all models across both sample periods, it becomes clear that the own volatility components of the Australian market remain for the most part statistically

[6]The tests show in most cases mild signs of misspecification, if any, and are available upon request.

significant and of highest relative magnitude, as expected, and the results for forecasting RV and C are broadly similar. Furthermore, in the majority of the cases, the impact particularly of the shorter-term MSCI World volatility components remains statistically significant as well, with highest weights assigned to the daily elements emerging from the non-overlapping trading times. Moreover, it becomes obvious that the volatility of WTI exhibits nearly no incremental information content for the one-step ahead volatility of the Australian market.

Furthermore, in the first sample period, the overall low t-values of the elements of the UBSCI suggest that in times of a crisis which emerges primarily from the equity markets, a broadly diversified commodity index contains only minor information concerning the future realized volatility in the equity market. Obviously, all relevant information is already fully subsumed in the series of the MSCI World Index volatility. On the other hand, both aluminium and copper appear to have a significant impact, especially in the case of daily and monthly continuous copper and daily aluminium volatility in the HAR-RV-CJ model, monthly continuous copper volatility in the HAR-C-CJ model and copper weekly jumps in the HAR-J-CJ model. The adjusted R^2 of the full models reported in the last row of Table 9 confirm that commodity realized volatility components indeed contain information which cannot be extracted from their MSCI World counterparts within the chosen methodology. Stepwise estimations of three-asset models (ASX, MSCI and aluminium or copper, not shown) provide evidence that the predominant portion of the increases in $R^2_{Adj.}$ of 1.3% (HAR-C-CJ) and 2.6% (HAR-J-CJ) in the full model as compared with the corresponding bivariate model including solely the MSCI is due to incorporating the volatility of copper futures contracts. This observation confirms the notion that copper times series are particularly well capable of reflecting economic cycles and the prevailing sentiment in global markets.

In the second sample period, the volatility components of the LME copper futures remain statistically significant after controlling for global equity risk as reflected in the time series of the MSCI World. This holds especially for RV and J models. Different in this period appears to be the pronounced relevance of the UBSCI. Its continuous component established after the previous day's close of the Australian market time is significant in all three models, along with jump components in the HAR-RV-CJ and HAR-C-CJ model. Comparing the extent of incremental explanatory power by considering three-asset models (ASX, MSCI and aluminium or UBS, not tabulated) shows that the gains of 2.3% (HAR-RV-CJ), 1.0% (HAR-C-CJ) and 3.4% (HAR-J-CJ) when extending the two-asset ASX-MSCI models to include all assets under consideration are due in almost equal weights to the copper and UBSCI volatility components. This suggests that in comparatively quieter times, there are significant spillover effects from international commodity markets to the volatility of an economy heavily reliant on commodity export and imports like the Australian. Moreover, this transmission effect holds even after controlling for global equity volatility.

Besides the results described so far, a comparison across models and subsample periods strongly favors the notion that volatility transmission exhibits notably different dynamics in the period of financial distress and in its aftermath. During the crisis period, only the own daily diffusion components are significant for forecasting jumps along with jumps from other markets, whereas in the subsequent period, short-term elements of both J and C appear to contain relevant additional information going beyond the own historical volatility (Table 8). In line with the aforementioned, presumed focus of equity markets on themselves during the crisis, it is also important to note that when modeling realized volatility without splitting it into jump and diffusion components in period 1 (Table 6), merely the jumps of MSCI World Index volatility appear to have a significant impact while in the period thereafter, jump components of other markets are assigned with significant weights as well.

Last, looking at the significant coefficients in the full models reveals that spillover effects are often attributable to non-synchronous trading hours, as expected, Additionally, in a number of cases, the corresponding monthly component is also statistically significant but with an opposite sign (copper and MSCI in period 1, aluminium in period 2 in the HAR-RV-CJ model, Table 6; MSCI in period 1 in HAR-C-CJ model, Table 7), implying a positive cross-market relationship between short-term shocks and future daily volatility, and a mean-reverting effect in the longer term.

5 Conclusion

The contribution of this study to the literature is first to provide a sophisticated and promising econometric framework to shed light on volatility transmission patterns when realized volatility is split into its continuous and jump components and overlapping and non-overlapping trading times are taken into account. The results are interesting and complement the burgeoning realized volatility literature. Furthermore, the study contributes to the set of literature on volatility transmission concerning the Australian equity market by studying, unlike any previous studies, spillovers emerging from major commodity markets.

The findings provide evidence that there are significant spillover effects from international commodity markets to the Australian stock market. These relationships hold after controlling for global equity risk as proxied by an established indicator quoted 24 hours a day as the MSCI World Index. Spillover effects are partially attributable to non-synchronous trading hours, but additional spillovers emerge from both short- and longer-term continuous and jump components of realized volatility. The documented incremental informational content is clearly discernible for all volatility components being considered as dependent variables. Pronounced differences in the transmission patterns in the crisis and post-crisis period can be observed. While during the crisis period spillovers emerge mostly from the LME copper futures market, the UBSCI appears to contain additional relevant information for the elements of the future Australian equity market volatility in the post-crisis time. In contrast, less incremental information is inherent in aluminium futures series and almost no spillover effects arise from a global benchmark of oil prices.

Of course, this study has some limitations, all of which suggest areas for future research. First, multi-asset HAR models contain a large number of parameters and needs generally to be treated with caution due to potential estimation instability issues. Second, the analysis is built on the default form of the HAR-CJ univariate model presenting future volatility as a function of daily, weekly and monthly historical volatilities. Despite the results of Craioveanu and Hillebrand (2013) who argue in favor of this lag structure based on an study of flexible lag selection for the thirty constituting stocks of the Dow Jones Industrial Average between 1995 and 2007, alternative time horizons may be able to shed further light on the volatility transmission mechanisms. The analysis may also be easily extended to longer-term future volatilities and spillover effects of bidirectional nature or to consider further assets as precious metals or energy commodities.

Appendix A: Tables

Table 1: Descriptive statistics

Variable		Mean	Std.Dev.	Skew	Kurt	Min	Max
ASJ							
$\log(RV_t)$	Period 1	-3.601	0.814	0.499	0.121	-5.476	-1.045
$\log(C_t)$		-3.842	0.738	0.306	-0.015	-5.909	-1.719
$\log(J_t + 1)$		0.011	0.028	4.480	25.095	0.000	0.249
$\log(RV_t)$	Period 2	-4.737	0.801	0.440	0.586	-6.807	-1.096
$\log(C_t)$		-4.967	0.739	0.483	1.091	-6.965	-1.096
$\log(J_t + 1)$		0.003	0.008	5.538	44.078	0.000	0.098
Aluminium							
$\log(RV_t)$	Period 1	-2.312	0.569	0.004	-0.006	-3.751	-0.148
$\log(C_t)$		-2.382	0.570	-0.118	0.003	-4.267	-0.352
$\log(J_t + 1)$		0.008	0.024	6.606	67.007	0.000	0.317
$\log(RV_t)$	Period 2	-2.911	0.518	0.376	0.106	-4.182	-1.296
$\log(C_t)$		-2.957	0.532	0.376	0.237	-4.456	-1.296
$\log(J_t + 1)$		0.002	0.006	2.916	8.845	0.000	0.040
Copper							
$\log(RV_t)$	Period 1	-2.025	0.786	0.641	0.174	-3.679	0.832
$\log(C_t)$		-2.054	0.780	0.576	0.030	-3.679	0.183
$\log(J_t + 1)$		0.006	0.046	17.201	342.022	0.000	0.940
$\log(RV_t)$	Period 2	-2.988	0.624	0.678	1.074	-4.810	-0.187
$\log(C_t)$		-3.014	0.631	0.585	1.086	-4.810	-0.187
$\log(J_t + 1)$		0.001	0.008	12.557	223.419	0.000	0.158
WTI							
$\log(RV_t)$	Period 1	-1.671	0.887	0.618	0.165	-4.105	1.547
$\log(C_t)$		-1.706	0.877	0.519	-0.116	-4.444	0.913
$\log(J_t + 1)$		0.014	0.089	11.317	146.638	0.000	1.326
$\log(RV_t)$	Period 2	-2.661	0.626	0.525	1.555	-4.578	0.395
$\log(C_t)$		-2.728	0.634	0.408	1.081	-4.578	-0.013
$\log(J_t + 1)$		0.005	0.034	22.567	575.183	0.000	0.892
UBSCI							
$\log(RV_t)$	Period 1	-3.690	0.640	0.694	2.744	-5.397	-0.256
$\log(C_t)$		-3.725	0.600	0.135	0.542	-5.397	-1.022
$\log(J_t + 1)$		0.003	0.031	14.545	227.705	0.000	0.548
$\log(RV_t)$	Period 2	-4.594	0.589	0.719	2.463	-6.693	-1.153
$\log(C_t)$		-4.632	0.541	0.247	0.527	-6.693	-2.671
$\log(J_t + 1)$		0.001	0.012	18.475	381.546	0.000	0.266
MSCI World							
$\log(RV_t)$	Period 1	-3.657	1.012	0.348	0.220	-7.204	-0.319
$\log(C_t)$		-3.798	1.013	0.321	0.353	-7.204	-0.319
$\log(J_t + 1)$		0.006	0.016	5.208	37.735	0.000	0.176
$\log(RV_t)$	Period 2	-4.448	0.887	-0.022	1.383	-8.311	-1.596
$\log(C_t)$		-4.607	0.874	-0.058	1.898	-8.869	-1.596
$\log(J_t + 1)$		0.003	0.008	5.644	40.708	0.000	0.083

Descriptive statistics for daily realized variance ($log(RV_t)$), continuous components ($log(C_t)$) and jumps ($log(J_t + 1)$). Period 1 runs from January 2008 to December 2009 and Period 2 from January 2010 to December 2012.

Table 2: Stand-alone models

	Period 1			Period 2		
Parameter	HAR-RV-CJ	HAR-C-CJ	HAR-J-CJ	HAR-RV-CJ	HAR-C-CJ	HAR-J-CJ
Cons	-0.361	-0.304	0.038***	-0.953***	-0.916***	0.010***
	(-1.56)	(-1.58)	(3.16)	(-3.35)	(-3.79)	(2.26)
C_D^A	0.280***	0.227***	0.003	0.294***	0.281***	0.001
	(4.52)	(4.22)	(0.78)	(7.36)	(5.84)	(0.89)
C_W^A	0.477***	0.413***	0.011**	0.483***	0.426***	0.003**
	(4.81)	(4.19)	(2.02)	(8.85)	(6.14)	(2.26)
C_M^A	0.111	0.298***	-0.005	0.011	0.130**	-0.002
	(1.25)	(3.26)	(-1.23)	(0.12)	(2.03)	(-1.57)
J_D^A	-1.605	0.139	-0.040	0.102	2.827	-0.072**
	(-1.61)	(0.15)	(-0.42)	(0.04)	(1.16)	(-2.36)
J_W^A	6.438***	1.951	0.507***	-0.976	9.168	-0.333**
	(4.71)	(1.10)	(3.08)	(-0.15)	(1.33)	(-2.39)
J_M^A	0.220	-1.678	-0.173	33.989**	5.739	0.699***
	(0.08)	(-0.60)	(-0.71)	(2.52)	(0.47)	(3.24)
α_0	0.040	0.017	-	0.015	0.080**	-
	(0.39)	(1.17)	-	(0.47)	(1.99)	-
α_1	0.120	0.029	-	0.077	0.095**	-
	(1.37)	(1.16)	-	(1.09)	(2.26)	-
α_2	0.774**	0.882***	-	0.906***	0.538***	-
	(2.05)	(9.99)	-	(9.78)	(2.61)	-
Diagnostics						
R^2_{Adj}	0.558	0.645	0.145	0.514	0.595	0.062
Q	13.77	23.75	28.11	34.03	37.50	29.97
	(0.952)	(0.476)	(0.255)	(0.084)	(0.039)	(0.186)
LM	16.25	16.15	42.00	24.51	23.73	26.80
	(0.180)	(0.185)	(0.000)	(0.017)	(0.022)	(0.008)

The tables contains estimation results for RV_t, C_t and J_t using continuous and jump elements as regressors according to equation (10). t-values are given in parentheses. Q represents the Ljung-Box Q-statistics for the null hypothesis of no autocorrelation up to lag 20 in the raw residuals. Similarly, LM represents Engle's LM test for ARCH effects up to lag 20 in the standardized residual series. For the latter two, the p-values are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively. Period 1 runs from January 2008 to December 2009 and Period 2 from January 2010 to December 2012.

Table 3: Bivariate HAR-RV-CJ models

Parameter	Period 1					Period 2				
	Alu	Copper	WTI	UBSCI	MSCI	Alu	Copper	WTI	UBSCI	MSCI
Cons	-0.318	-0.089	-0.442	-0.261	-0.440	-1.122***	-0.993***	-1.162*	-0.814*	-1.293***
	(-0.93)	(-0.27)	(-1.54)	(-0.99)	(-1.42)	(-3.24)	(-2.76)	(-3.20)	(-2.85)	(-3.33)
C_D^A	0.241***	0.228***	0.231***	0.278***	0.166**	0.222***	0.220***	0.222*	0.226*	0.176
	(3.71)	(3.54)	(3.51)	(5.57)	(2.57)	(4.05)	(3.99)	(3.98)	(5.90)	(1.49)
C_W^A	0.425***	0.395***	0.471***	0.422***	0.342***	0.513***	0.422***	0.522***	0.441***	0.426**
	(3.59)	(3.32)	(3.83)	(5.62)	(2.62)	(5.90)	(4.69)	(5.86)	(6.49)	(2.20)
C_M^A	0.220*	0.218*	0.179	0.204***	0.349***	0.075	0.120	-0.049	0.011	-0.080
	(1.89)	(1.83)	(1.42)	(3.14)	(2.66)	(0.93)	(1.43)	(-0.51)	(0.11)	(-0.13)
J_D^A	-1.127	-1.687	-1.442	-1.416***	-1.718	-2.427	-0.757	-2.184	-1.850	-2.874
	(-1.02)	(-1.52)	(-1.28)	(-2.84)	(-1.55)	(-0.79)	(-0.25)	(-0.72)	(-0.76)	(-0.77)
J_W^A	5.605**	5.696**	3.949*	5.797***	3.802*	-3.376	-10.045	-4.445	-5.247	-11.410
	(2.50)	(2.28)	(1.68)	(6.13)	(1.76)	(-0.40)	(-1.17)	(-0.52)	(-0.92)	-(1.30)
J_M^A	1.874	-1.346	2.001	0.081	1.071	42.229***	51.496***	44.119***	50.177***	35.961
	(0.53)	(-0.32)	(0.55)	(0.03)	(0.30)	(2.95)	(3.47)	(3.00)	(4.12)	(1.52)
$C_{D,N}^S$	0.151**	0.209***	0.099*	0.018	0.182***	0.338***	0.324***	0.221***	0.255***	0.200***
	(2.36)	(2.92)	(1.68)	(0.37)	(4.49)	(5.85)	(5.95)	(4.95)	(4.93)	(4.53)
$C_{D,T}^S$	-0.015	-0.040	0.032	-	0.007	0.076*	0.040	0.052	-	0.087**
	(-0.38)	(-0.73)	(0.69)	-	(0.18)	(1.79)	(0.84)	(1.07)	-	(2.47)
C_W^S	-0.074	0.119	0.045	0.096	0.104	-0.163	-0.017	-0.172	-0.013	-0.010
	(-0.74)	(0.85)	(0.37)	(1.38)	(1.23)	(-1.43)	(-0.17)	(-2.03)	(-0.13)	(-0.06)
C_M^S	-0.109	-0.236**	-0.196*	-0.129*	-0.298***	-0.251**	-0.297***	0.060	-0.087	-0.008
	(-1.14)	(-1.96)	(-1.70)	(-1.75)	(-3.15)	(-2.18)	(-2.89)	(0.57)	(-0.74)	(-0.02)
$J_{D,N}^S$	2.206	2.179	-0.438	0.114	3.872**	12.853**	7.734**	0.639	-2.725***	12.822**
	(1.08)	(1.50)	(-1.51)	(0.56)	(1.88)	(2.08)	(2.47)	(1.07)	(-5.79)	(1.67)
$J_{D,N}^S$	0.017	0.028	-0.004	-	0.045	0.026	-0.066	-0.130	-	0.002
	(0.40)	(0.73)	(-0.08)	-	(0.70)	(0.50)	(-1.14)	(-1.13)	-	(0.00)
J_W^S	0.285	-0.753	-1.026*	0.146	-7.378*	-1.791	-8.165	-0.480	0.875	-2.028
	(0.11)	(-0.59)	(-1.95)	(0.24)	(-1.80)	(-0.21)	(-1.23)	(-0.42)	(0.74)	(-0.28)
J_M^S	-4.582	-0.279	1.829*	-3.696*	12.901	7.734	3.205	0.036	11.281***	16.238
	(-0.98)	(-0.12)	(1.73)	(-1.72)	(1.45)	(0.53)	(0.25)	(0.02)	(2.97)	(0.70)
d	-0.060	-0.094	-	-0.049	-	0.031	-0.012	0.303	-0.113	-
	(-0.27)	(-0.43)	-	(-0.37)	-	(0.18)	(-0.07)	(0.53)	(-1.29)	-
ω	0.038	0.004	0.060	0.077	0.058	0.042	0.043	0.039	0.099	0.032
	(0.40)	(0.21)	(0.57)	(0.82)	(0.00)	(1.31)	(1.20)	(0.96)	(1.91)	(1.26)
α_1	-	-	0.008	0.177***	-	0.033	0.030	0.021	0.186	0.049
	-	-	(0.16)	(3.92)	-	(1.50)	(1.36)	(1.10)	(3.08)	(1.84)
α_2	0.866*	0.986**	0.779*	0.752***	0.786***	0.825***	0.822***	0.846***	0.669***	0.836***
	(1.68)	(2.01)	(1.89)	(3.92)	(3.14)	(7.04)	(6.27)	(5.90)	(5.48)	(7.91)
Diagnostics										
R^2_{Adj}	0.555	0.560	0.555	0.557	0.580	0.532	0.538	0.528	0.534	0.555
Wald	10.60	16.04	11.80	7.48	41.81	44.91	54.35	35.60	115.04	92.65
	(0.225)	(0.042)	(0.161)	(0.279)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q	14.32	16.71	12.25	13.67	14.28	31.52	27.88	31.72	28.52	31.65
	(0.939)	(0.861)	(0.977)	(0.954)	(0.940)	(0.139)	(0.265)	(0.134)	(0.239)	(0.136)
LM	20.75	21.32	16.68	18.05	17.72	21.80	16.43	13.90	19.14	27.10
	(0.054)	(0.046)	(0.162)	(0.114)	(0.124)	(0.040)	(0.172)	(0.307)	(0.085)	(0.008)

ML parameter estimates and diagnostics are presented for the unrestricted bivariate transmission models according to equation (10). Columns 2–6 report estimates based on Period 1 (January 2008 to December 2009) and columns 5–11 the estimates based on Period 2 (January 2010 to December 2012). The corresponding t-statistics are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively. Wald reports F-statistics of the Wald test for the joint null hypothesis that $\beta_7 = .. = \beta_{14} = 0$ in (11). Q represents the Ljung-Box Q-statistics for the null hypothesis of no autocorrelation up to lag 20 in the raw standardized residuals and LM represents the LM test statisic for ARCH effects up to lag 20 in the same series. For all tests, the p-values are given in parentheses.

Table 4: Bivariate HAR-C-CJ models

Parameter	Period 1					Period 2				
	Alu	Copper	WTI	UBSCI	MSCI	Alu	Copper	WTI	UBSCI	MSCI
Cons	-0.349	-0.156	0.213	-0.446	-0.149	-1.166***	-1.413***	-1.337***	-0.901***	-1.544***
	(-1.26)	(-0.60)	(-1.27)	(-1.74)	(-0.59)	(-3.96)	(-4.58)	(-4.43)	(-2.60)	(-5.02)
C_D^A	0.214***	0.209***	0.421***	0.217***	0.157***	0.242***	0.212***	0.232***	0.239***	0.212***
	(4.05)	(3.92)	(3.90)	(3.98)	(2.98)	(5.01)	(4.36)	(4.71)	(4.95)	(4.44)
C_W^A	0.361***	0.355***	0.281***	0.362***	0.306***	0.426***	0.405***	0.462***	0.421***	0.406***
	(3.74)	(3.57)	(4.09)	(3.26)	(2.78)	(5.80)	(5.35)	(6.05)	(5.93)	(4.87)
C_M^A	0.374***	0.344***	0.059***	0.386***	0.479***	0.160**	0.179**	0.041	0.064	0.010
	(4.00)	(3.53)	(2.61)	(3.82)	(4.47)	(2.26)	(2.48)	(0.50)	(0.81)	(0.09)
J_D^A	0.154	-0.137	0.949	0.085	-0.427	1.415	2.168	1.105	1.255	0.322
	(0.17)	(-0.15)	(0.06)	(0.09)	(-0.47)	(0.58)	(0.88)	(0.44)	(0.53)	(0.13)
J_W^A	3.110**	3.184**	-0.399	1.750	-0.290	9.728	6.282	10.581	9.846	5.016
	(1.69)	(1.54)	(0.46)	(0.98)	(-0.16)	(1.41)	(0.89)	(1.51)	(1.42)	(0.69)
J_M^A	-1.497	-3.084	-0.041	-0.591	0.987	6.991	18.103	8.839	16.828	7.534
	(-0.53)	(-0.91)	(-0.13)	(-0.21)	(0.34)	(0.57)	(1.42)	(0.71)	(1.31)	(0.53)
$C_{D,N}^S$	0.093*	0.142**	0.449***	0.006	0.181***	0.176***	0.197***	0.116***	0.197***	0.089***
	(1.81)	(2.41)	(2.79)	(0.10)	(5.56)	(3.62)	(4.21)	(3.04)	(4.11)	(3.22)
$C_{D,T}^S$	-0.011	-0.014	-0.008	-	0.013	0.077**	0.122***	0.080**	-	0.117***
	(-0.35)	(-0.32)	(-0.30)	-	(0.38)	(2.18)	(2.94)	(2.01)	-	(4.04)
C_W^S	0.065	0.149	-0.089	0.084	0.106	-0.112	-0.137	-0.194**	-0.072	-0.043
	(0.81)	(1.33)	(-0.08)	(0.86)	(1.53)	(-1.18)	(-1.50)	(-2.76)	(-0.82)	(-0.66)
C_M^S	-0.220***	-0.220**	0.129	-0.160	-0.268***	-0.108	-0.126	0.133	0.008	0.008
	(-2.75)	(-2.18)	(-0.95)	(-1.70)	(-3.48)	(-1.11)	(-1.43)	(1.54)	(0.07)	(0.07)
$J_{D,N}^S$	2.025	1.180	0.441*	0.397	-0.368	2.859	-1.033	-0.039	-2.239	1.548
	(1.23)	(0.95)	(1.79)	(0.57)	(-0.22)	(0.55)	(-0.40)	(-0.08)	(-1.51)	(0.57)
$J_{D,T}^S$	0.009	0.031	-0.350	-	0.021	0.075*	-0.029	-0.150	-	0.159
	(0.26)	(0.97)	(-1.08)	-	(0.39)	(1.75)	(-0.61)	(-1.58)	-	(1.65)
J_W^S	-3.966*	-1.709	0.675	-0.123	-7.028**	-4.976	-8.981	-0.999	0.758	-2.382
	(-1.79)	(-1.60)	(-0.78)	(-0.08)	(-2.15)	(-0.69)	(-1.63)	(-1.04)	(0.27)	(-0.38)
J_M^S	-0.397*	-1.336	-0.012	-7.104**	3.846	4.743	-9.385	0.401	15.003**	20.763
	(-0.10)	(-0.67)	(0.76)	(-2.14)	(0.55)	(0.38)	(-0.86)	(0.24)	(2.50)	(1.70)
d	-0.119	-0.146	-	-0.095	-	0.163	0.118	0.419	0.120	-
	(-0.68)	(-0.83)	-	(-0.80)	-	(1.18)	(0.87)	(0.86)	(1.17)	-
α_0	0.019	0.017	0.029	0.016	0.030	0.083*	0.080**	0.096*	0.090**	0.046
	(0.56)	(0.47)	(0.97)	(1.06)	(0.91)	(1.94)	(2.00)	(1.90)	(2.16)	(1.36)
α_1	0.013	0.014	0.072	0.023	0.020	0.085**	0.080**	0.078*	0.099**	0.068
	(0.50)	(0.53)	(1.04)	(0.95)	(0.57)	(2.09)	(2.01)	(1.77)	(2.15)	(1.46)
α_2	0.884***	0.896***	0.872***	0.889***	0.806***	0.521**	0.534***	0.464*	0.472**	0.708***
	(4.57)	(4.30)	(7.52)	(9.48)	(4.00)	(2.33)	(2.52)	(1.77)	(2.13)	(3.53)
Diagnostics										
R^2_{Adj}	0.652	0.650	0.647	0.646	0.673	0.604	0.611	0.607	0.608	0.615
Wald	16.32	13.98	11.54	7.91	50.62	22.57	36.37	24.96	30.74	46.21
	(0.038)	(0.082)	(0.173)	(0.245)	(0.000)	(0.004)	(0.000)	(0.002)	(0.000)	(0.000)
Q	22.80	24.07	22.52	25.12	25.29	39.44	40.75	37.31	34.23	33.18
	(0.532)	(0.457)	(0.548)	(0.399)	(0.390)	(0.025)	(0.018)	(0.041)	(0.081)	(0.100)
LM	18.42	19.71	17.31	19.24	17.29	21.27	18.69	15.63	20.90	16.89
	(0.104)	(0.073)	(0.138)	(0.083)	(0.139)	(0.047)	(0.096)	(0.209)	(0.052)	(0.154)

ML parameter estimates and diagnostics are presented for the unrestricted bivariate transmission models according to equation (11). Columns 2–6 report estimates based on Period 1 (January 2008 to December 2009) and columns 5–11 the estimates based on Period 2 (January 2010 to December 2012). The corresponding t-statistics are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively. Wald reports F-statistics of the Wald test for the joint null hypothesis that $\beta_7 = .. = \beta_{14} = 0$ in (10). Q represents the Ljung-Box Q-statistics for the null hypothesis of no autocorrelation up to lag 20 in the raw standardized residuals and LM represents an LM test for ARCH effects up to lag 20 in the same series. For all tests, the p-values are given in parentheses.

Table 5: Bivariate HAR-J-CJ models

Parameter	Period 1					Period 2				
	Alu	Copper	WTI	UBSCI	MSCI	Alu	Copper	WTI	UBSCI	MSCI
Cons	0.023	0.034*	0.022***	0.052	0.008	0.010	0.014**	0.013	0.014*	0.018***
	(1.28)	(1.72)	(1.27)	(3.12)	(0.38)	(1.69)	(2.09)	(2.54)	(1.86)	(3.74)
C_D^A	0.002	0.002	0.002	0.002	-0.001	0.000	0.000	0.000	0.000	0.000
	(0.69)	(0.59)	(0.41)	(0.68)	(-0.17)	(0.11)	(0.29)	(0.05)	(0.16)	(0.00)
C_W^A	0.010*	0.010	0.011	0.012*	0.010	0.003**	0.002	0.003	0.002*	0.001
	(1.58)	(1.65)	(1.58)	(1.88)	(1.51)	(2.06)	(1.26)	(1.76)	(1.77)	(0.98)
C_M^A	-0.006	-0.006	-0.004	-0.007	-0.005	-0.001	-0.001***	-0.001	-0.001	-0.003
	(-0.75)	(-0.92)	(-0.55)	(-0.99)	(-0.72)	(-1.25)	(-0.58)	(-0.74)	(-1.10)	(-1.38)
J_D^A	-0.059	-0.102**	-0.048	-0.043	-0.070*	-0.089	-0.066	-0.093	-0.085	-0.062
	(-1.36)	(-2.26)	(-1.31)	(-1.19)	(-1.76)	(-1.31)	(-1.07)	(-1.53)	(-1.39)	(-1.11)
J_W^A	0.412***	0.230*	0.393***	0.502***	0.505***	-0.334***	-0.398***	-0.391***	-0.359***	-0.425***
	(4.19)	(1.88)	(4.10)	(5.88)	(5.49)	(-2.97)	(-3.48)	(-3.40)	(-3.11)	(-3.94)
J_M^A	-0.057	0.005	-0.060	-0.253	-0.338	0.717***	0.720***	0.804***	0.768***	0.377
	(-0.31)	(0.02)	(-0.35)	(-1.68)	(-1.95)	(2.77)	(2.91)	(3.75)	(3.67)	(1.47)
$C_{D,N}^S$	0.002	0.003	-0.001	0.002	0.002	0.004***	0.003***	0.003***	0.003***	0.003***
	(0.43)	(0.66)	(-0.24)	(0.64)	(0.71)	(5.03)	(3.85)	(4.89)	(3.63)	(6.87)
$C_{D,T}^S$	0.003	-0.001	0.003	-	0.002	0.000	0.000	0.000	-	-0.001
	(1.70)	(-0.38)	(1.15)	-	(0.74)	(0.76)	(-0.55)	(-0.23)	-	(-1.48)
C_W^S	-0.005	0.001	0.002	0.003	-0.001	-0.002	0.001	-0.001	-0.001	0.000
	(-0.98)	(0.17)	(0.22)	(0.39)	(-0.14)	(-0.87)	(0.50)	(-0.58)	(-0.48)	(0.22)
C_M^S	0.001	-0.003	-0.007	-0.001	-0.004	-0.002	-0.003*	-0.002	-0.001	0.001
	(0.24)	(-0.63)	(-1.02)	(-0.14)	(-0.77)	(-0.85)	(-1.85)	(-0.83)	(-0.50)	(0.60)
$J_{D,N}^S$	0.107**	0.161	-0.006	-0.030	0.327***	0.258***	0.300***	0.013	-0.021	0.302***
	(1.29)	(2.21)	(-0.25)	(-0.31)	(6.09)	(3.38)	(5.33)	(0.66)	(-0.41)	(15.38)
$J_{D,T}^S$	0.003	0.003**	0.000	-	0.007**	0.000	-0.001	0.000	-	-0.003**
	(1.52)	(2.22)	(-0.02)	-	(2.46)	(0.11)	(-0.75)	(0.10)	-	(-2.21)
J_W^S	0.319**	0.204***	-0.063	-0.043	-0.366**	-0.021	-0.034	0.001	-0.027	0.052
	(2.37)	(4.07)	(-0.81)	(-0.67)	(-2.00)	(-0.18)	(-0.24)	(0.03)	(-0.24)	(0.60)
J_M^S	-0.259	0.024	0.145***	0.173	1.148**	0.026	0.223	0.002	0.000	-0.041
	(-0.90)	(0.20)	(3.39)	(0.89)	(2.42)	(0.11)	(1.10)	(0.05)	(0.00)	-(0.26)
d	0.003	0.003	-	-0.001	-	-0.002	-0.002	0.002	-0.003	-
	(0.22)	(0.27)	-	(-0.07)	-	(-0.59)	(-0.64)	(0.00)	(-0.80)	-
Diagnostics										
R^2_{Adj}	0.156	0.199	0.156	0.140	0.185	0.087	0.140	0.089	0.082	0.176
Wald	22.85	60.87	24.33	2.82	75.12	34.54	57.44	26.66	15.83	392.32
	(0.004)	(0.000)	(0.002)	(0.832)	(0.000)	(0.000)	(0.000)	(0.001)	(0.015)	(0.000)
Q	27.21	37.17	28.13	29.83	27.55	28.60	33.80	21.67	24.29	22.55
	(0.295)	(0.042)	(0.255)	(0.190)	(0.280)	(0.236)	(0.088)	(0.599)	(0.445)	(0.547)
LM	36.61	26.05	34.65	49.46	38.68	54.86	59.03	48.10	52.83	14.93
	(0.000)	(0.011)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.245)

OLS parameter estimates with a Newey-West adjustment of the standard errors and diagnostics are presented for the unrestricted bivariate transmission models according to equation (11). Columns 2–6 report estimates based on Period 1 (January 2008 to December 2009) and columns 5–11 the estimates based on Period 2 (January 2010 to December 2012). The corresponding t-statistics are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively. Wald reports F-statistics of the Wald test for the joint null hypothesis that $\beta_7 = .. = \beta_{14} = 0$ in (10). Q represents the Ljung-Box Q-statistics for the null hypothesis of no autocorrelation up to lag 20 in the raw standardized residuals and LM represents the LM test statistic for ARCH effects up to lag 20 in the same series. For all tests, the p-values are given in parentheses.

Table 6: Full HAR-RV-CJ Models

Asset	Continuous components				Jump components			
	$C_{D,T}$	$C_{D,N}$	C_W	C_M	$J_{D,T}$	$J_{D,N}$	J_W	J_M
Period 1: 2008-2009								
ASX	0.194***		0.327***	0.317***		-	2.528**	-
	(3.76)		(3.97)	(3.71)		-	(2.45)	-
Alu	-	-0.081**	-	-	-	-	-	-
	-	(-2.19)	-	-	-	-	-	-
Copper	-	0.104**	-	-0.163**	-	-	-	-
	-	(2.02)	-	(-2.00)	-	-	-	-
WTI	-	-	-	-	-	-	-	-
UBSCI	-	-	-	-	-	-	-	-
MSCI	-	0.194***	-	-0.071	-	4.185**	-	-
	-	(4.50)	-	(-0.98)	-	(2.34)	-	-
Period 2: 2010-2012								
ASX	0.134***	-	0.396***	-	-	-	34.923***	-
	(3.62)	-	(6.88)	-	-	-	(4.22)	-
Alu	-	0.142***	-	-0.254***	-	7.407	-	-
	-	(2.88)	-	(-3.81)	-	(1.19)	-	-
Copper	-	0.073	-	0.016	-	3.520***	-	-
	-	(1.24)	-	(0.28)	-	(3.03)	-	-
WTI	-	-0.045	-	-	-	-	-	-
	-	(-1.09)	-	-	-	-	-	-
UBSCI	-	0.090**	-	-	-	0.587***	-	-5.345**
	-	(2.35)	-	-	-	(3.68)	-	(-2.17)
MSCI	0.092***	0.124***	-	-	-	12.547***	-	-
	(2.69)	(3.69)	-	-	-	(4.93)	-	-

ML parameter estimates are presented for the multi-asset transmission models involving all volatility components from the bivariate HAR-RV-CJ models which are significant at least at the 5% level (Table 3). The corresponding t-statistics are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively.

Table 7: Full HAR-C-CJ Models

Asset	Continuous components				Jump components			
	$C_{D,T}$	$C_{D,N}$	C_W	C_M	$J_{D,T}$	$J_{D,N}$	J_W	J_M
Period 1: 2008-2009								
ASX	0.151***		0.289***	0.523***	-		0.153	-
	(6.02)		(3.25)	(4.58)	-		(0.18)	-
Alu	-	-	-	0.004	-	-	-	-
	-	-	-	(0.04)	-	-	-	-
Copper	-	0.018	-	-0.151***	-	-	-	-
	-	(0.33)	-	(-2.85)	-	-	-	
WTI	-	-0.045	-	-	-	-	-	-
	-	(-1.11)	-	-	-	-	-	-
UBSCI	-	-	-	-	-	-	-	-4.845*
	-	-	-	-	-	-	-	(-1.91)
MSCI	-	0.207***	-	-0.114**	-	-	-5.750***	-
	-	(4.85)	-	(-1.99)	-	-	(-3.08)	-
Period 2: 2010-2012								
ASX	0.220***		0.375***	0.042	-		-	-
	(4.93)		(6.26)	(0.99)	-		-	-
Alu	-0.035	0.056	-	-	-		-	-
	(-1.17)	(1.55)	-	-	-	-	-	-
Copper	-0.001	0.059	-	-	-	-	-	-
	(-0.02)	(1.30)	-	-	-	-	-	-
WTI	0.038	-0.031	0.002	-	-	-	-	-
	(1.13)	(-0.89)	(0.90)	-	-	-	-	-
UBSCI	-	0.090***	-	-	-	-	-	7.745**
	-	(2.49)	-	-	-	-	-	(2.55)
MSCI	0.100***	0.061*	-	-	-	-	-	-
	(2.73)	(1.88)	-	-	-	-	-	-

ML parameter estimates are presented for the multi-asset transmission models involving all volatility components from the bivariate HAR-C-CJ models which are significant at least at the 5% level (Table 4). The corresponding t-statistics are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively.

Table 8: Full HAR-J-CJ Models

Asset	Continuous components				Jump components			
	$C_{D,T}$	$C_{D,N}$	C_W	C_M	$J_{D,T}$	$J_{D,N}$	J_W	J_M
Period 1: 2008-2009								
ASX	0.004**		-	-	-		0.127	-
	(1.99)		-	-	-		(1.09)	-
Alu	-	-	-	-	-	0.032	0.058	-
	-	-	-	-	-	(0.27)	(0.79)	-
Copper	-	-	-	-	0.003	-	0.212***	-
	-	-	-	-	(1.18)	-	(5.98)	-
WTI	-	-	-	-	-	-	-	-0.020
	-	-	-	-	-	-	-	(-0.34)
UBSCI	-	-	-	-	-	-	-	-
	-	-	-	-	-	-	-	
MSCI	-	-	-	-	0.007*	0.227	-0.355	0.443
	-	-	-	-	(1.80)	(1.51)	(-1.63)	(0.83)
Period 2: 2010-2012								
ASX	-		0.007**	-	-0.091***		0.486***	-0.323*
	-		(2.29)	-	(-3.06)		(5.68)	(-1.85)
Alu	-	-0.001	-	-	-	0.139	-	-
	-	(-0.51)	-	-	-	(0.81)	-	-
Copper	-	0.001	-	-	-	0.254***	-	-
	-	(0.30)	-	-	-	(4.31)	-	-
WTI	-	-0.007***	-	-	-	-	-	-
	-	(-2.79)	-	-	-	-	-	-
UBSCI	-	0.005**	-	-	-	-	-	-
	-	(2.05)	-	-	-	-	-	-
MSCI	-	0.003**	-	-	0.004	0.335**	-	-
	-	(2.38)	-	-	(1.35)	(2.30)	-	-

OLS parameter estimates with a Newey-West adjustment of the standard errors are presented for the multi-asset transmission models involving all volatility components from the bivariate HAR-J-CJ models which are significant at least at the 5% level (Table 5). The corresponding t-statistics are given in parentheses. *, **, and *** indicate statistical significance at the 10 %, 5 % and 1 % level, respectively.

Table 9: Adjusted R^2 of all models

	Realized Volatility		**Continuous Component**		**Jump Component**	
Model	**2008-09**	**2010-12**	**2008-09**	**2010-12**	**2008-09**	**2010-12**
ASX Standalone	0.558	0.514	0.645	0.595	0.145	0.062
ASX + Alu	0.555	0.532	0.652	0.604	0.156	0.087
ASX + Copper	0.560	0.538	0.650	0.611	0.199	0.140
ASX + WTI	0.555	0.528	0.647	0.607	0.156	0.089
ASX + UBSCI	0.557	0.534	0.646	0.608	0.140	0.082
ASX + MSCI	0.580	0.555	0.673	0.615	0.185	0.176
Full model	0.587	0.578	0.686	0.625	0.211	0.210

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