Cross-market trading dynamics in related commodity futures

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Abstract

We investigate cross-market trading dynamics in futures contracts written on seemingly unrelated commodities consumed by a common industry. On the Tokyo Commodity Exchange, we find such evidence in natural rubber (NR), aluminium (AL) and gasoline (GA) futures markets, which are exposed to Japan's prominent automobile industry. Our results indicate that i) for shorter dynamics, NR and GA volatility both influence AL volatility; GA volume affects NR volatility and volume; the GA market is immune to both NR and AL trading activities; ii) for longer dynamics, AL volume affects both NR volume and GA volatility; NR volume influences GA volume. These results are robust to lag-specifications, volatility measures, alternative measures of trading activity and an alternative multivariate specification in full BEKK-GARCH. Further analysis, which benchmarks against the silver futures market, TOCOM index and TOPIX transportation equipment index, confirm that our main results are driven by a common industry exposure, and not a commodity market factor. Our study offers new insights into how commodity and equity markets relate at an industry level, and provide multi-commodity hedging implications for automobile companies.

JEL classification: G14, G15.

Key words: volatility, volume, cross-market, trading dynamics, VAR, commodity futures.

1 Introduction

Cross-market information flow is well-documented in the literature. The empirical support for such linkages between markets is generally robust over time and across asset classes. Indeed, it is important to model such inherent information flow to better understand the nature of existing cross-market trading dynamics. Regulatory bodies apply such knowledge to monitor and alter the nature of such information flows to curb excessive volatility spill-overs. Fund managers incorporate cross-border linkages between financial markets to formulate investment strategies and portfolio formation. Firms incorporate covariations across relevant markets in corporate hedging policies.

Interestingly, existing studies on cross-market information flow generally fall into one of two categories. The first category constitutes a conceptually clear linkage between markets that are either fundamentally identical e.g. cross-listed stocks, similar/competing derivative contracts, or technically distinct but linked by arbitrage e.g. spot-futures-options. While the strong empirical support for such linkages is not surprising, it is paramount to provide detailed scholarly documentations for various combinations of markets. The second category contains studies that examine markets which are empirically linked ex-post, but with fundamental linkages that are not immediately obvious ex-ante e.g. international equity or currency markets, gold and silver[1], crude oil and equity. These empirical linkages are sometimes explained using behavioral or reputational channels. Despite an unclear fundamental justification, the careful empirical examination of such linkages is relevant to practitioners since, if they persist in the data, would need to be acknowledged and documented. We provide a non-exhaustive list of studies from both categories in Figure 1.

INSERT FIGURE 1

We have two related objectives in this paper. First, we propose a simple structural system to demonstrate cross-elasticity among commodities that share a common and non-trivial exposure, in this case the automobile industry. Price-quantity interactions within the system

[1]This case was highlighted to us in a CBOT futures research symposium, where Professor Bill Fung question the motivation to test for cointegration between gold and silver, given that gold is a storage of value that the reserve banks of most countries hold as foreign reserves, and is not normally regarded as a substitute for silver.

can be triggered by either an industry demand-shock that transmits across complementary inputs[2] or a supply-shock in commodity i that, by affecting the common industry, spill over to other complementary commodities[3]. Second, we empirically test for the presence of cross-market volatility (price) and volume (quantity) transmission effects across seemingly unrelated commodities. Specifically, we examine the Tokyo Commodity Exchange (TOCOM) futures contracts written on commodities that are consumed by the automobile industry: natural rubber (NR) used in the manufacturing of tires; aluminium (AL) used in making engine parts and constitutes an increasingly make-up of a car's body[4]; gasoline (GA) used to power internal-combustion engines. We choose TOCOM since Japan is the top automobile manufacturing country in the world, as shown in Figure 2, and it is home to world-class automobile companies[5]. In addition, TOCOM offers futures trading in all three underlying commodities. Ideally, a cross-market study should be restricted to the same or very similar market microstructure environment to avoid any technically-induced lead-lag dynamics.[6]

INSERT FIGURE 2

Our study is driven by four motivations. Our prime motivation stems from the literature's focus on markets that are either fundamentally similar or empirically linked without offering a clear economic reasoning. Our cross-market study on commodity futures written on a soft, a metal and a fuel is based on a simple economic argument. If a set of commodities constitute essential inputs pertaining to a common output, then despite of physical dissimilarities, idiosyncratic seasonality and production cycles, they would also share a common industry exposure. If the common exposure is non-trivial, then industry-specific information would directly transmit across input commodities. Information specific to commodity

[2]E.g. An exogenous shock that increases automobile sales volume will increase the demand for complementary input commodities NR, PA and GA.

[3]E.g. An exogenous downward supply shock in gasoline will, by causing a downturn in the automobile industry, reduce the demand for NR and PA.

[4]Japanese and European car manufacturers typically employ a higher aluminium content to lower production cost since aluminium is easier to manipulate than steel. It also saves up to 95% of energy and emissions from primary production since aluminium is easy to recycle. It also achieves better fuel efficiency since aluminium is one-third the density of steel. The comprise in safety is countered by their renowned emphasis and innovation in cutting-edge safety technology e.g. ABS, ETC, crush-zones, safety cages, air-bags etc.

[5]E.g. Toyota, Honda, Nissan, Mitsubishi, Mazda, Subaru, Suzuki, Isuzu.

[6]For example, if NR is floor-traded on Exchange A but GA is screen-traded on Exchange B at the same time, then any cross-market trading dynamics could be induced by dissimilar trading platforms rather than information effects.

i would indirectly transmit to other complementary commodities. Either way, these effects are empirically manifested in cross-commodity return-volatility-volume dynamics.

Second, most existing studies examine commodity futures traded on NYMEX, CBOT and/or LME. Studies on Japanese commodity futures markets are limited. This is despite TOCOM being ranked sixth overall in global commodity futures trading volume in 2006. It is also the largest commodity exchange in Japan, handling 83% of all commodity futures trading volume (in nominal value). More relevant to this study is the fact that TOCOM is the third largest exchange in fuel-base futures trading, second largest in metal-base futures trading and hosts the world's largest natural rubber futures market.

Third, unlike a financial security, it is awkward to identify a commodity's spot market, which often straddles across multiple farming, processing and trading centers.[7] Following Tirole's (1991) definition of a market[8], the trading center, which entails the interaction between producers and consumers, is a suitable spot market. Unfortunately, there are easily more trading centers for a commodity than (say) for a stock. Producers and consumers at one trading are often unclear as to which trading center(s) performs price discovery for NR (Singapore, Shanghai or Tokyo), AL (London, Shanghai or New York) and GA (London, Dubai or Texas). It is well-entrenched that futures price leads stock price[9]. With TOCOM as the largest commodity exchange of the world's top automobile producing country, we speculate that the NR, AL and GA contracts a vital price discovery role, both in Asia-Pacific and globally.[10] From there, the investigation of cross-market trading dynamics becomes pertinent.

Lastly, understanding the nature of cross-market trading dynamics in related commodities is relevant for the proper setting of regulatory and hedging policies. Fujihara and Mougoue (1997) state that a better understanding of linear and non-linear volume-volatility causal relationships across petroleum futures markets is helpful to evaluate the effectiveness of reg-

[7]Take NR for example. Its farming/processing centers are in Thailand, Indonesia and Malaysia, but its trading centers are in Singapore, Shanghai and Tokyo.

[8]According to Tirole (1991), a market is a social arrangement that allows buyers and sellers to interact and discover information for the purpose of carrying out a voluntary exchange of goods or services.

[9]See Garbade and Silber (1983), Kawaller et al (1987) and Stoll and Whaley (1990). Such information externality is often attributed to lower transaction costs (Brorson 1991), higher leverage and liquidity in futures markets (Subrahmanyam 1991).

[10]A senior researcher of the Shanghai Futures Exchange (SHFE) commented that most Chinese NR traders often refer to some weighted-average of SHFE and TOCOM NR futures prices as their benchmark.

ulatory constraints such as daily price and position limits. Evidence of cross-market trading dynamics in related commodity futures has implications for jointly setting price and position limits across trading in such related commodities on a futures exchange. The presence of cross-market trading dynamics has similar implications for hedging errors if inherent covariations across related commodities are not formally considered.[11] Our study provides evidence of covariations among seemingly unrelated commodity futures markets.

Our main results show that NR and GA lag-1 volatility both influence AL volatility; GA volume affects NR volatility and volume; the GA market is immune to both NR and AL trading activities. AL lag-2 volume affects both NR volume and GA volatility; NR volume influences GA volume. These results are robust to lag-specifications, volatility measures and other trading activity measures. They reveal significant short-term cross-market dynamics between NR and AL, and from GA to NR and AL. There is also evidence of feedback effects from AL to both NR and GA, as well as from NR to GA. The latter, which has the highest trading volume among the three commodities, is immune to NR and AL lag-1 dynamics. However, NR and (especially) AL both provide feedback effects in volume to GA at lag-2, lag-5 and even lag-10. Interestingly, AL and GA volatility are not affected by their own-market lag-1 volumes. Instead, AL volatility is affected by both NA and GA lag-1 volatility, while GA volatility is affected by AL lag-2 volume. From our analysis to determine the nature of the latent common exposure, results across VAR, BEKK-GARCH, PCA and VMA estimations have all attributed evident cross-market trading dynamics in NR, AL and GA to their common and non-trivial industry exposure, and not a commodity market factor.

The preceding results are generated from a four-stage empirical analysis. First, we present preliminary results with correlation tables, stationarity, Granger-causality, and lag-specification tests. These provide some insight into own- and cross-market dynamics in the return, volatility and volume variables of the three commodities. Second, we estimate a six-equation VAR to test the significance of own-market and cross-market volatility-volume variables among the NR, AL and GA contracts. We focus on results that are robust to different lag specifications, volatility measures and sub-samples. Third, we check if evidence of cross-market trading dy-

[11]For example, a car manufacturer attempting to minimize exposure to NR, AL and GA would typically compute hedge ratios to set optimal positions in individual commodity contract. This could generate hedging errors if covariations across commodities are non-trivial.

namics (if any) indicated by the VAR results are consistent with i) other measures of trading activity, namely, price reversals and variance ratios and ii) an alternative system estimation that formally models conditional volatility transmission effects, namely, tri-variate full BEKK-GARCH (1,1). Since we do not include volume in our GARCH estimation, they are not presented as main results.[12] In contrast, the price-quantity structural system we propose in the next section is more consistent with a VAR specification of cross-market volatility-volume interactions. Fourth, we contemplate the possibility that any evident cross-market interactions among NR, AL and GA is simply due to the presence of a commodity market factor. The latter implies interactions across all commodities to varying degrees.

We perform various tests to determine the nature of the common exposure. We conduct VAR and BEKK-GARCH estimations for pairwise comparisons between each of NR, AL, GA and the silver (SL) futures contract. Here, we assume that SL has a trivial (if any) exposure to the automobile industry.[13] If volume-volatility interactions is indeed driven by a common industry exposure rather than commodity market factor, we should not find any significant evidence of cross-market interactions from the pairwise estimations. Next, we perform two rounds of principal components analysis (PCA), with SL added to the second round, to understand the nature of the first principal component that is explaining variances across commodity returns. Lastly, we separately use the TOPIX Transportation Equipment (TE) index (proxy for industry exposure) and TOCOM index (proxy for commodity market factor) to extract residual return/volatility for NR, AL and GA. These are subsequently employed in two sets of vector moving average (VMA) estimations. The VMA with fewer significant variables corresponds to the more relevant index, since the more relevant index is more adequate at explaining cross-market interactions.

The rest of the paper is organized as follow. The model and estimation are outlined in section 2. Institutional details, data and results are discussed in section 3. Section 4 offers implications on multi-commodity hedging and policy-setting. Section 5 concludes.

[12]Schwert (1989) identifies fluctuations in trading activity as a key explanation for time varying volatility. Lamoureux and Lastrapes (1990) report that volume provides incremental explanatory power when modeling GARCH effects. Wu and Xu (2000) argue that information processing by capital markets is manifested in volatility and trading volume.

[13]While Audi made headlines a few years ago for delivering to a prince of the UAE an Audi A8 whose outer body is made entirely out of pure silver, suffice to say, pure silver-bodied cars are not in the production lines of any Japanese car manufacturers.

2 Model and estimation

In this section, we outline our conceptual argument for possible price-quantity interactions among complementary commodities that are consumed by a common industry. This leads to our empirical methodology to investigate possible cross-market trading linkages between commodity futures markets.

2.1 A commodity price-quantity structural system

We convey our idea with a general structural system that entails price-quantity interactions between commodity inputs i (where i=N,A,G in natural rubber, aluminium and gasoline respectively) and automobile output y. In equation (1), consider a set of three input commodity prices P_i with their corresponding global stockpiles Q_i. Faced with P_i, automobile manufacturers exhibit a set of cost-minimizing input demand q_i for the three commodities in order to produce output level Q_y. Assume an unobservable production technology factor Φ affects the entire system.

$$\begin{aligned} P_i &= f_i(Q_y, \Phi; Q_i) + \xi_{P_i} \\ q_i &= g_i(Q_y, \Phi; P_i) + \xi_{q_i} \\ Q_y &= h(P_i, \Phi; P_y) + \xi_y \end{aligned} \tag{1}$$

The specification of equation (1) is based on the following assertions. First, the prices charged by commodity suppliers are affected by automobile output. The quantity of each commodity consumed by the automobile industry depends on output level. The latter, in turn, is influenced by its selling price P_y as well as commodity input costs. Since the actual interaction within the structural system is unknown, the individual equations are specified with unknown functional forms $\{f_i, g_i, h\}$. In addition, denote $\{\xi_{P_i}, \xi_{q_i}, \xi_y\}$ as the corresponding residuals to indicate that i) natural rubber, aluminium and gasoline are not the only commodities relevant to the automobile industry; ii) there exists relevant exogenous factors other than Φ and iii) commodity-specific effects e.g seasonality and production cycle.

Despite the lack of an analytical form, equation (1) does convey the idea of automobile output and production technology as common factors that induce price-quantity interactions across seemingly unrelated futures contracts written on a soft, a metal and a fuel commodity. The reduced form of the structural system is presented in equation (2). If automobile output is affected by commodity input prices, and if each commodity input price relates to both the quantity consumed by the automobile industry as well as global stockpile, then the price and quantity of related commodities $P_{j \neq i}, q_j, Q_j$ would all enter the price equation of commodity i. Similarly, the industry demand for a given input commodity q_i is affected, through Q_y, by the price and quantity of related commodities $P_j, q_{j \neq i}, Q_j$.

To note, we have three reasons to focus on an industry-specific quantity q_i rather than global stockpile Q_i. First, we are unaware of reliable daily data on Q_i for the three commodities. Second, q_i better reflects trading demand by commodity speculators and hedging demand by car makers, which is suitably analyzed using futures data. Third, if we focus on Q_i, then P_i would correspond to commodity spot prices. This introduces complications as commodity spot markets are less well-defined, while a cross-market study ideally involves markets that operate under the same or similar trading environment.

$$
\begin{aligned}
P_i &= f_i^*(P_y, \Phi; P_{j \neq i}, q_j, Q_j) + \xi_{P_i}^* \\
q_i &= g_i^*(P_y, \Phi; P_j, q_{j \neq i}, Q_j) + \xi_{q_i}^*
\end{aligned}
\tag{2}
$$

Equation (2) demonstrates price-quantity interactions among commodities that share a common industry exposure. In economic terms, a common yet dominant industry exposure implies non-trivial cross-elasticity that induce price-quantity interactions among related commodities. In finance terms, a common industry exposure implies non-zero return-volatility-volume covariance structures across related commodities. Co-movement due to a common industry exposure induces contemporaneous covariation. But the presence of market frictions and slow information diffusion documented in Grinblatt and Moskowitz (1999) suggest lead-lag responses among related commodities to the common industry exposure. In time series terms, this implies the presence of Granger-causality and cross-market return-volatility-volume dynamics, which can be examined using multivariate time-series systems estimation.

2.2 Empirical methodology

We consider various empirical representations of equation (2) to test for cross-market trading dynamics in related commodity futures markets. Denote p_{it} as the commodity i daily closing price and $r_{it} = Ln(\frac{p_{it}}{p_{it-1}})$ as the daily return. We apply volatility $\sigma_{it} = |r_{it}|$ and Yen-volume v_{it} to proxy the price-quantity variables discussed in the previous section. With different contract multipliers, units of measurement, and contract size alterations during the sample period[14], we construct our volume variables in Yen rather than number of contracts to facilitate a more standardized comparison of quantity across markets.

Stationarity, autocorrelation and causality features

First, we examine the correlation matrix and autocorrelation functions of the variables of various commodities. We perform Augmented Dickey Fuller (ADF) stationarity tests and pairwise Granger Causality tests to acquire some preliminary results on the own-market and cross-market dynamics in the volatility-volume variables.

VAR estimation

In this paper, although we perform multivariate GARCH (1,1) estimation to analyze cross-market volatility transmission, it does not formally incorporate volume effects in the estimation. The role of volume is well-documented in the literature, both theoretically[15] and empirically[16]. In commodities markets, Clark (1973) identifies a positive casual volume-volatility relation in cotton futures. Cornell (1981) finds positive contemporaneous volume-volatility relations in a comprehensive study covering using daily data on 17 commodities futures contracts. Bessembinder and Seguin (1993) provide similar findings that are robust across currency, metal, agriculture and financial futures contracts. Malliaris and Urrutia (1998) formalize and empirically document price-volume relationships for a series of agricultural futures contracts. Ciner (2002) examines the informativeness of volume in affecting volatility and return for platinium, gold and rubber futures traded on TOCOM. The study

[14]The NR contract size is 10,000kg prior to 26th Jan 2005, after which it was downsized to 5,000kg.
[15]See Admati and Pfleiderer (1988), Foster and Viswanathan (1990, 1993), Wang (1994).
[16]See Gallant, Rossi and Tauchen (1992), Gannon (1994).

finds lagged volume is relevant for predicting absolute return.

$$\sigma_{it} = \beta_{0i} + \sum_{j} \sum_{s=1}^{S} (\beta_{1ijs}\sigma_{jt-s} + \beta_{2ijs}v_{jt-s}) + u_{1it}$$
$$v_{it} = \gamma_{0i} + \sum_{j} \sum_{s=1}^{S} (\gamma_{1ijs}\sigma_{jt-s} + \gamma_{2ijs}v_{jt-s}) + u_{2it} \qquad (3)$$

We estimate a six-equation VAR model in equation (3) to test for potential cross-market volume-volatility transmission effects among NR, AL and GA. The presence of a common industry exposure and time-varying technology exposure implies possible heteroskedasticity and contemporaneous covariance in the cross-equation residuals u_{1it}, u_{2it}. Accordingly, we estimate equation (3) using seemingly unrelated regression (SUR) procedure.[17] In the empirical section, we discuss a series of diagnostic tests to determine the appropriate lag specification to estimate the six-equation VAR. This is vital since VAR estimates are often case-sensitive to the specified lag structure.[18]

Robustness checks

In this section, we outline a series of robustness checks. First, the NR futures contract underwent two contract alterations in Jan 2005: i) the contract was moved from the traditional Itayose batch trading system[19] to the computerized continuous trading system on 4th Jan 2005; ii) the contract was downsized from 10,000kg to 5,000kg on 26th Jan 2005. Webb (1995) suggests that the Itayose system, which is a modified version of the Walrasian market adopted by Japanese commodity futures exchanges, generates prices that are less 'noisy' than their open outcry floor-traded US counterparts. We perform a sub-sample anal-

[17]The SUR or Zellner's method, estimates the parameters of the system, accounting for heteroskedasticity and contemporaneous correlation in the cross-equation residuals. The estimates of the cross-equation covariance matrix are based on the unweighted system's parameter estimates. We check that the full-sample results are generally consistent between SUR and full-information maximum likelihood estimation.

[18]However, we are mindful of not over-fitting the model. For every lag, there will be 6 lagged exogenous volume and volatility variables for each equation, or a total of 36 coefficients to estimate for the entire system. E.g. A VAR (2) will involve estimating 6*6*2=72 coefficients, excluding constant and other exogenous variables.

[19]Under this method, there are five trading rounds for the NR contract that occur at designated times during a trading day: two in the morning at 9:45 and 10:45, and three in the afternoon at 13:45, 14:45 and 15:30. The exchange staff will begin a trading round by announcing a provisional price to the floor. Floor members respond by submitting buy or sell orders. These orders are consolidated and analyzed by the exchange staff. The provisional price is subsequently adjusted according to the net buying pressure. The process is repeated until a price that matches all buy and sell orders is identified. As such, the NR market will only generate five market-clearing trade prices in a given trading day.

ysis pre and post end-of-Jan 2005 to test whether structural changes in the NR market affect cross-market information flow in related commodities.

Second, we examine if our VAR results are robust to an alternative volatility measure. As true volatility is unobservable, empirical results may be sensitive to the chosen volatility measure. The Parkinson (1980) and Garman and Klass (1980) critique of the squared return variance $\sigma_{it}^2 = r_{it}^2$ or absolute return volatility $\sigma_{it} = |r_{it}|$ rests on the intuition that both the opening price p_{it}^o and closing price p_{it} are snapshots of the return generating process. In contrast, the day t high price p_{it}^h and low price p_{it}^l require continuous monitoring during the course of trading to establish their values. This is an important consideration given the NR contract migrated to computerized trading in Jan 2005. We investigate if using a volatility measure based on more continuously observed prices p_{it}^h and p_{it}^l would affect the relevance of σ_{NRt} in cross-market dynamics, particularly in the post Jan 2005 sub-sample.

The Parkinson (1980) high-low volatility is $\sigma_{it}^{HL} = \sqrt{Ln(\frac{p_{it}^h}{p_{it}^l})^2/4Ln(2)}$. Garman and Klass (2007) extend both the σ_{it}^{HL} measure and their own volatility measure in Garman and Klass (1980) to derive an analytical scale-invariant[20] volatility estimator σ_{it}^{GK}, shown below, that incorporates all four daily prices $\{p_{it}^o, p_{it}^h, p_{it}^l, p_{it}\}$. They proceed to show that a composite volatility measure σ_{it}^* in equation (4), a weighted-average of the overnight price change and σ_{it}^{GK}, is eight times more efficient that the commonly used σ_{it} measure. The parameter f denotes the proportion of a day when the market is closed.[21] The σ_{it}^* measure encompasses a richer set of publicly accessible daily prices and should provide insight into commodity futures trading activity. We present VAR results based on both σ_{it} and σ_{it}^*.

$$\sigma_{it}^{GK} = \sqrt{\frac{1}{2}Ln(\frac{p_{it}^h}{p_{it}^l}^2) - (2Ln(2)-1)Ln(\frac{p_{it}}{p_{it}^o})^2}$$

$$\sigma_{it}^* = \sqrt{\frac{0.12}{f}Ln(\frac{p_{it}^o}{p_{it-1}})^2 + (\frac{0.88}{1-f})(\sigma_{it}^{GK})^2} \tag{4}$$

Third, we investigate if our VAR results are consistent with results based on other mea-

[20]This is an attractive property since the time interval between p_{it}^h and p_{it}^l varies randomly from one trading day to the next.

[21]If the difference between the market closing time yesterday (p_{it-1}) and opening time today (p_{it}^o) is 18 hours, then f=0.75.

sures of trading activity. In this paper, we apply both the Stoll and Whaley (1991) price reversals and Hasbrouck and Schwartz (1988) variance ratios. Both are commonly used measures of a market's price discovery. While VAR results could indicate the presence of cross-market trading dynamics in related commodities, it may not always provide a clear indication of the pecking-order of information flow across markets. If there is evidence that lagged volume/volaitlity in (say) gasoline is significant in the volume/volaitlity of related commodities, this should be consistent with results from analyzing price reversals and variance ratios.

$$r_{it}^{night} = Ln(\frac{p_{it}^{o}}{p_{it-1}^{c}});\ r_{it}^{day} = Ln(\frac{p_{it}^{c}}{p_{it}^{o}})$$

$$Rev_{it}^{night} = \begin{cases} 1, & \text{if } r_{it}^{night} > (\leq)0 \text{ and } r_{it-1}^{day} \leq (>)0 \\ 0, & \text{otherwise.} \end{cases}$$

$$Rev_{it}^{day} = \begin{cases} 1, & \text{if } r_{it}^{day} > (\leq)0 \text{ and } r_{it}^{night} \leq (>)0 \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

Kim and Rhee (1997) propose that price reversals indicate a market's ability to adjust from overreaction to new information. They interpret price continuation as a sign of delayed price reaction, which indicates poor price discovery ability. Outlined in equation (5), the night and day price reversals $Rev_{it}^{night}, Rev_{it}^{day}$ are indicator variables conditional on the signs of sequential previous day return r_{it-1}^{day}, overnight return r_{it}^{night} and following day return r_{it}^{day}. These are calculated from opening and closing prices p_{it}^{o}, p_{it}^{c}.

$$Rev_{it}^{night} = \sum_{s=1,2}\sum_{j}(\beta_{1sj}\sigma_{jt-s} + \beta_{2sj}v_{jt-s}) + u_{1it}$$

$$Rev_{it}^{day} = \sum_{s=1,2}\sum_{j}(\gamma_{1sj}\sigma_{jt-s} + \gamma_{2sj}v_{jt-s}) + u_{2it} \tag{6}$$

In addition to a direct comparison of the proportion of continuations and reversals for each market, we perform a probit estimation in equation (6) to test if the night and day price reversals exhibited by a commodity market i are influenced by the lag-1 volatility-volume variables across all three commodity markets. We analyze for both the entire sample period and between sub-samples to separately consider the NR contract downsizing.

Hasbrouck and Schwartz (1988) propose that the variance ratio VR_{it} reflects the signal-to-noise mix embedded in a market's trading activity, and is inversely related to the level of noise trading. As the name suggests, the T-period variance ratio VR_{it}^T in equation (7) is the ratio of a long-term variance $Var(r_{it}^T)$ divided by a short-term variance $Var(r_{it})$ standardized for the time horizon. Noise trading induces a persistent bias in the temporary component of volatility. This is more easily captured by the shorter horizon volatility measure, which causes a downward bias in a VR_{it} value below 1. The more severe the level of noise trading is in a market, the smaller will be its variance ratio.

$$VR_{it}^T = \frac{Var(r_{it}^T)}{T \times Var(r_{it})}$$

$$VR_{it}^T = \sum_j (\gamma_{ij} v_{jt-1}) + u_{it} \tag{7}$$

Our preliminary analysis indicate significant dynamics at the 2^{nd}, 5^{th} and 10^{th} lags. As such, we consider both VR_{it}^5 and VR_{it}^{10}. Specifically, we investigate if VR_{it} is influenced by lagged trading volume of all three commodity markets. We estimate VR_{it}^T as a 3-equation system using generalized method of moments (GMM). With the VAR, we apply SUR estimation to allow for contemporaneous correlation in the residuals of related commodities induced by a common industry exposure. Given that VR_{it}^T is an interval measure[22] and it proxy the level of noise-trading, a more general system-estimation method that is robust to unknown autocorrelation and/or heteroskedasticity in the residuals is more suitable. As with price reversals, we perform both full and sub-sample estimations.

Full BEKK-GARCH estimation

We estimate a tri-variate full BEKK-GARCH (1,1) to analyze the underlying conditional covariance structures of related commodity futures markets. The model is presented in equation (8). Engle and Kroner (1995) propose the BEKK-GARCH model as an empirically convenient representation to estimate a system of equations. They show that by construction, the BEKK-GARCH guarantees a positive definite conditional variance-covariance matrix H_t under very weak conditions. This is essential when utilizing an optimization algorithm like

[22] The explanatory variable covers across 5 time-series observations, which is estimated against daily volume variables.

maximum likelihood estimation (MLE).

The estimation involves extracting a set of i zero-mean residuals ε_{it} from the return equations r_{it}. Denote Ω_{t-1} as the information set embedded in past values of ε_{it}, such that $\varepsilon_{it}|\Omega_{t-1} \sim N(0, H_t)$, where H_t is the 3x3 conditional variance-covariance matrix. Since the estimation involves expressing each element of H_t in terms of lagged values of squared or cross-products of ε_t and lagged values of H_t elements, the estimation of H_t is conditional on Ω_{t-1}. C_0 is a 3x3 upper triangular matrix of constants; coefficient matrices A and G correspond to the residual variance-covariance matrix of ARCH terms ϵ_t, and lag-1 conditional variance-covariance matrix of GARCH terms H_{t-1}. To note, both H_t and ϵ_t are symmetric.

$$r_{it} = \phi_{i0} + \sum_{s=1}^{S}(\phi_{is} r_{it-s}) + \theta_i MON_t + \varepsilon_{it}, \text{ where i=N,A,G}; \varepsilon_{it}|\Omega_{t-1} \sim N(0, H_t)$$

$$H_t = \begin{pmatrix} h_{NNt} & h_{NAt} & h_{NGt} \\ h_{ANt} & h_{AAt} & h_{AGt} \\ h_{GNt} & h_{GAt} & h_{GGt} \end{pmatrix}; \ \epsilon_t = \begin{pmatrix} \varepsilon_{Nt}^2 & \varepsilon_{Nt}\varepsilon_{At} & \varepsilon_{Nt}\varepsilon_{Gt} \\ \varepsilon_{At}\varepsilon_{Nt} & \varepsilon_{At}^2 & \varepsilon_{At}\varepsilon_{Gt} \\ \varepsilon_{Gt}\varepsilon_{Nt} & \varepsilon_{Gt}\varepsilon_{At} & \varepsilon_{Gt}^2 \end{pmatrix}$$

$$C_0 = \begin{pmatrix} c_{11} & c_{12} & c_{13} \\ 0 & c_{22} & c_{23} \\ 0 & 0 & c_{33} \end{pmatrix}; \ A = \begin{pmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{pmatrix}; \ G = \begin{pmatrix} g_{11} & g_{12} & g_{13} \\ g_{21} & g_{22} & g_{23} \\ g_{31} & g_{32} & g_{33} \end{pmatrix}$$

$$H_t = C_0' C_0 + A' \epsilon_{t-1} A + G' H_{t-1} G \tag{8}$$

It can be easily shown that matrix multiplication on H_t in equation (8) yields six equations: h_{NNt}, h_{AAt}, h_{GGt}, h_{NAt}, h_{NGt}, h_{AGt}. But unlike restricted versions e.g. diagonal BEKK-GARCH, the full BEKK-GARCH provides a richer interaction amongst lagged squared and cross-product of residuals $\{\varepsilon_{Nt}, \varepsilon_{At}, \varepsilon_{Gt}\}$ i.e. ARCH terms and elements of H_{t-1} i.e. GARCH terms in each of the six conditional variance and conditional covariance equations. The estimation of equation (8), which allows covariance terms to enter the conditional variance equations, is paramount to our current analysis of cross-market dynamics in possibly related NR, AL and GA markets. Involving all three markets in the same estimation framework promotes consistency when comparing with VAR estimation results. This is despite the computational challenges involved in estimating a tri-variate full BEKK-GARCH.

Industry exposure or commodity market factor

In recent years, soaring prices and increasing volatility have seen the rise of commodity as a stand-alone asset class in the investment community. In our final analysis, we address the possibility that any cross-market trading dynamics among NR, AL and GA is simply due to some overall commodity market factor. We perform two sets of tests to acquire more insight into the latent exposure that is responsible for cross-market interactions (if any) among NR, AL and GA. The first set involves TOCOM's silver (SL) futures market. The second involves the TOCOM index M[23] and TOPIX Transportation Equipment (TE) Index I[24] to proxy for exposures to the commodity market portfolio and automobile industry respectively.

First, we undertake VAR and BEKK-GARCH estimations for pairwise comparisons between each of NR, AL and GA against SL. We assume that silver has a trivial (if any) exposure to the automobile industry. If a non-trivial commodity market factor exists, then we should find cross-market interactions among all commodities. But if volume-volatility interactions are driven by a common industry exposure, then there should be limited evidence of cross-market interaction from the various pairwise estimations.

In addition, we conduct two rounds of principle components analysis (PCA) to detect the presence (if any) of a dominant first component that is driving return variability across the three commodities. The first round involves PCA on $\{r_{Nt}, r_{At}, r_{Gt}\}$ to acquire some insight on the first principle component and the relevance of each commodity to various components. In the second round, we include r_{St} in the PCA. The three-market PCA will draw out the presence (if any) of a dominant first component that explains variability across $\{r_{Nt}, r_{At}, r_{Gt}\}$. While the three-market PCA confirms the presence of a latent common exposure, the four-market PCA will provide insight into the nature of that exposure. If the first principal component from the three-market PCA corresponds to an industry exposure, then the inclusion of SL will cause the variance explained by the first principal component to drop. The value corresponding to silver in the first eigenvector should also be trivial. The variance explained by the second principle component will increase, and silver's weight in

[23]The TOCOM Index is a value-weighted index based on the prices of all the underlying commodities that TOCOM derivative contracts are written on. This includes platinum, gold, silver, palladium, aluminum, gasoline, kerosene, crude oil, gas oil, and rubber. As it covers every market division (precious metals, non-ferrous metal, fuel and soft), the TOCOM Index provides an overall representation of TOCOM as a whole.

[24]In brief, the TOPIX index series divides constituent stocks listed on the Tokyo Stock Exchange into 33 categories according to industrial sectors as defined by the Securities Identification Code Committee (SICC). The SICC is Japan's national securities coding system.

the second eigenvector will be significantly larger than those of NA, AL or GA.

Second, we perform a quasi vector-moving-average (VMA) estimation[25] on the residuals of NR, AL and GA after adjustments for a common exposure. We separately consider r_{it} and σ_{it}. The latter is used to elaborate. Corresponding to the VAR estimation, the idea here is to substitute the lagged variables of commodity $j \neq i$ in σ_{it} (e.g. σ_{At-1} and σ_{Gt-1} in the σ_{Nt} equation) with σ_{It-1}, under the assumption that an industry exposure drives cross-market interactions. As there ceases to be any link between the $\sigma_{Nt}, \sigma_{At}, \sigma_{Gt}$ equations, they are estimated as single equations. In equation (9), the industry-adjusted residual volatility $\{v_{INt}, v_{IAt}, v_{IGt}\}$ extracted from the first round single equation regressions are used in a second round quasi-VMA estimation. The process is repeated to estimate a quasi-VMA of $\{v_{MNt}, v_{MAt}, v_{MGt}\}$ after adjustments for a commodity market factor σ_{Mt}.

$$\begin{aligned}
\sigma_{it} &= \alpha_0 + \sum_{k=1}^{K}(\alpha_k \sigma_{it-k} + \beta_{kI}\sigma_{It-k}) + v_{Iit} \ \forall i = N, A, G \\
\sigma_{Nt} &= v_{INt} + \sum_{s=1}^{S}(\phi_{1s} v_{INt-s} + \gamma_{1s} v_{IAt-s} + \delta_{1s} v_{IGt-s}) \\
\sigma_{At} &= v_{IAt} + \sum_{s=1}^{S}(\phi_{2s} v_{INt-s} + \gamma_{2s} v_{IAt-s} + \delta_{2s} v_{IGt-s}) \\
\sigma_{Gt} &= v_{IGt} + \sum_{s=1}^{S}(\phi_{3s} v_{INt-s} + \gamma_{3s} v_{IAt-s} + \delta_{3s} v_{IGt-s})
\end{aligned} \tag{9}$$

If cross-market interactions among NA, AL and GA are mainly driven by a common industry exposure rather than a commodity market factor, this will be revealed from the two sets of VMA estimation. When we estimate $\{v_{INt}, v_{IAt}, v_{IGt}\}$ as a system using σ_{It} to filter cross-market interactions, we should not find evident cross-market dynamics among $\{v_{INt}, v_{IAt}, v_{IGt}\}$. Following on, since the commodity market factor is trivial, σ_{Mt} is a less adequate filter of cross-market interactions. As a common exposure remains in $\{v_{MNt}, v_{MAt}, v_{MGt}\}$, this is manifested in relatively more evident cross-market interaction from the corresponding VMA estimation. Conversely, if cross-market interactions among NA, AL and GA are driven mainly by a commodity market factor, we would find less significant interactions among $\{v_{MNt}, v_{MAt}, v_{MGt}\}$, and comparatively more evident interactions among $\{v_{INt}, v_{IAt}, v_{IGt}\}$.

[25]This is not a standard vector moving average (VMA) estimation since the residuals are not extracted from a corresponding VAR estimation.

3 Background, data and results

3.1 Institutional details, data and sampling

Our daily data is downloaded directly from the TOCOM website. It contains opening, high, low and closing prices, as well as volume and open interest for all contract cycles. The main contractual specifications are provided in Table 1. Introduced in Jul 1999, GA is the newest among the three commodity contracts. As such, our sample period between 4^{th} Jan 2000 and 31^{st} Jul 2007 is chosen to allow half a year for market participants to adapt to the GA contract, with Jul 2007 correspond to the latest data that is available.

INSERT TABLE 1

The three commodity contracts are traded on a computerized platform from 4th Jan 2005. The morning session runs from 9:00 to 11:00 and the afternoon session runs from 12:30 to 15:30. The opening trade for each session is determined by the Ita-Awase method, where orders across different prices on both sides of the market are accumulated, and the opening price is set in such a way as to maximize the total number of contracts that can be traded. The Zaraba method, or continuous double-auction system, applies for the rest of the session. The daily closing price we employ is the closing price from the afternoon session.

Trading activity in most futures markets, including US commodities, tend to cluster on the front (nearest-to-maturity) contract. In stark contrast, trading activity in Japanese commodity futures is concentrated on the most deferred contract. Webb (1995) suggests that this is due to Japanese speculators allowing more time for their longer maturity futures positions to become profitable. When constructing each commodity's time series sample from various contract cycles, we use daily open interest as a guide to acquire a sense of the switch dates when market participants migrate from one contract to the next.[26] Specifically, we identify the day(s) when open interest in contract cycle t starts to decline and open interest in contract cycle $t+1$ starts to increase. We find that traders on TOCOM switch at the end of the month, when the next contract cycle becomes available.[27] The end-of-month switching phenomenon on TOCOM is consistent across NR, AL and GA contracts.

[26] The appropriate switch date is an empirical question and is often contract-specific.

[27] For example, trading interest during Feb 2001 centers on the Jul 2001 contract. Towards the end of

In Nov 2003, the AL contract cycle was extended to follow an even-month cycle up to 6 cycles ahead. In the months that follow, new AL contracts were conceived every month, and traders continued to switch to the most deferred contract. Accordingly, the maturity of the contract that attracts the most trading interest gradually extended out to a year.[28] From Apr 2004, contracts were rolled out every 2 months e.g. the most deferred contract during Apr-May 2004 is the Feb 05 contract; the most deferred contract during Jun-Jul 2004 is the Apr 2005 contract etc. This was taken into account in forming the AL sample.[29]

3.2 Preliminary results and diagnostic tests

In this section, we perform diagnostic tests to obtain preliminary results on some basic time-series properties of key variables.

Descriptive statistics and stationary tests

Table 2 contains basic descriptive statistics in Panel A, correlation matrix of the variables in Panel B, stationary test statistics in Panel C, and in Panel D, results relating to the variables' autocorrelation features.

INSERT TABLE 2

In Panel A, r_{Nt}, r_{At} and r_{Gt} all display slight negative skewness but with kurtosis close to 3 i.e. normally distributed. This is not surprising given the return series are based on daily data over seven years. To note, both skewness and kurtosis for σ^*_{it} are more extreme than those of σ_{it}. This is expected given σ^*_{it} is constructed from more extreme prices.

In Panel B, there is some correlation between r_{Nt} and r_{At} of 0.187, between r_{Nt} and r_{Gt} of 0.154 and also between r_{At} and r_{Gt} of 0.182. Existing correlations between own-market volatility and volume variables is also not surprising. However, the volatility-volume corre-

Feb 2001, open interest in the Jul 2001 contract starts to decline, but this is accompanied by the Aug 2001 contract open interest starting its climb.

[28]E.g. In Dec 2003, the Jun 2004 contract, which has a 7-month maturity, became available and attracted the most trading interest; In Jan 2004, the Aug 2004 contract, which has an 8-month maturity, drew open interest from the Jun 2004 contract; In Feb 2004, the Oct 2004 contract, which has a 9-month maturity, drew open interest from the Aug 2004 contract etc.

[29]While the AL switching pattern is consistent, we did perform some sensitivity analysis based on pre and post extension samples, but did not find any difference in results.

lation for all three commodities is comparatively stronger between σ^*_{it} and v_{it}. For example, the correlation between σ_{Nt} and v_{Nt} is 0.214, while the correlation σ^*_{Nt} and v_{Nt} increases to 0.611. This, together with the basic statistical properties of the two volatility measures in Panel A, justifies performing subsequent empirical analysis based on both volatility measures and focus on results that are consistent across both measures. In terms of cross-market correlations, a strong relation is displayed between the volatility of NR and AL. NR trading volume is also correlated with AL volatility. The correlation matrix indicates that GA does not appear to co-vary with either NR or AL. We shall note if this preliminary observation is consistent with subsequent VAR results.

In Panel C, as daily returns display near-zero mean and limited time-trend over a seven year horizon, we apply ADF Test 1[30] on r_{it}. Conversely, we apply ADF Test 3 on v_{it}. Panel A reveals that the mean of the volume series is non-zero. We also expect trading volume to display a time trend as the markets establish themselves and gather liquidity over time. Lastly, we apply ADF Test 2 on both σ_{it} and σ^*_{it}. While there is no reason for volatility to increase over time, the mean volatility should be greater than zero, especially for daily futures prices. The test statistics in Panel C indicate that r_{it}, σ_{it}, σ^*_{it} and v_{it} are all stationary.

In Panel D, we examine the variables' autocorrelation features. r_{Nt}, r_{At} and r_{Gt} are all serially uncorrelated. For the volatility variables, there is significance up to the 3^{rd} lag, then there is significance between the 5^{th} to 7^{th} lag for some volatility variables. Lastly, significance is also exhibited at the 10^{th} lag. For the volume variables, the partial autocorrelation function (PACF) of v_{Nt} and v_{Gt} are significant up to the 3^{rd} lag. However, the 10^{th} lag is significant. For v_{At}, autocorrelation extends up to the 5^{th} lag. Autocorrelation in all volume and volatility variables are insignificant beyond the 10^{th} lag. The results in Panel D provide some insight for determining the appropriate lag specification for VAR estimation.

Granger causality tests

Granger causality test results are reported in Table 3. The F-test statistic and p-value in a given cell correspond to whether the row variable Granger-causes the column variable.[31]

[30] ADF Test 1 regress the returns series with neither intercept nor time trend; Test 2 includes an intercept only; Test 3 includes both intercept and time trend.

[31] For example, in the last row, second-last column, the cell that contains a F-statistic of 2.03326 and a p-value of 0.042 corresponds to the test of whether v_{Gt} Granger-causes v_{At}.

INSERT TABLE 3

The volume-volatility causality relations offer some interesting observations. Table 3 shows that own-market volatility Granger-causes trading volume. This is consistent across all three commodities for both σ_{it} and σ^*_{it}. Conversely, for the case of AL and GA, own-market trading volume does not Granger-cause both volatility measures. NR and GA volatility Granger-cause AL volatility, but not AL volume. v_{Gt} Granger-causes both σ_{Nt} and v_{Nt}. The latter in turn Granger-causes both v_{At} and v_{Gt}. Lastly, v_{At} Granger-causes σ_{Gt} and v_{Nt}. Later on, we shall compare the results in Table 3 with with VAR estimation results.

Determining optimal lag specification

As VAR estimation constitutes our main results, the appropriate lag specification is a pertinent consideration. To address this issue, we utilize standard techniques in model selection for each of σ_{it} and σ^*_{it} to determine the appropriate lag specification. With futures daily data, we conjecture that it is unlikely for volatility-volume dynamics to extend beyond two weeks i.e. 10 lags. Indeed, in Panel D of Table 2, the PACF results reveal that autocorrelation coefficients for all volatility and volume variables beyond the 10^{th} lag are insignificant.[32]

INSERT TABLE 4

In this paper, we apply a three-step 'top-down' approach. First, we examine an array of information criteria[33] in Table 4a to 'short-list' lag specifications for further testing. Conflicts exist between the various criteria. Across both panels, there is support for lag-2 by SIC and HQC, and for lag-10 by the sequential LR-test. There is support for lag-5 from both FPR and AIC in Panel A, although both criteria switch to lag-7 in Panel B.

Second, we sequentially back-test a VAR(12)[34] at each lag based on Chi-square and Wald-test statistics for individual variable and joint variables significance respectively. Reported in Table 4b, we focus on lags that are highlighted in Table 4a. For both panels, most variables

[32]As such, we specify a maximum lag length of 12 in our diagnostic tests, which involves sequentially trimming back the lag specification.

[33]These include log-likelihood, sequential likelihood ratio (LR) statistics, Akaike information criterion (AIC), Schwarz information criterion (SIC), final prediction error (FPE) and Hannan-Quinn criterion (HQC).

[34]Under the assumption that any own- or cross-market dynamics in daily data do not extend beyond two weeks i.e. 10 lags.

are individually and jointly significant at lags 2 and 10. In Panel B, most lag-7 variables are individually and jointly significant. Conversely, in Panel A, while lag-5 individual variables are insignificant, they are jointly significant. Most of the lags in between the short-listed lags are jointly insignificant e.g. lags 4, 6, 7, 8, 9, in Panel A; lags 4, 5, 6, 8, 9 in Panel B. It appears that after lag 2, the relevance of subsequent lags declined, until spikes at lags 5/7, then decline, only to spike again at lag 10. Further lags beyond lag-10 are all insignificant.

There is consistency between Tables 4a and 4b in suggesting that a formal likelihood ratio (LR) test[35] be conducted based on the following restrictions. For σ_{it}, we test between VAR(2)-VAR(5), and if necessary, between VAR(5)-VAR(10). For σ^*_{it}, between VAR(2)-VAR(7), and if necessary, between VAR(7)-VAR(10). For σ_{it}, the LR-test fails to reject VAR(2), but rejects VAR(10) in favor of VAR(5). In stark contrast, for the σ^*_{it} measure, the LR-test rejects VAR(2) in favor of VAR(7), which is in term rejected in favor of VAR(10). Given daily futures data, the prevalence of the 10^{th} lag could be due to day-of-the-week trading regularities e.g. Monday and/or Friday effect. To address this possibility, we repeat all our tests with Monday and Friday dummies. The support for a lag(10) specification persists.

Given the mixed outcome, we apply VAR estimation on all short-listed lags. Specifically, we estimate both VAR(2) and VAR(2-10) based on σ_{it} and σ^*_{it}. To note, VAR(2-10) denotes a VAR(2) that includes only lag-10 variables[36]. In addition, we fit a VAR(2-5) using σ_{it} and a VAR(2-7) using σ^*_{it}. Interim lags are not included for three reasons: i) Table 4b indicates that most interim lags between 2, 5 or 7, and 10 are insignificant; ii) including all lags for all VAR specifications lead to a voluminous set of results that is awkward to present and discuss and iii) we are concern with model over-fitting, especially with a six equation VAR(10). Our focus will only be on results that are robust across these six VAR specifications.

3.3 VAR estimation results

[35]Following Hamilton (1994), the LR test statistic is calculated by estimating both the m-lag (null hypothesis) restricted q-equation VAR and (m+l)-lag unrestricted VAR. For the restricted VAR, obtain a Txq variance covariance matric R. Construct a q x q matrix $\Sigma = R'R$. Denote $SLag_m = |\frac{\Sigma}{T}|$. The process is repeated for the unrestricted VAR to obtain $SLag_{m+l}$. Compute the LR test statistic $= Tlog(\frac{SLag_m}{SLag_{m+l}})$, which is χ^2 distributed with q^2l degree of freedom.

[36]This is simply because a six-equation VAR (10) will generate 360 estimated coefficients!

We report VAR(2) estimates in Table 5, VAR(2-10) estimates in Table 6, VAR(2-5) and VAR(2-7) estimates in Table 7. To reiterate, results based on σ_{it} are presented in Panel A and those based on σ^*_{it} are presented in Panel B. Due to the voluminous results, our discussion shall proceed as follow. First, we comment on results within each table, starting with own-market dynamics, and proceeding to cross-market dynamics, if any. Next, we highlight results that are robust across both panels of a given table. Finally, we highlight results that are consistent across both VAR specifications and volatility measures.

INSERT TABLE 5

In Table 5, $\sigma_{Nt-1}, \sigma_{At-1}, \sigma_{Gt-1}$ are significant in both their own-market volume and volatility equations. Both v_{At-1} and v_{Gt-1} are significant only in their corresponding volume equation. v_{Nt-1} is significant in both σ_{Nt} and v_{Nt} equations. $\sigma_{Nt-2}, \sigma_{At-2}, \sigma_{Gt-2}$ are significant in their corresponding volatility equations, while $v_{Nt-2}, v_{At-2}, v_{Gt-2}$ are also significant in their corresponding volume equations. All the results discussed thus far are robust across both panels. σ_{Nt-2} is significant in the v_{Nt} equation, but only in Panel A. Similarly, σ_{Gt-2} is significant in the v_{Gt} equation, but only in Panel B. Both v_{Nt-2} and v_{Gt-2} are significant in their corresponding σ_{Nt} and σ_{Gt} equations, but only in Panel A. σ_{At-2} and v_{At-2} are significant in both σ_{At} and v_{At} across both panels.

Next we discuss cross-market effects. For the NR market, σ_{Nt} is influenced by v_{Gt-1}, while v_{Nt} is affected by both v_{Gt-1}, v_{Gt-2} and v_{At-2}. These are robust across panels. Both σ_{Nt} and v_{Nt} are also influenced by σ_{At-2}, but only in Panel A. For the AL market, σ_{At} is affected by σ_{Nt-1} and σ_{Gt-1} for both panels. v_{At} is affected by σ_{Gt-1} for Panel B. The AL market also appears to be influenced by v_{Nt-2}, although this is evident only in Panel A. Lastly, the only cross-market variable that influence GA trading volume is σ_{Nt-2}. Both σ_{Gt}, v_{Gt} are affected by σ_{At-2} in Panel B. σ_{Gt} is affected by v_{At-2} in Panel A. Thus far, the results do indicate the presence of cross-market dynamics. Specifically, trading dynamics in the NR market seem to be influence by lagged AL and GA volume effects. Conversely, the AL market is affected by lagged NR and GA volatility effects. While the GA market volatility and volume processes also exhibit evident own-market dynamics, it appears immune to cross-market dynamics with v_{Nt-2} the only variable that is significant in the GA volume equation in both panels.

INSERT TABLE 6

In Table 6, we present VAR(2-10) estimation results. Both own- and cross-market results are largely consistent with those from VAR(2). E.g. across both panels, $\sigma_{Nt-1}, \sigma_{At-1}, \sigma_{Gt-1}$ remain significant in both their own-market volume and volatility equations in both panels. Both v_{At-1} and v_{Gt-1} are still significant only in their corresponding volume equation. v_{Nt-1} is significant in both σ_{Nt} and v_{Nt} equations. For the lag-10 variables, it is interesting to note that across both panels, $\sigma_{Nt-10}, \sigma_{At-10}, \sigma_{Gt-10}$ are significant in their corresponding own-volatility equations, but not in their own-volume equations. Similarly, $v_{Nt-10}, v_{At-10}, v_{Gt-10}$ are significant in their corresponding own-volume equations, but not in their own-volatility equations. Cross-market dynamics is exerted primarily by the GA market. Across both panels, v_{Gt-10} is significant in the v_{Nt} and v_{At} equations. σ_{Gt-10} is significant in both the NR and AL volatility equations. Both σ^*_{Nt-10} and v_{Nt-10} exert some influence on the σ^*_{Gt} equation.

INSERT TABLE 7

In Table 7, we present VAR(2-5) and VAR(2-7) results in panels A and B respectively. As with VAR(2-10), the own- and cross-market results for lag-1 and lag-2 variables are generally consistent with those from VAR(2). Results for the lag-5 and lag-7 estimates are also consistent with those from the lag-10 variables in VAR(2-10). In Panel A, $\sigma_{Nt-5}, \sigma_{At-5}, \sigma_{Gt-5}$ are significant in their corresponding own-volatility equations, but not in their own-volume equations. $v_{Nt-5}, v_{At-5}, v_{Gt-5}$ are significant in their corresponding own-volume equations, but not in their own-volatility equations. Lag-7 volatility and volume variables in Panel B exhibit the same patterns. Similar to Table 6, v_{Gt-5} and v_{Gt-7} are significant in both v_{Nt} and v_{At} equations in the corresponding panels. The NR market is also found to exert cross-market influence on AL, with v_{Nt-5} and v_{Nt-7} significant in the corresponding σ_{At} equations.

INSERT TABLE 8

Lastly, we examine the robustness of VAR results across lag specifications and volatility measures. Such a comparison is awkward given the sheer amount of results involved. Since our interest is on the role that lagged exogenous variables play in each of the six volatility-volume processes of the three commodities, we propose a simplified approach in Table 8, which we refer to as a VAR significance score-board. The values represent the number of times that a given lagged exogenous variable is significant in a given equation from a given VAR estimation. We isolate on lag-1 and lag-2 variables since they are present across all six sets of VAR estimations. Accordingly, the maximum (minimum) score that a variable could achieve is 6 (0).[37] We regard a score of 5 or 6 as indication that a variable is robustly significant. Similarly, a score of 0 or 1 would suggest that a variable is robustly insignificant.

As before, we shall discuss own-market trading dynamics, and then proceed to examine cross-market dynamics. Table 8 shows that lag-1 volatility is significant in both own-market volatility and volume equations. A maximum score of 6 is achieved across all three commodities. Conversely, lag-1 volume is robustly significant only in own-volume equations. Interestingly, v_{At-1} and v_{Gt-1} are irrelevant in their own-market volatility equations, where both scored zero. Lag-2 volatility variables are robustly significant in their own-volatility equations, all achieving maximum scores. However, their significance is no longer robust in the volume equations. σ_{Nt-2}, σ_{At-2} and σ_{Gt-2} achieve corresponding scores of 3, 3, and 2 in the v_{Nt}, v_{At} and v_{Gt} equations. Lag-2 volume variables all scored 6 in their own-volume equations. Their relevance in the own-market volatility equations is not robust, with v_{Nt-2} and v_{Gt-2} obtaining scores of 3 and 4. v_{At-2} is the only exception, playing an important role in its own-market volatility process with a score of 6.

For cross-market dynamics, σ_{Nt-1} and σ_{Gt-1} exert a robust and significant influence on the σ_{At} process, with both scoring 6. GA trading volume has a significant and robust impact on NR, with v_{Gt-1} scoring 6 in both σ_{Nt} and v_{Nt} equations. Conversely, both σ_{Gt} and v_{Gt} processes appear to be immune to lag-1 cross-market dynamics from NR and AL, with all their lag-1 variables scoring either 0 or 1. For lag-2 variables, the only evidence of cross-market volatility is exhibited by σ_{At-2} on both NR and GA volatility-volume equations. However, the results are not totally robust, with σ_{At-2} scoring 4 on the NR market and 2 on the GA market. Lag-2 volume variables provide more evidence of cross-market dynamics. Again AL plays a prominent role, with v_{At-2} scoring 6 in NR trading volume and 5 in GA volatility. There is also evidence of NR trading volume affecting cross-market dynamics,

[37] For example, σ_{Nt-1} scored 6 in both the σ_{Nt} and v_{Nt} equations. This means that lag-1 volatility for NR is prevalent in its own-market volatility and volume equations across all three VAR specifications for both volatility measures.

with v_{Nt-2} scoring 6 in the v_{Gt} equation. Although the results are not robust, v_{Nt-2} seems to influence the AL market, with scores of 4 and 2 in the σ_{At} and v_{At} equations respectively.

In sum, VAR estimates reveal some interesting aspects of cross-market trading dynamics in the three related commodity markets. The most surprising result is that v_{At-1} and v_{Gt-1} have completely no impact on σ_{At} and σ_{Gt} whatsoever.[38] Instead, v_{At-2} influences v_{Nt} and σ_{Gt}, and both in turn flow through to the σ_{At} equation. Note also that cross-market dynamics experienced in NR and AL markets occur at lag-1, where GA plays an active role. In contrast, cross-market dynamics experienced by the GA market occur at lag-2, and are predominately exerted by NR and AL volume variables. Taken together, the results that are robust do suggest the GA market is more responsive to news than NR and AL, influencing both NR and AL at lag-1, but is itself immune to NR and AL lag-1 variables. The AL market has no influence on NR and GA markets at lag-1, but subsequently provides feedback effect in volume at lag-2, affecting both NR volume and GA volatility. NR is somewhat 'in-between'; it exerts some influence, but only on AL at lag-1 and only on GA at lag-2.

3.4 Results from robustness checks

Sub-sample analysis

We re-estimate the VAR specifications in Tables 5, 6 and 7 based on sub-samples to consider if results are affected by the NR contract's downsizing and migration to TOCOM's computerized trading platform, both occurring in Jan 05.[39] While estimation results between the two sub-samples for some VAR specifications differ from those based on the full sample, their corresponding VAR score-boards are similar to Table 8. Specifically, NR lag-1 volatility remain influential in the AL volatility equation; v_{Gt-1} plays an important role in both σ_{Nt} and v_{Nt} equations in both sub-samples; AL lag-2 trading volume still affects NR trading volume. An overall result that is quite evident is the relatively stronger presence of cross-market volume effects in the post Jan 05 sub-sample. An obvious reason for this would be the fact that since Jan 05, all three commodities are effectively traded under the same computerized

[38]This is in sharp contrast to the series of bivariate VAR estimations of own-market volume and volatility dynamics. In those results, which are available upon request, both lag-1 volume and volatility variables are significant in both equations for each market for both volatility measures.

[39]Due to space constraint, they are not included in the paper, but are be available upon request.

platform, which allows common information flow in related commodities to manifest more easily into cross-market volatility-volume effects.

Price reversals results

First, we comment from direct observations of overnight and day price reversals. For the entire sample, the NR market exhibits 47.1% overnight reversals and 48.1% day reversals; the AL contract exhibits 50.6% overnight reversals and 52.8% day reversals; the GA contract exhibits 48.6% overnight reversals and 54.1% day reversals. We examine the sub-sample proportions for NA before and after the structural changes in Jan 05, as well as for the AL contract before and after its contract cycle was doubled to 2 months in Nov 03. In both cases, the sub-sample proportions are very similar to those of the entire sample.

INSERT TABLE 9

Results from probit estimation on price reversals are presented in Table 9. We make a general observation that across both panels, there are more significant cross-market variables than there are own-market variables. Specifically, in Panel A, there are four significant own-market variables ($\sigma_{Gt-1}, v_{Nt-1}, \sigma_{Nt-2}, v_{Nt-2}$) and six significant cross-market variables: σ_{Nt-1} in Rev_{At}^{night}; σ_{At-1} in Rev_{Gt}^{day}; σ_{Gt-1} in Rev_{Nt}^{day}; v_{Gt-1} in Rev_{Nt}^{night}; both σ_{Gt-2}, v_{Nt-2} in Rev_{At}^{day}. Similarly in Panel B, only three own-market variables are significant: $\sigma^*_{Nt-1}, v_{Nt-1}, v_{Nt-2}$. In contrast, seven cross-market variables are significant: both $\sigma^*_{Nt-1}, v_{Nt-1}$ in Rev_{At}^{night}; v_{Gt-1} in Rev_{Nt}^{night}; σ^*_{Nt-1} in both $Rev_{At}^{night}, Rev_{At}^{day}$ and v_{Nt-2} in Rev_{At}^{day}.

Next we focus on the cross-market variables which are significant in both panels and contrast with their corresponding VAR scores in Table 8. First, lag-1 volatility for NR and GA are both significant in affecting price reversals in the AL market. This is consistent with σ_{Nt-1} and σ_{Gt-1} both scoring 6 in the σ_{At} equation. Second, lag-1 trading volume for GA is significant in NR overnight price reversal. This is again supported in Table 8 with v_{Gt-1} scoring 6 in the σ_{Nt} equation. Lastly, lag-2 NR trading volume affects the AL contract day price reversal. In Table 8, v_{Nt-2} scored 4 in the σ_{At} equation.

Variance ratios results

Results from the analysis of weekly and fortnightly variance ratios are presented in Table

10. We consider both lag-2 and lag-5 specifications for the GMM estimation of VR_{it}^5 in Panel A. In Panel B, we fit both lag-2 and lag-10 specifications for VR_{it}^{10}. The lag-5 and lag-10 dynamics are consistent with a weekly and fortnightly variance ratio. In addition, lag-2, lag-5 and lag-10 specifications are supported from earlier diagnostic tests on the extent of dynamics in the volume-volatility variables of the three commodities.

INSERT TABLE 10

First, we discuss results from a lag-2 specification across both panels. v_{Gt-1} is significant in both VR_{Nt}^5 and VR_{Nt}^{10}. This is consistent with v_{Gt} displaying a VAR score of 6 in the σ_{Nt} equation in Table 8. Second, v_{At-2} is significant in both VR_{Nt}^5 and VR_{Nt}^{10}. Although v_{At-2} scored zero in the σ_{Nt} equation, it has a score of 6 in the v_{Nt} equation. We postulate that the influence of v_{At-2} on the NR variance ratios is being transmitted through volume effects on volatility. Next we discuss results from lag-5 and lag-10 specifications. v_{At-5} and v_{At-10} are significant in the corresponding VR_{Nt}^5 and VR_{Nt}^{10} equations. This is supported by results in Tables 6 and 7, which indicate that longer dynamics in AL volume do seem to exert some influence on the NR volatility process. v_{Nt-5} being significant in the VR_{Nt}^5 equation, which is consistent with the significance of v_{Nt-5} in both the σ_{At} and σ_{At}^* equations in Table 7. Lastly, v_{Gt-10} is significant in the VR_{At}^{10} equation, which is consistent with the significance of v_{Gt-10} in the σ_{At} equation in Table 6.[40]

Full BEKK-GARCH results

From our diagnostic results in Table 1, all three commodity daily returns do not display any significant autocorrelation, but they do exhibit a Monday effect. As such, the GARCH return equations are specified to include only a constant with coefficient ϕ_{i0} and Monday dummy variable with coefficient θ_i. [41] While there is strong evidence of longer dynamics up to lag-10 in the data, we are unable to consider beyond lag-1 in a tri-variate full BEKK-GARCH estimation due to convergence problems.

INSERT TABLE 11

[40]Again, we examine the sub-sample proportions for NA before and after the structural changes in Jan 05, as well as for the AL contract before and after its contract cycle was doubled to 2 months in Nov 03. In both cases, the significance of the cross-market variables is consistent with the full sample results.

[41]We have also tested for a Friday dummy variable, but it is not significant.

The estimation results are presented in Table 11.[42]. To note, Panel A reports individual coefficient estimates and their corresponding p-values. The results in Panel B are the composite coefficients of ARCH and GARCH variables in each variance or covariance equation. These composite coefficients are functions of the individual coefficients reported in Panel A. As such, their values are calculated from values of the corresponding estimates reported in Panel A. A composite coefficient is deemed significant if and only if all its individual coefficients are significantly different from zero.[43]

The results are consistent with main findings based on VAR estimation. First, GARCH results are consistent with VAR results of short-run dynamics between the NR and AL markets. The variable $\varepsilon_{Nt-1}\varepsilon_{At-1}$ is significant in all but the h_{GGt} equation, and h_{NAt-1} is the only variable that is significant across all three covariance equations. Second, GARCH results also support the finding that AL has limited impact on both NR and GA in the short-run. ε^2_{At-1} is significant only in the h_{AAt} equation, while h_{AAt-1} is significant in the h_{AAt} and h_{AGt} equations. Conversely, AL itself is heavily influenced by both NR and GA. Third, GARCH results also reveal the influence that GA imposes on both NA and AL, with $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ significant in all but the h_{NAt} equation. Unlike the VAR results, we do find some influence from NR onto GA, with both ε^2_{Nt-1} and $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ significant in the h_{GGt} equation. We are unable to ascertain if the AL exerts any feedback effect in longer dynamics i.e. lag-5 or lag-10 in the GARCH framework.

Industry exposure or commodity market factor

First, we report VAR, BEKK-GARCH and PCA results from comparisons against silver. In Table 12, we report VAR(2) volume-volatility estimation results between NR-SL, AL -SL and GA-SL in panels A, B and C. respectively.[44] We could investigate cross-market volume-volatility interaction by estimating an eight-equation VAR that includes all four commodities.

[42]The results are generated from maximum likelihood estimation assuming multivariate normal distributions. The MLE algorithm for the full BEKK-GARCH model is programmed in Mathlab.

[43]For example, the coefficient for $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ in the h_{GGt} equation is $2a_{13}a_{33}$. Since $a_{13} = 0.05412$ and $a_{33} = 0.2515$, hence the value of the composite coefficient is 0.02723. And since both a_{13}, a_{33} are significant, the composite coefficient is also significant. This is denoted with a *.

[44]To note, we also estimate VARs with different lag specifications and volatility measures, but the results are similar. Due to space constraint, we report only results for a VAR(2) based on the absolute return measure of volatility.

But for consistency, we focus on pairwise comparisons for both VAR and BEKK-GARCH.[45]

INSERT TABLE 12

With the exception of σ_{St-2} in the v_{Nt} equation, the VAR results clearly indicate an absence of cross-market volume-volatility interaction between NR and SL in Panel A, and between GA and SL in Panel C. There is some evidence of cross-market interaction between the two metal futures markets. Both σ_{St-1} and σ_{St-2} are significant in the σ_{At} equation. Additionally, σ_{At-2} and v_{St-2} are significant in the σ_{St} and v_{St} equation respectively.

INSERT TABLE 13

In Table 13, we report bivariate full BEKK-GARCH estimation results. These are very similar to results from the preceding VAR estimation. In Tables 13a and 13c, only the own-lag ARCH and GARCH terms are significant in the corresponding equations. But the bivariate estimation of AL and SL in Table 13b shows that every single ARCH and GARCH term is significant in the h_{SSt} equation. In the conditional covariance equation, other than the own-lag variables, h_{ASt} is also affected by both ϵ^2_{AAt-1} and h_{AAt-1}. In contrast, the h_{AAt} equation is only influenced by its own-market lag variables ϵ^2_{AAt-1} and h_{AAt-1}. The results in Table 13b do suggest that the AL market affects the SL market, but not vice-versa. Thus far, VAR and BEKK-GARCH estimation do not suggest any interaction between NR-SL and between GA-SL. While cross-market interaction between the two metal futures AL and SL is interesting, any further analysis is beyond the scope of our paper.

INSERT TABLE 14

Next, we discuss PCA results in Table 14. The three-market PCA reveals that the first principal component explains 98.7% of the variances across $\{r_{Nt}, r_{At}, r_{Gt}\}$. The weights in the first eigenvector are similar across NR, Al and GA. When SL is included in the PCA, the variance explained by the first principal component dropped to 74.15%. While the weights

[45] We are unable to estimate a four-market full BEKK-GARCH, which will involve the specification of four conditional variance and six conditional covariance equations.

corresponding to NR, AL and GA in the first eigenvector remain stable, the weight attributed to SL is around 10% of the other three weights, which is trivial. To follow, the second principal component now explains 24.94% of variances across $\{r_{Nt}, r_{At}, r_{Gt}, r_{St}\}$, compared to 1.29% in the first PCA. This is entirely associated with SL, whose weight in the second eigenvector is ten times larger than the other three weights.

INSERT TABLE 15

Lastly, we discuss VMA results. To note, we report the analysis based on lag-1 and lag-2 return variables in single-equation estimations, and accordingly, a quasi-VMA(2) specification based on residual returns.[46] While the corresponding results based on residual volatility are not as clear-cut, they are consistent with the results in Table 15. VMA estimates based on commodity market adjusted returns are presented in Panel A, while Panel B report estimates based on industry-adjusted returns.

When r_{Mt-1}, r_{Mt-2} are used as filters to extract $\{v_{MNt}, v_{MAt}, v_{MGt}\}$, cross-market interaction remains evident in the VMA estimation. Except v_{MNt-2} in r_{At} and v_{MAt-2} in r_{Nt}, the remaining 10 cross-market variables are significant in Panel A. When r_{It-1}, r_{It-2} are used as filters to extract $\{v_{INt}, v_{IAt}, v_{IGt}\}$ for the VMA estimation, the results in Panel B are in stark contrast to those in Panel A. In fact, with the exception of v_{IAt-1} in the r_{Gt} equation, the remaining 11 cross-market variables in Panel B are all insignificant. Interestingly, all own-market lagged returns are significant across both panels, despite the inclusion of own-market lagged returns in single equation estimations.

For VMA estimation based on residual volatility,[47] 7 out of 12 cross-market variables are significant in Panel A. But in Panel B, only 2 variables are significant. While VMA results based on σ_{it} are not as clean-cut as those based on r_{it}, there is consistency between the two measures in terms of more evident cross-market interaction in Panel A relative to Panel B.

[46] Again, we checked with different lags, but the overall main finding is consistent.

[47] These results are available upon request.

4 Hedging and regulatory implications

We offer some implications of our main finding for multi-commodity hedging and policy-setting. We believe both issues warrant investigation, but as separate papers.

Hedging multi-commodity risk

Using futures f_i to hedge against an underlying spot s_i involves calculating the risk-minimizing optimal hedge ratio (OHR) $h_i^* = \frac{\sigma_{isf}}{\sigma_{if}^2}$, where σ_{isf} is the spot-futures return covariance and σ_{if}^2 is the futures return variance. h_i^* measures the sensitivity between s_i and f_i. For a static hedge, h_i^* is time-invariant i.e. the position is fixed for the duration of the hedging period. In contrast, a dynamic hedge recognizes $h_i^* = h_{it}^*$ i.e. time-varying hedge ratio, due to variance and/or covariance changing during the hedging period. The hedging literature is devoted to evaluating the hedging performance of i) different techniques/models for forecasting σ_{isft} and/or σ_{ift}^2, for a given hedging instrument; ii) similar competing hedging instruments, for a given technique/model for forecasting $\sigma_{isft}, \sigma_{ift}^2$.

Our main finding has implications for both aspects. The first aspect focuses on extracting more information from data on (say) f_{Ni} and s_{Ni} to improve the modeling and hence forecasting of h_{Nt+1}^* for the purpose of hedging against natural rubber exposure. Short-run cross-market interactions between NR and GA, and longer-run influence of AL on NR and GA imply potential improvements from harnessing incremental information embedded in inherent covariations between NR, AL and GA are formally modeled. The second aspect involves two contrasting angles: a) the hedging performance of an array of substitute hedging instruments for a given exposure; b) the performance of a given hedging instrument on an array of similar exposures i.e. cross-hedging[48]. Our study on complementary commodities adds a third angle. Consider a car manufacturer who is exposed to NR and AL in terms of material costs, and GA in terms of transport/assembly costs and output sales volume. The hedging literature offers guidance on substitute contracts that differ in contractual specifications and/or trading platforms.[49] as well as a list of factors to consider in cross-hedging[50].

[48]E.g. A Japanese sushi-rice farmer using Thai jasmine-rice futures contracts.

[49]E.g. NR contract in Singapore (SICOM), AL contract in Shanghai (SHFE) and GA contract in New York.

[50]E.g. using crude oil futures instead of GA futures to hedge falling car sales; using (SICOM) technically-specified rubber futures in addition to NR futures to improve hedging performance against NR exposure

In most studies, either the hedging instrument or exposure is fixed. But a car manufacturer is simultaneously exposed to multiple commodities. In the absence of commodity covariance, a car manufacturer can separately hedge against commodity-specific risks brought on by NR, AL and GA, and set positions based on commodity-specific variance-covariance matrices. But if non-trivial covariations exist among complementary commodities, setting positions on a commodity-by-commodity basis leads to hedging errors. We provide an analytical demonstration in the appendix.

Multi-commodity policy-setting

The main finding in this paper offers policy-setting implications for margin requirements, price limits and position limits. Studies on margin requirements and price limits in the 1990s are motivated by the October 1987 Wall Street crash. The usual suspects include speculative traders, index arbitragers and portfolio insurers. A huge debate followed questioning the role of such contractual features in curbing speculative trading and excessive volatility, and whether they should merely be altered in response to the changing nature of market volatility.

Our findings are not relevant to the debate on whether these contractual features should be proactive or reactive to volatility. However, our findings are relevant to the extent that an established relation, of debatable nature, exists between margin requirement (or price limit) and volatility. As with multi-commodity hedging, setting margins on a commodity-by-commodity basis may be inappropriate if the volatility of commodity i contains both commodity-specific and common commodity components. Put differently, given evident covariation among complementary commodities, it may be more appropriate for a commodity exchange to set its margin policy based on a set of related commodities rather than on a commodity-by-commodity basis. To follow, covariation across related commodities necessarily implies covariation in margin alterations on such related commodity contracts.

Position limits consider the risk exposure of a commodity-specific position. But if more prominent hedgers are engaged in multi-contract hedging in commodities used to produce a common output, and if there is evident co-movement across these related commodities, then the setting and alteration of position limits should not be a commodity-specific consideration.

etc.

5 Concluding remarks

In this paper, we put forth a simple economic argument for potential cross-market trading dynamics in seemingly unrelated commodities that share a common and non-trivial industry exposure. Using the reduced-form of a price-quantity structural system, we apply VAR estimation to empirically investigate the relevance of cross-market volatility-volume transmission effects in the NR, AL and GA futures markets of TOCOM, all of which are exposed to Japan's renowned automobile industry.

Our main findings, which survived stringent robustness tests and model specifications, document short-run cross-market dynamics between NR and AL, and from GA to NR and AL. GA itself is relatively immune to NR and AL short-run trading dynamics. Instead, cross-market effects experienced by GA is felt in longer dynamics, mainly through NR and AL volume, particularly the latter. Interestingly, σ_{ALt} and σ_{GAt} are not affected by their own lagged volume. Instead, σ_{ALt} is affected by σ_{NAt-1}, while σ_{GAt} is affected by v_{ALt-2}. Our results provide strong and robust evidence of a common industry exposure, and not commodity market factor, that is driving cross-market trading dynamics in futures contracts on complementary commodities .

A few avenues for future research are evident. The idea in this paper can be easily expanded to accommodate various sets of commodities that constitute (say) raw materials to an array of industries, which can be represented by various market sub-indices e.g. construction and material sub-index with metal-based futures contracts. A recent paper by Hong, Torous and Valkanov (2007) document strong evidence of some industries, including metal and petroleum, leading the overall stock market by up to two months. Their findings are robust across US and eight major non-US stock markets. In conjunction with evidence documented in this paper, an interesting question to ask is whether there is evidence of trading activity in a 'leading' industry, such as metal and petroleum, being influenced by trading activity in related metal- and fuel-based futures markets, and the implications in terms of a profitable trading strategy. That question is currently being investigated.

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Appendix

Here we provide an analytical demonstration of possible hedging errors generated from ignoring non-trivial covariance between related commodities. For brevity, we present a case involving NR and AL, suppressing all time subscripts. The algebra can be easily expanded to encompass all three commodities.

Case 1: Risk-minimizing hedge ratio: Natural Rubber

A NR farmer wishing to minimize the variability of his overall position will take up NR futures to hedge against exposure of his produce. The variance of his overall position $Var(S_N - h_N F_N)$ is given by

$$\begin{aligned} \sigma_1^2 &= \sigma_{Ns}^2 + h_N^2 \sigma_{Nf}^2 - 2h_N \sigma_{Nsf} \\ \frac{\partial \sigma_1^2}{\partial h_N} &= 2h_N \sigma_{Nf}^2 - 2\sigma_{Nsf} = 0 \\ h_N^* &= \frac{\sigma_{Nsf}}{\sigma_{Nf}^2} \end{aligned} \tag{10}$$

Case 2: Risk-minimizing hedge ratios: Natural Rubber and Aluminium

A car manufacturer wishing to minimize the variability of its overall input cost will take up NR and AL futures to hedge against rising commodity prices. The variance of its overall position is $Var(S_N - h_N F_N) + Var(S_A - h_A F_A) + Cov[(S_N - h_N F_N)(S_A - h_A F_A)]$.[51] We show below that multi-commodity hedging based on h_N^* and h_A^* i.e. commodity-by-commodity, is valid only when there is no relation between NR and AL. For example, when NR futures and AL spot covariance σ_{NfAs} and NR and AL futures covariance σ_{NAf} are both zero, h_N reduces to the single-commodity setting h_N^*. The case for h_A reducing to h_A^* is similarly described.

$$\begin{aligned} \sigma_2^2 = {} & (\sigma_{Ns}^2 + h_N^2 \sigma_{Nf}^2 - 2h_N \sigma_{Nsf}) + (\sigma_{As}^2 + h_P^2 \sigma_{Af}^2 - 2h_A \sigma_{Asf}) \\ & + \sigma_{NAs} + h_N h_A \sigma_{NAf} - h_N \sigma_{NfAs} - h_A \sigma_{NsAf} \end{aligned}$$

$$\begin{aligned} \frac{\partial \sigma_2^2}{\partial h_N} &= 2h_N \sigma_{Nf}^2 - 2\sigma_{Nsf} + h_P \sigma_{NAf} - \sigma_{NfAs} = 0 \\ h_N &= h_N^* + \frac{\sigma_{NfAs} - h_P \sigma_{NAf}}{2\sigma_{Nf}^2} \end{aligned}$$

$$\begin{aligned} \frac{\partial \sigma_2^2}{\partial h_A} &= 2h_A \sigma_{Pf}^2 - 2\sigma_{Asf} + h_N \sigma_{NAf} - \sigma_{NsAf} = 0 \\ h_A &= h_A^* + \frac{\sigma_{NsAf} - h_N \sigma_{NAf}}{2\sigma_{Af}^2} \end{aligned} \tag{11}$$

[51] Strictly speaking, the payoff should be $(h_N F_N - S_N)$, and is the opposite of a farmer's position. But since this does not affect the subsequent results, we keep the same order for consistency.

Table 1: TOCOM commodity futures contract specifications

	Natural rubber (NR)	Aluminum (AL)	Gasoline (GA)
Listing date	12th Dec 1952	7th Apr 1997	5ht July 1999
Underlying asset	Ribbed smoked sheet (RSS) No. 3	Min 99.7% purity; Max iron content: 0.20% Max silicon content: 0.10%	JIS K2202 grade 2 Max sulfur content: 10 ppm
Trading platform and hours	Before 4th Jan 05: Itayose After 4th Jan 05: Computerized continuous trading 9am ~11:00 am; 12:30pm~3:30pm.	Computerized continuous trading 9am ~11:00 am; 12:30pm~3:30pm	Computerized continuous trading 9am ~11:00 am; 12:30pm~3:30pm.
Delivery months	Monthly contract cycles traded up to 6 consecutive months ahead	2 month cycles; even months up to 1 year ahead	Monthly contract cycles traded up to 6 consecutive months ahead
Contract size	Before 26th Jan 05: 10,000 kilogram (kg) After 26h Jan 05: 5,000 kg	5,000 kg	50 kiloliters (kl)
Minimum tick	0.1 Yen/kg	0.1 Yen/kg	10 Yen/kl
Price and position limit	Current month: 200 2nd month: 600 3rd month: 1600 Others: 3,000/contract month	Current month: 400 2nd month: 800 Others: 2,400/contract month	Current month: 250 2nd month: 500 Others: 1,500/contract month
Last trading Day	4th business day before end of contract month	3rd business day before end of contract month	25th day of the month that precedes the delivery month
Settlement	Physical delivery	Physical delivery	Physical delivery
Margin requirement	Front contract: 112,500 Others: 75,000 yen	Front contract: 112,500 Others: 75,000	Front contract: 202,500 Others: 135,000

Table 2: Descriptive statistics and diagnostic tests

Panel A: Descriptive statistics on key variables

Variables	*Mean*	*Median*	*Max*	*Min*	*Std dev*	*Skewness*	*Kurtosis*
$r_{N\,t}$	0.000717	0.001226	0.069996	-0.07004	0.018731	-0.11069	3.428933
$r_{A\,t}$	0.000354	0.000559	0.034382	-0.03385	0.010375	-0.05379	3.201277
$r_{G\,t}$	0.000521	0.00111	0.042925	-0.06484	0.015959	-0.275	3.031389
σ_{Nt}	0.014596	0.011848	0.07004	0	0.011756	1.179036	4.556793
σ_{At}	0.008041	0.006379	0.034382	0	0.006563	1.046979	3.590174
σ_{Gt}	0.012528	0.010029	0.064844	0	0.009896	0.880516	3.651368
σ^*_{Nt}	0.017531	0.015254	0.080279	0.001707	0.010568	1.510866	6.414017
σ^*_{At}	0.008786	0.007865	0.044135	0.000994	0.004547	1.985095	10.90106
σ^*_{Gt}	0.016895	0.015127	0.087813	0.000628	0.008091	1.467108	7.381439
$v_{N\,t}$	1418354	889446.3	9335033	83140.6	1368246	1.909705	7.316232
$v_{A\,t}$	83282.66	62101.1	789132.4	433.875	75888.74	2.245733	11.71777
$v_{G\,t}$	2346197	2028430	12360033	57684.8	1596371	1.616203	7.428491

Panel B: Correlation matrix of key variables

	$r_{N\,t}$	$r_{A\,t}$	$r_{G\,t}$	σ_{Nt}	σ_{At}	σ_{Gt}	σ^*_{Nt}	σ^*_{At}	σ^*_{Gt}	$v_{N\,t}$	$v_{A\,t}$	$v_{G\,t}$
$r_{N\,t}$	1											
$r_{A\,t}$	0.187	1										
$r_{G\,t}$	0.154	0.182	1									
σ_{Nt}	-0.007	-0.006	-0.007	1								
σ_{At}	-0.033	0.021	-0.007	0.1035	1							
σ_{Gt}	0.028	0.0003	-0.077	0.046	0.097	1						
σ^*_{Nt}	-0.0499	-0.006	0.009	0.363	0.164	0.032	1					
σ^*_{At}	-0.006	-0.054	0.0141	0.109	0.368	0.057	0.202	1				
σ^*_{Gt}	-0.025	-0.043	-0.069	0.037	0.064	0.174	0.055	0.082	1			
$v_{N\,t}$	-0.024	0.010	0.003	0.214	0.221	-0.017	0.611	0.237	-0.087	1		
$v_{A\,t}$	0.053	0.018	0.0312	0.043	0.221	-0.005	-0.115	0.247	0.049	-0.159	1	
$v_{G\,t}$	-0.001	-0.006	0.010	-0.081	-0.029	0.147	-0.083	-0.067	0.351	-0.059	-0.045	1

Panel C: Augmented Dickey Fuller (ADF) tests on key variables

Variable	$r_{N\,t}$ Test 1	$r_{A\,t}$ Test 1	$r_{G\,t}$ Test 1	$v_{N\,t}$ Test 3	$v_{A\,t}$ Test 3	$v_{G\,t}$ Test 3
t-stat / *p-value*	-43.14 (0.000)**	-43.17 (0.000)**	-41.82 (0.000)**	-3.89 (0.012)*	-10.6 (0.000)**	-12.60 (0.000)**
Max lag	0	0	0	23	3	2
Variable	σ_{Nt} Test 2	σ_{At} Test 2	σ_{Gt} Test 2	σ^*_{Nt} Test 2	σ^*_{At} Test 2	σ^*_{Gt} Test 2
t-stat / *p-value*	-11.9526 (0.000)**	-15.9668 (0.000)**	-11.9636 (0.000)**	-6.64727 (0.000)**	-8.8477 (0.000)**	-10.66 (0.000)**
Max lag	5	3	5	6	6	4

**: Significant at 1% level
*: Significant at 5% level

Panel D: Autocorrelation features of key variables

	$r_{N\,t}$		$r_{A\,t}$		$r_{G\,t}$		$v_{N\,t}$		$v_{A\,t}$		$v_{G\,t}$	
Lags	*PACF*[a]	*Q-stat*[b]	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*
1	-0.002	0.01	-0.003	0.017	0.029	1.53	0.861*	1380**	0.612*	697**	0.584*	634**
2	-0.027	1.402	-0.001	0.018	-0.005	1.567	0.207*	2558**	0.317*	1307**	0.251*	1111**
3	-0.011	1.63	-0.027	1.40	0.017	2.11	0.167*	3642**	0.19*	1852**	0.14*	1496**
5	-0.024	3.68	-0.037	5.23	-0.034	4.99	0.105*	5607**	0.062*	2702**	0.041	1944**
10	-0.007	11.38	0.019	8.36	-0.03	12.6	0.086*	9893**	-0.008	4347**	0.065*	2554**
15	0.03	15.48	-0.029	12.4	0.007	21.7	0.01	13714**	-0.034	5504**	0.033	3038**

	σ_{Nt}		σ_{At}		σ_{Gt}		σ^*_{Nt}		σ^*_{At}		σ^*_{Gt}	
Lags	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*	*PACF*	*Q-stat*
1	0.091*	15.44**	0.16*	47.5**	0.11*	22.44**	0.503*	471**	0.313*	182**	0.297*	164**
2	0.141*	56.3**	0.149*	102**	0.099*	44.8**	0.27*	856**	0.212*	337**	0.207*	307**
3	0.109*	87.7**	0.09*	134**	0.129*	85.4**	0.219*	1240**	0.157*	476**	0.177*	454**
5	0.097*	153**	0.059*	197**	0.082*	151**	0.087*	1910**	0.054*	737**	0.11*	748**
10	0.042	273**	0.083*	308**	0.068*	290**	0.056*	3452**	0.032	1211**	0.036	1191**
15	0.025	365**	0.045	381**	0.041*	374**	0.005	4796**	-0.002	1554**	0.015	1560**

*Significance at the 5% level; **Significance at the 1% level
[a]If the PACF lies within the 95% confidence interval range (-0.04547, 0.04547), it is not significant
[b]Q(k) is the Ljung-Box test statistics of joint significance for the first to the k^{th} order autocorrelation, and is χ^2-distributed.

Table 3: Pairwise Granger-Causality F-test statistics

	r_{Nt}	r_{At}	r_{Gt}	σ_{Nt}	σ_{At}	σ_{Gt}	σ^*_{Nt}	σ^*_{At}	σ^*_{Gt}	v_{Nt}	v_{At}	v_{Gt}
r_{Nt}	~	0.38783[a]	0.84872	6.12197	1.10597	1.425	2.10868	1.94088	1.22077	4.82909	0.82908	0.81598
	~	(0.910)[b]	(0.547)	(0.000)**	(0.356)	(0.191)	(0.040)*	(0.050)*	(0.288)	(0.000)**	(0.563)	(0.574)
r_{At}	1.06725	~	0.75877	0.99376	1.43468	1.06306	0.53339	3.98074	2.23137	1.20134	1.9935	1.0162
	(0.382)	~	(0.622)	(0.434)	(0.187)	(0.385)	(0.810)	(0.000)**	(0.029)*	(0.299)	(0.050)*	(0.418)
r_{Gt}	1.28347	0.34948	~	0.73243	0.29266	0.58019	0.42945	1.08752	1.22066	0.53805	0.86194	1.109
	(0.254)	(0.931)	~	(0.644)	(0.957)	(0.773)	(0.884)	(0.369)	(0.288)	(0.806)	(0.536)	(0.354)
σ_{Nt}	1.24111	0.80883	1.56759	~	2.0455	0.45852	14.5072	2.06582	0.94141	8.92361	0.79404	1.23093
	(0.277)	(0.580)	(0.141)	~	(0.046)*	(0.865)	(0.000)**	(0.044)*	(0.473)	(0.000)**	(0.592)	(0.282)
σ_{At}	0.61282	1.8243	1.97848	0.89375	~	0.55615	2.59479	12.6472	1.14079	0.81849	4.64746	0.79132
	(0.746)	(0.079)	(0.050)*	(0.510)	~	(0.792)	(0.012)*	(0.000)**	(0.334)	(0.572)	(0.000)**	(0.595)
σ_{Gt}	1.25389	0.45694	0.67876	0.77663	2.36061	~	0.98963	1.9512	20.1462	0.56812	1.18726	7.07777
	(0.270)	(0.866)	(0.690)	(0.607)	(0.018)**	~	(0.437)	(0.037)*	(0.000)**	(0.782)	(0.307)	(0.000)**
σ^*_{Nt}	0.81022	0.69139	0.52486	1.77079	4.29133	1.07677	~	2.80229	1.17334	5.77136	2.94302	1.79574
	(0.579)	(0.679)	(0.816)	(0.089)	(0.000)**	(0.376)	~	(0.007)**	(0.315)	(0.000)**	(0.004)**	(0.048)*
σ^*_{At}	1.70622	0.6486	1.39265	1.35201	5.51991	1.30441	1.62946	~	0.71155	2.41352	3.01268	0.22762
	(0.103)	(0.716)	(0.204)	(0.222)	(0.000)**	(0.244)	(0.123)	~	(0.662)	(0.018)*	(0.004)**	(0.979)
σ^*_{Gt}	0.37215	1.50109	1.10087	0.40046	1.925	5.50054	1.76593	2.15386	~	1.33277	1.6087	9.66218
	(0.919)	(0.162)	(0.360)	(0.902)	(0.048)*	(0.000)**	(0.041)*	(0.036)*	~	(0.231)	(0.128)	(0.000)**
v_{Nt}	0.67073	1.04107	0.34084	2.94703	6.24237	1.41202	6.79408	2.90545	1.55396	~	2.14425	2.50301
	(0.697)	(0.400)	(0.935)	(0.004)**	(0.000)**	(0.196)	(0.000)**	(0.005)**	(0.145)	~	(0.036)*	(0.015)*
v_{At}	0.62556	0.54861	0.31961	1.33306	0.45193	2.37078	1.03662	0.49244	0.75688	2.03326	~	1.23896
	(0.735)	(0.798)	(0.945)	(0.230)	(0.869)	(0.021)*	(0.403)	(0.841)	(0.624)	(0.042)*	~	(0.278)
v_{Gt}	0.76091	0.47711	1.99771	2.35807	1.78676	0.86711	1.57401	1.50104	0.89891	3.48794	1.40969	~
	(0.620)	(0.852)	(0.042)*	(0.021)*	(0.046)*	(0.532)	(0.139)	(0.162)	(0.506)	(0.001)**	(0.197)	~

[a] The direction of causality tested runs from the row variable to the column variable. E.g. the result here correspond to the test of whether r_{Nt} Granger-causes r_{At} .

[b] p-values in parentheses

**: Significant at 1% level

*: Significant at 5% level

Table 4a: Information criteria for lag specification

	Panel A: Absolute return measure of volatility						Panel B: Composite measure of volatility					
Lag	*Log-Likelihood*	*LR*	*FPE*	*AIC*	*SIC*	*HQC*	*Log-Likelihood*	*LR*	*FPE*	*AIC*	*SIC*	*HQC*
0	-62708.96	NA	1.25E+22	67.910	67.928	67.917	-60912.21	NA	1.79E+21	65.964	65.982	65.971
1	-60552.26	4297.048	1.26E+21	65.614	65.739	65.660	-58413.66	4978.153	1.24E+20	63.298	63.424	63.344
2	-60240.59	618.946	9.36E+20	65.315	65.548*	65.341*	-58101.48	619.967	9.23E+19	62.999	63.220*	62.963*
3	-60125.52	227.792	8.59E+20	65.230	65.570	65.355	-57935.06	329.417	8.01E+19	62.858	63.238	62.983
4	-60073.35	102.915	8.44E+20	65.212	65.660	65.377	-57843.87	179.914	7.55E+19	62.798	63.246	62.993
5	-60021.48	101.999	8.30e+20*	65.195*	65.751	65.400	-57798.4	89.421	7.47E+19	62.788	63.344	63.019
6	-59986.51	68.551	8.31E+20	65.196	65.860	65.441	-57750.39	94.098	7.38E+19	62.775	63.438	63.050
7	-59956.37	58.874	8.36E+20	65.202	65.974	65.487	-57706.52	85.686	7.31e+19*	62.766*	63.537	63.085
8	-59926.9	57.378	8.42E+20	65.209	66.088	65.533	-57684.13	43.589	7.42E+19	62.781	63.660	63.105
9	-59898.76	54.591	8.49E+20	65.218	66.204	65.582	-57646.34	73.328	7.41E+19	62.779	63.765	63.143
10	-59865.26	64.801*	8.51E+20	65.221	66.315	65.624	-57618.26	54.304*	7.47E+19	62.788	63.882	63.191
11	-59850.81	27.844	8.72E+20	65.244	66.446	65.687	-57602.05	31.258	7.63E+19	62.809	64.011	63.252
12	-59827.15	45.454	8.83E+20	65.257	66.567	65.740	-57580.43	41.530	7.76E+19	62.825	64.134	63.307

*: lag order selected by the corresponding criterion

Table 4b: Chi-square and Wald statistics from lag exclusion test

	Panel A: Absolute return measure of volatility							Panel B: Composite measure of volatility						
Lag	σ_{Nt}	σ_{At}	σ_{Gt}	v_{Nt}	v_{At}	v_{Gt}	Joint	σ^*_{Nt}	σ^*_{At}	σ^*_{Gt}	v_{Nt}	v_{At}	v_{Gt}	Joint
1	10.227	24.076	6.282	721.946	201.343	310.729	1364	100.079	59.663	30.818	645.165	182.017	296.213	1386.378
	(0.115)[a]	(0.001)**	(0.392)	(0.000)**	(0.000)**	(0000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**
2	19.766	26.667	14.445	33.551	70.300	58.035	228.989	15.532	27.092	25.582	10.994	65.705	47.249	198.215
	(0.003)	(0.000)**	(0.025)	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.017)	(0.000)**	(0.000)**	(0.089)	(0.000)**	(0.000)**	(0.000)**
3	7.783	17.594	17.116	5.919	31.008	27.365	116.664	23.802	19.068	20.691	10.499	31.602	37.080	140.412
	(0.254)	(0.007)**	(0.009)**	(0.432)	(0.000)**	(0.000)**	(0.000)**	(0.001)**	(0.004)**	(0.002)**	(0.105)	(0.000)**	(0.000)**	(0.000)**
4	7.631	10.446	16.520	2.943	3.955	3.091	43.562	9.583	35.430	35.372	9.335	3.462	15.943	104.532
	(0.266)	(0.107)	(0.011)*	(0.816)	(0.683)	(0.797)	(0.181)	(0.143)	(0.000)**	(0.000)**	(0.156)	(0.749)	(0.140)	(0.216)
5	11.073	5.228	12.201	7.844	9.325	5.576	56.538	5.493	4.472	13.850	10.000	4.633	4.260	39.819
	(0.086)	(0.515)	(0.058)	(0.250)	(0.156)	(0.472)	(0.016)*	(0.482)	(0.613)	(0.031)*	(0.125)	(0.591)	(0.641)	(0.303)
6	12.017	3.892	10.947	2.734	6.538	6.849	46.953	26.642	15.905	3.454	7.573	6.521	5.728	57.264
	(0.061)	(0.691)	(0.090)	(0.841)	(0.365)	(0.335)	(0.104)	(0.000)**	(0.413)	(0.750)	(0.271)	(0.367)	(0.454)	(0.140)
7	6.181	5.893	10.992	7.128	7.795	2.205	38.134	14.675	13.157	6.855	17.148	8.601	2.338	57.455
	(0.403)	(0.435)	(0.088)	(0.309)	(0.253)	(0.899)	(0.372)	(0.022)*	(0.041)*	(0.335)	(0.008)**	(0.197)	(0.886)	(0.013)*
8	8.049	11.846	7.259	1.781	9.231	3.169	45.991	6.646	10.039	6.637	6.528	5.808	4.892	37.014
	(0.235)	(0.065)	(0.297)	(0.938)	(0.161)	(0.787)	(0.123)	(0.354)	(0.123)	(0.355)	(0.366)	(0.445)	(0.557)	(0.421)
9	3.568	1.040	16.281	5.384	15.182	1.840	43.719	7.166	5.167	5.957	8.437	8.547	6.600	43.488
	(0.734)	(0.984)	(0.012)*	(0.495)	(0.018)*	(0.933)	(0.176)	(0.305)	(0.523)	(0.428)	(0.207)	(0.201)	(0.359)	(0.182)
10	4.647	14.714	12.603	12.631	5.988	7.868	58.687	13.559	3.295	3.660	22.363	15.513	1.267	61.701
	(0.589)	(0.022)*	(0.049)*	(0.049)*	(0.421)	(0.248)	(0.010)*	(0.035)*	(0.771)	(0.723)	(0.001)**	(0.016)*	(0.973)	(0.004)**
11	3.549	3.996	3.946	5.422	2.518	6.184	26.865	6.423	5.394	8.710	2.433	0.807	3.295	28.938
	(0.737)	(0.677)	(0.682)	(0.490)	(0.866)	(0.402)	(0.865)	(0.377)	(0.494)	(0.190)	(0.875)	(0.991)	(0.771)	(0.792)
12	5.141	9.122	3.362	13.745	10.381	3.890	45.617	8.718	7.141	4.425	13.979	4.878	4.300	41.677
	(0.525)	(0.166)	(0.762)	(0.032)*	(0.109)	(0.691)	(0.130)	(0.190)	(0.308)	(0.619)	(0.029)*	(0.559)	(0.635)	(0.237)

[a] p-values in parentheses
**: Significant at 1% level
*: Significant at 5% level

Table 5: VAR (2) estimation results

Panel A: Absolute return measure of volatility

	c	D1	σ_{Nt-1}	σ_{At-1}	σ_{Gt-1}	v_{Nt-1}	v_{At-1}	v_{Gt-1}	σ_{Nt-2}	σ_{At-2}	σ_{Gt-2}	v_{Nt-2}	v_{At-2}	v_{Gt-2}
σ_{Nt}	0.012	0.001	0.076	0.027	-0.001	0.000	0.000	0.000	0.116	0.085	0.011	0.000	0.000	0.000
	(0.000)[a]**	(0.179)	(0.001)**	(0.533)	(0.978)	(0.007)**	(0.869)	(0.015)*	(0.000)**	(0.041)*	(0.683)	(0.000)**	(0.659)	(0.169)
v_{Nt}	133452	-86590	8725k	3593k	-1403k	0.650	0.084	0.025	-8474k	6416k	2359439	0.228	-0.742	-0.025
	(0.013)**	(0.022)*	(0.000)**	(0.157)	(0.378)	(0.000)**	(0.755)	(0.043)*	(0.000)**	(0.011)*	(0.142)	(0.000)**	(0.005)**	(0.035)*
σ_{At}	0.003	0.000	0.036	0.092	0.042	0.000	0.000	0.000	-0.002	0.091	0.005	0.000	0.000	0.000
	(0.000)**	(0.445)	(0.006)**	(0.000)**	(0.006)**	(0.945)	(0.924)	(0.842)	(0.848)	(0.000)**	(0.733)	(0.000)**	(0.005)**	(0.512)
v_{At}	27369	57.519	-53548	813350	-86807	0.000	0.390	0.000	-100226	-432119	-28745	-0.004	0.329	0.001
	(0.000)**	(0.986)	(0.648)	(0.000)**	(0.522)	(0.861)	(0.000)**	(0.816)	(0.386)	(0.044)*	(0.834)	(0.040)*	(0.000)**	(0.326)
σ_{Gt}	0.010	0.002	0.013	0.059	0.088	0.000	0.000	0.000	-0.011	0.051	0.085	0.000	0.000	0.000
	(0.000)**	(0.004)**	(0.515)	(0.111)	(0.000)**	(0.823)	(0.493)	(0.576)	(0.593)	(0.167)	(0.000)**	(0.203)	(0.012)*	(0.009)**
v_{Gt}	829231	-108791	-1372k	-1928k	19923k	0.063	-0.671	0.412	-3898k	-983k	-1533k	-0.117	-0.402	0.250
	(0.000)**	(0.122)	(0.593)	(0.683)	(0.000)**	(0.147)	(0.178)	(0.000)**	(0.123)	(0.834)	(0.609)	(0.006)**	(0.415)	(0.000)**

Panel B: Composite measure of volatility

	c	D1	σ^*_{Nt-1}	σ^*_{At-1}	σ^*_{Gt-1}	v_{Nt-1}	v_{At-1}	v_{Gt-1}	σ^*_{Nt-2}	σ^*_{At-2}	σ^*_{Gt-2}	v_{Nt-2}	v_{At-2}	v_{Gt-2}
σ^*_{Nt}	0.007	-0.001	0.237	0.101	0.048	0.000	0.000	0.000	0.183	0.029	0.013	0.000	0.000	0.000
	(0.000)**	(0.022)*	(0.000)**	(0.043)*	(0.011)*	(0.000)**	(0.811)	(0.027)*	(0.000)**	(0.560)	(0.658)	(0.451)	(0.122)	(0.827)
v_{Nt}	212296	-95981	-5113682	11323k	-644202	0.699	0.051	0.027	-361808	1054511	-961371	0.200	-0.685	-0.028
	(0.001)*	(0.013)*	(0.012)*	(0.004)**	(0.780)	(0.000)**	(0.857)	(0.041)*	(0.858)	(0.789)	(0.680)	(0.000)**	(0.014)*	(0.046)*
σ^*_{At}	0.004	0.000	0.024	0.219	0.052	0.000	0.000	0.000	-0.004	0.166	0.004	0.000	0.000	0.000
	(0.000)**	(0.049)*	(0.045)*	(0.000)**	(0.000)**	(0.257)	(0.469)	(0.126)	(0.740)	(0.000)**	(0.796)	(0.294)	(0.039)*	(0.994)
v_{At}	34115	257.510	-343091	-674647	489853	0.003	0.415	-0.001	-177470	-840651	138168	-0.003	0.323	0.001
	(0.000)**	(0.936)	(0.042)*	(0.041)*	(0.011)*	(0.115)	(0.000)**	(0.198)	(0.294)	(0.011)*	(0.476)	(0.188)	(0.000)**	(0.412)
σ^*_{Gt}	0.008	-0.001	0.022	0.044	0.226	0.000	0.000	0.000	0.049	0.116	0.177	0.000	0.000	0.000
	(0.000)**	(0.008)**	(0.328)	(0.315)	(0.000)**	(0.190)	(0.623)	(0.658)	(0.029)*	(0.008)**	(0.000)**	(0.219)	(0.809)	(0.303)
v_{Gt}	1192139	-118722	-5474k	7904107	-25182k	0.058	-0.535	0.483	11041k	14520k	-8395k	-0.186	-0.735	0.247
	(0.000)**	(0.0490)*	(0.137)	(0.272)	(0.000)**	(0.209)	(0.294)	(0.000)**	(0.003)**	(0.043)*	(0.047)*	(0.000)**	(0.148)	(0.000)**

[a] p-values in parentheses

**: Significant at 1% level

*: Significant at 5% level

Table 6: VAR (2-10) estimation results

Panel A: Absolute return measure of volatility

	c	σ_{Nt-1}	σ_{At-1}	σ_{Gt-1}	V_{Nt-1}	V_{At-1}	V_{Gt-1}	σ_{Nt-2}	σ_{At-2}	σ_{Gt-2}	V_{Nt-2}	V_{At-2}	V_{Gt-2}	σ_{Nt-10}	σ_{At-10}	σ_{Gt-10}	V_{Nt-10}	V_{At-10}	V_{Gt-10}
σ_{Nt}	0.011	0.074	0.018	0.004	0.000	0.000	0.000	0.102	0.090	0.016	0.000	0.000	0.000	0.065	-0.032	-0.021	0.000	0.000	0.000
	(0.000)[a]**	(0.002)**	(0.675)	(0.884)	(0.011)*	(0.532)	(0.023)*	(0.000)**	(0.040)*	(0.570)	(0.000)**	(0.939)	(0.291)	(0.006)**	(0.472)	(0.444)	(0.691)	(0.023)*	(0.384)
V_{Nt}	103k	9123k	2441k	-879k	0.597	0.371	0.032	-7627k	4808k	2135k	0.180	-0.507	-0.013	39791	-3019k	-950k	0.143	-0.380	-0.022
	(0.096)	(0.000)**	(0.329)	(0.576)	(0.000)**	(0.171)	(0.008)**	(0.000)**	(0.045)*	(0.178)	(0.000)**	(0.047)*	(0.286)	(0.976)	(0.226)	(0.544)	(0.000)**	(0.110)	(0.030)*
σ_{At}	0.003	0.034	0.085	0.037	0.000	0.000	0.000	-0.004	0.087	0.003	0.000	0.000	0.000	-0.004	0.072	0.029	0.000	0.000	0.000
	(0.000)**	(0.008)**	(0.000)**	(0.014)*	(0.927)	(0.770)	(0.662)	(0.771)	(0.000)**	(0.843)	(0.000)**	(0.013)*	(0.206)	(0.728)	(0.003)**	(0.045)*	(0.741)	(0.257)	(0.084)
V_{At}	24605	-91126	827k	-119k	0.002	0.362	0.000	-1739k	-334k	-5632	-0.004	0.302	0.001	189k	33312	153k	-0.002	0.089	-0.002
	(0.000)**	(0.437)	(0.000)**	(0.382)	(0.415)	(0.000)**	(0.892)	(0.136)	(0.123)	(0.967)	(0.046)*	(0.000)**	(0.225)	(0.102)	(0.877)	(0.258)	(0.152)	(0.000)**	(0.038)*
σ_{Gt}	0.008	0.013	0.064	0.076	0.000	0.000	0.000	-0.010	0.053	0.075	0.000	0.000	0.000	0.001	0.017	0.103	0.000	0.000	0.000
	(0.000)**	(0.535)	(0.035)*	(0.001)**	(0.760)	(0.383)	(0.461)	(0.618)	(0.153)	(0.001)**	(0.163)	(0.015)*	(0.022)*	(0.944)	(0.638)	(0.000)**	(0.886)	(0.589)	(0.110)
V_{Gt}	674k	-1426k	-578k	1950k	0.077	-0.871	0.401	-3649k	228447	-1807k	-0.110	-0.495	0.236	-1346k	-5544k	3029k	-0.008	0.679	0.075
	(0.000)**	(0.579)	(0.903)	(0.000)**	(0.038)*	(0.039)*	(0.000)**	(0.153)	(0.962)	(0.547)	(0.011)*	(0.327)	(0.000)**	(0.596)	(0.241)	(0.307)	(0.796)	(0.131)	(0.000)**

Panel B: Composite measure of volatility

	c	σ^*_{Nt-1}	σ^*_{At-1}	σ^*_{Gt-1}	V_{Nt-1}	V_{At-1}	V_{Gt-1}	σ^*_{Nt-2}	σ^*_{At-2}	σ^*_{Gt-2}	V_{Nt-2}	V_{At-2}	V_{Gt-2}	σ^*_{Nt-10}	σ^*_{At-10}	σ^*_{Gt-10}	V_{Nt-10}	V_{At-10}	V_{Gt-10}
σ^*_{Nt}	0.005	0.224	0.094	0.034	0.000	0.000	0.000	0.165	0.024	-0.007	0.000	0.000	0.000	0.101	-0.022	0.071	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.041)*	(0.250)	(0.000)**	(0.569)	(0.047)*	(0.000)**	(0.635)	(0.805)	(0.987)	(0.205)	(0.743)	(0.000)**	(0.647)	(0.010)*	(0.170)	(0.835)	(0.213)
V_{Nt}	147k	-5562k	9857k	-383k	0.648	0.369	0.033	-1156k	-643k	-2179k	0.148	-0.395	-0.013	1877k	3425k	1410k	0.139	-0.588	-0.024
	(0.039)*	(0.005)**	(0.012)*	(0.867)	(0.000)**	(0.192)	(0.016)*	(0.564)	(0.869)	(0.345)	(0.000)**	(0.158)	(0.357)	(0.325)	(0.367)	(0.514)	(0.000)**	(0.016)*	(0.030)*
σ^*_{At}	0.003	0.022	0.206	0.047	0.000	0.000	0.000	-0.007	0.154	-0.003	0.000	0.000	0.000	0.010	0.093	0.019	0.000	0.000	0.000
	(0.000)**	(0.046)*	(0.000)**	(0.001)**	(0.197)	(0.425)	(0.155)	(0.590)	(0.000)**	(0.848)	(0.571)	(0.045)*	(0.835)	(0.413)	(0.000)**	(0.024)*	(0.948)	(0.655)	(0.671)
V_{At}	30988	-368k	-614k	401033	0.004	0.386	-0.001	-267k	-871k	53222	-0.002	0.297	0.001	281k	-319k	412629	-0.002	0.097	-0.003
	(0.000)**	(0.032)*	(0.046)*	(0.038)*	(0.046)*	(0.000)**	(0.316)	(0.115)	(0.008)**	(0.785)	(0.355)	(0.000)**	(0.204)	(0.042)*	(0.321)	(0.164)	(0.282)	(0.000)**	(0.005)**
σ^*_{Gt}	0.007	0.012	0.038	0.206	0.000	0.000	0.000	0.043	0.109	0.166	0.000	0.000	0.000	0.056	0.006	0.092	0.000	0.000	0.000
	(0.000)**	(0.594)	(0.395)	(0.000)**	(0.409)	(0.677)	(0.733)	(0.047)*	(0.013)*	(0.000)**	(0.497)	(0.770)	(0.499)	(0.009)**	(0.885)	(0.000)**	(0.012)*	(0.874)	(0.261)
V_{Gt}	1054k	-5928k	9000k	-2496k	0.077	-0.697	0.471	11066k	16061k	-7486k	-0.175	-0.846	0.231	689k	-4137k	-2420k	-0.024	0.591	0.086
	(0.000)**	(0.108)	(0.215)	(0.000)**	(0.103)	(0.183)	(0.000)**	(0.003)**	(0.026)*	(0.038)*	(0.000)**	(0.013)*	(0.000)**	(0.846)	(0.556)	(0.545)	(0.486)	(0.189)	(0.000)**

[a] p-values in parentheses
**: Significant at 1% level
*: Significant at 5% level

Table 7: VAR (2-5) and VAR (2-7) estimation results

Panel A: Absolute return measure of volatility for VAR (2-5)

	c	σ_{Nt-1}	σ_{At-1}	σ_{Gt-1}	v_{Nt-1}	v_{At-1}	v_{Gt-1}	σ_{Nt-2}	σ_{At-2}	σ_{Gt-2}	v_{Nt-2}	v_{At-2}	v_{Gt-2}	σ_{Nt-5}	σ_{At-5}	σ_{Gt-5}	v_{Nt-5}	v_{At-5}	v_{Gt-5}
σ_{Nt}	0.010	0.064	0.022	0.002	0.000	0.000	0.000	0.106	0.075	0.009	0.000	0.000	0.000	0.089	-0.024	0.027	0.000	0.000	0.000
	(0.000)[a]**	(0.007)**	(0.617)	(0.949)	(0.006)**	(0.491)	(0.035)*	(0.000)**	(0.088)	(0.748)	(0.001)**	(0.799)	(0.596)	(0.000)**	(0.582)	(0.336)	(0.270)	(0.012)*	(0.095)
v_{Nt}	110K	8587k	1971k	-1221k	0.607	0.321	0.035	-7452k	5740k	2308k	0.159	-0.519	-0.010	-1777k	1330k	-434k	0.142	-0.350	-0.028
	(0.063)	(0.000)**	(0.434)	(0.439)	(0.000)**	(0.238)	(0.003)**	(0.000)**	(0.022)*	(0.148)	(0.000)**	(0.042)*	(0.445)	(0.186)	(0.595)	(0.785)	(0.000)**	(0.173)	(0.011)**
σ_{At}	0.003	0.032	0.083	0.042	0.000	0.000	0.000	-0.001	0.090	0.006	0.000	0.000	0.000	-0.002	0.029	-0.001	0.000	0.000	0.000
	(0.000)**	(0.014)*	(0.001)**	(0.005)**	(0.667)	(0.734)	(0.678)	(0.950)	(0.000)**	(0.706)	(0.001)**	(0.044)*	(0.302)	(0.904)	(0.033)*	(0.926)	(0.046)*	(0.043)*	(0.619)
v_{At}	246k	-891k	893k	-767k	0.002	0.351	0.000	-165k	-327k	-465k	-0.002	0.280	0.002	142k	-456k	219k	-0.003	0.136	-0.002
	(0.000)**	(0.446)	(0.000)**	(0.570)	(0.329)	(0.000)**	(0.814)	(0.152)	(0.127)	(0.733)	(0.308)	(0.000)**	(0.048)*	(0.218)	(0.227)	(0.106)	(0.031)*	(0.000)**	(0.045)*
σ_{Gt}	0.009	0.015	0.056	0.076	0.000	0.000	0.000	-0.001	0.044	0.076	0.000	0.000	0.000	-0.018	-0.007	0.093	0.000	0.000	0.000
	(0.000)**	(0.464)	(0.133)	(0.001)**	(0.858)	(0.555)	(0.512)	(0.945)	(0.233)	(0.001)**	(0.039)*	(0.014)*	(0.030)*	(0.377)	(0.848)	(0.000)**	(0.036)*	(0.755)	(0.434)
v_{Gt}	833k	-965k	-408k	200k	0.079	-0.832	0.400	-366k	768k	-720k	-0.095	-0.751	0.225	-367k	-8042k	-207k	-0.032	0.696	0.067
	(0.000)**	(0.708)	(0.932)	(0.000)**	(0.033)*	(0.104)	(0.000)**	(0.150)	(0.871)	(0.811)	(0.035)*	(0.151)	(0.000)**	(0.147)	(0.048)*	(0.489)	(0.352)	(0.150)	(0.001)*

Panel B: Composite measure of volatility for VAR (2-7) estimation

	c	σ^*_{Nt-1}	σ^*_{At-1}	σ^*_{Gt-1}	v_{Nt-1}	v_{At-1}	v_{Gt-1}	σ^*_{Nt-2}	σ^*_{At-2}	σ^*_{Gt-2}	v_{Nt-2}	v_{At-2}	v_{Gt-2}	σ^*_{Nt-7}	σ^*_{At-7}	σ^*_{Gt-7}	v_{Nt-7}	v_{At-7}	v_{Gt-7}
σ^*_{Nt}	0.005	0.204	0.022	0.040	0.000	0.000	0.000	0.166	0.097	0.057	0.000	0.000	0.000	0.139	-0.029	0.000	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.498)	(0.046)*	(0.000)**	(0.730)	(0.032)*	(0.000)**	(0.003)**	(0.005)**	(0.775)	(0.029)*	(0.684)	(0.000)**	(0.369)	(0.987)	(0.219)	(0.040)*	(0.945)
v_{Nt}	160k	-6810k	2521k	-1045k	0.667	0.321	0.036	-1563k	5006	1563k	0.144	-0.669	-0.018	504k	159k	240k	0.113	-0.063	-0.030
	(0.010)*	(0.001)**	(0.325)	(0.516)	(0.000)**	(0.246)	(0.003)**	(0.434)	(0.049)*	(0.336)	(0.000)**	(0.015)*	(0.137)	(0.009)**	(0.950)	(0.882)	(0.000)**	(0.800)	(0.004)**
σ^*_{At}	0.004	0.044	0.084	0.043	0.000	0.000	0.000	-0.004	0.086	0.002	0.000	0.000	0.000	-0.017	0.018	0.009	0.000	0.000	0.000
	(0.000)**	(0.022)*	(0.001)**	(0.005)**	(0.465)	(0.806)	(0.515)	(0.851)	(0.000)**	(0.914)	(0.003)**	(0.008)**	(0.180)	(0.347)	(0.036)*	(0.551)	(0.046)*	(0.834)	(0.104)
v_{At}	260k	-4001k	858k	-716k	0.002	0.350	0.000	-257k	-322k	2217	-0.002	0.285	0.001	249k	-366k	152k	-0.001	0.142	-0.001
	(0.000)**	(0.018)*	(0.000)**	(0.597)	(0.320)	(0.000)**	(0.940)	(0.125)	(0.133)	(0.987)	(0.308)	(0.000)**	(0.230)	(0.122)	(0.449)	(0.263)	(0.425)	(0.000)**	(0.007)**
σ^*_{Gt}	0.007	0.032	0.055	0.069	0.000	0.000	0.000	0.084	0.050	0.068	0.000	0.000	0.000	0.044	-0.011	0.078	0.000	0.000	0.000
	(0.000)**	(0.282)	(0.138)	(0.003)**	(0.990)	(0.542)	(0.787)	(0.004)**	(0.177)	(0.004)**	(0.027)*	(0.002)**	(0.029)*	(0.114)	(0.767)	(0.001)**	(0.414)	(0.119)	(0.246)
v_{Gt}	6977k	-9599k	-1363k	19321k	0.118	-0.790	0.407	8439k	-451k	-1441k	-0.154	-0.653	0.235	-3062k	-3446k	2263k	-0.020	0.503	0.051
	(0.000)**	(0.010)*	(0.774)	(0.000)**	(0.012)*	(0.125)	(0.000)**	(0.023)**	(0.924)	(0.633)	(0.001)**	(0.201)	(0.000)**	(0.932)	(0.464)	(0.450)	(0.566)	(0.274)	(0.009)**

[a] p-values in parentheses

**: Significant at 1% level

*: Significant at 5% level

Table 8: VAR significance score-board

	σ_{Nt-1}	σ_{At-1}	σ_{Gt-1}	v_{Nt-1}	v_{At-1}	v_{Gt-1}	σ_{Nt-2}	σ_{At-2}	σ_{Gt-2}	v_{Nt-2}	v_{At-2}	v_{Gt-2}
σ_{Nt}	**6**^	**0**	2	**6**	**0**	**6**	**6**	4	**1**	**3**	**0**	**0**
v_{Nt}	**6**	**0**	**0**	**6**	**0**	**6**	**3**	4	**0**	**6**	**6**	2
σ_{At}	**6**+	**6**	**6**	**0**	**0**	**0**	**0**	**6**	**0**	**4**	**6**	**0**
v_{At}	2	**6**	2	**1**	**6**	**0**	**0**	**3**	**0**	2	**6**	**1**
σ_{Gt}	**0**	**1**	**6**	**0**	**0**	**0**	**1**	2	**6**	2	**5**	**4**
v_{Gt}	**1**	**0**	**6**	**1**	**1**	**6**	**1**	2	**2**	**6**	**1**	**6**

^: These scores represent the number of times that a given lagged exogenous variable is significant in a given VAR estimation. We consider three different VAR specifications for each of the two volatility measures. Accordingly, the maximum score that a variable can achieve is 6. We consider these as the super-robust results.

+: Blue (Red) denotes cells corresponding to own-market (cross-market) effects. Cross-market cells that achieve scores of less than 3 are ignored.

Table 9: Probit regressions results of price reversals against lagged volatility and volume variables

Panel A: Absolute return measure of volatility

	σ_{Nt-1}	σ_{At-1}	σ_{Gt-1}	V_{Nt-1}	V_{At-1}	V_{Gt-1}	σ_{Nt-2}	σ_{At-2}	σ_{Gt-2}	V_{Nt-2}	V_{At-2}	V_{Gt-2}
Rev_{Nt}^{night}	-3.4897	5.5463	1.0541	0.0000	0.0000	0.0000	12.0217	-6.6471	-3.4659	0.0000	0.0000	0.0000
	(0.164)[a]	(0.249)	(0.720)	(0.788)	(0.356)	(0.049)*	(0.000)**	(0.163)	(0.249)	(0.593)	(0.561)	(0.735)
Rev_{Nt}^{day}	2.9855	-2.5705	1.2872	0.0000	0.0000	0.0000	-0.8371	-0.5509	-4.1024	0.0000	0.0000	0.0000
	(0.228)	(0.590)	(0.658)	(0.020)*	(0.490)	(0.973)	(0.738)	(0.908)	(0.172)	(0.027)*	(0.899)	(0.501)
Rev_{At}^{night}	4.7587	-0.1655	-5.5798	0.0000	0.0000	0.0000	-0.4426	-4.5562	-0.6065	0.0000	0.0000	0.0000
	(0.050)*	(0.972)	(0.048)*	(0.129)	(0.224)	(0.349)	(0.859)	(0.338)	(0.840)	(0.479)	(0.246)	(0.317)
Rev_{At}^{day}	-3.2356	4.0193	-3.8353	0.0000	0.0000	0.0000	2.2829	6.7086	9.7368	0.0000	0.0000	0.0000
	(0.194)	(0.401)	(0.191)	(0.413)	(0.336)	(0.439)	(0.362)	(0.161)	(0.001)**	(0.047)*	(0.214)	(0.225)
Rev_{Gt}^{night}	2.9142	-7.0520	3.1433	0.0000	0.0000	0.0000	1.3767	-0.2144	-2.2000	0.0000	0.0000	0.0000
	(0.240)	(0.138)	(0.282)	(0.446)	(0.935)	(0.771)	(0.580)	(0.964)	(0.461)	(0.886)	(0.924)	(0.935)
Rev_{Gt}^{day}	-1.1071	-14.1673	8.2751	0.0000	0.0000	0.0000	1.0516	4.3379	3.1269	0.0000	0.0000	0.0000
	(0.658)	(0.003)**	(0.005)**	(0.603)	(0.322)	(0.507)	(0.676)	(0.365)	(0.298)	(0.660)	(0.484)	(0.835)

Panel B: Composite measure of volatility

	σ^*_{Nt-1}	σ^*_{At-1}	σ^*_{Gt-1}	V_{Nt-1}	V_{At-1}	V_{Gt-1}	σ^*_{Nt-2}	σ^*_{At-2}	σ^*_{Gt-2}	V_{Nt-2}	V_{At-2}	V_{Gt-2}
Rev_{Nt}^{night}	8.9438	1.6943	-1.8482	0.0000	0.0000	0.0000	-1.8674	-3.7828	0.3246	0.0000	0.0000	0.0000
	(0.016)*	(0.814)	(0.660)	(0.255)	(0.468)	(0.015)*	(0.615)	(0.600)	(0.939)	(0.836)	(0.490)	(0.774)
Rev_{Nt}^{day}	-5.0564	-4.2777	-6.4189	0.0000	0.0000	0.0000	-0.0099	10.6600	1.5818	0.0000	0.0000	0.0000
	(0.176)	(0.553)	(0.133)	(0.004) **	(0.847)	(0.466)	(0.998)	(0.142)	(0.710)	(0.028)*	(0.723)	(0.789)
Rev_{At}^{night}	-4.4730	2.6688	-5.3400	0.0000	0.0000	0.0000	7.9772	-4.4474	0.4711	0.0000	0.0000	0.0000
	(0.224)	(0.712)	(0.049)*	(0.655)	(0.342)	(0.521)	(0.031)*	(0.535)	(0.911)	(0.436)	(0.252)	(0.659)
Rev_{At}^{day}	-6.5368	-2.0810	2.4017	0.0000	0.0000	0.0000	7.3810	3.1792	-1.2384	0.0000	0.0000	0.0000
	(0.049)*	(0.772)	(0.565)	(0.047)*	(0.185)	(0.377)	(0.050)*	(0.658)	(0.770)	(0.033)*	(0.392)	(0.574)
Rev_{Gt}^{night}	4.2619	0.7867	-6.4557	0.0000	0.0000	0.0000	0.5954	0.7525	-1.9817	0.0000	0.0000	0.0000
	(0.253)	(0.913)	(0.127)	(0.330)	(0.955)	(0.279)	(0.873)	(0.917)	(0.642)	(0.834)	(0.783)	(0.852)
Rev_{Gt}^{day}	-4.0004	3.1225	4.7586	0.0000	0.0000	0.0000	3.8965	0.5145	-4.5188	0.0000	0.0000	0.0000
	(0.280)	(0.664)	(0.268)	(0.474)	(0.731)	(0.628)	(0.301)	(0.943)	(0.289)	(0.420)	(0.255)	(0.671)

[a] p-values in parentheses

**: Significant at 1% level

*: Significant at 5% level

Table 10: GMM estimation of variance ratios against lagged volume variables

Panel A: Ratio between weekly variance and daily variance

	c	V_{Nt-1}	V_{At-1}	V_{Gt-1}	V_{Nt-2}	V_{At-2}	V_{Gt-2}	c	V_{Nt-1}	V_{At-1}	V_{Gt-1}	V_{Nt-5}	V_{At-5}	V_{Gt-5}
VR^{5}_{Nt}	0.874212	2.04E-07	-3.95E-07	-1.3E-08	-4.68E-08	-7.75E-07	2.51E-08	1.00330	2.66E-07	-8.58E-07	-3.32E-09	-1.43E-07	-4.06E-07	-1.56E-08
	(0.000)[a]**	(0.007)**	(0.461)	(0.035)*	(0.490)	(0.049)*	(0.632)	(0.000)**	(0.006)**	(0.125)	(0.917)	(0.047)*	(0.032)*	(0.636)
VR^{5}_{At}	0.659386	-5.58E-08	2.8E-06	-3.05E-08	1.17E-07	-6.61E-07	8.61E-09	0.77592	5.84E-08	2.93E-06	-3.08E-08	-2.63E-08	-1.32E-06	-3.95E-09
	(0.000)**	(0.531)	(0.015)*	(0.225)	(0.346)	(0.455)	(0.718)	(0.000)**	(0.364)	(0.005)**	(0.193)	(0.045)*	(0.027)*	(0.903)
VR^{5}_{Gt}	1.071641	1.31E-07	1.41E-06	2.1E-07	-6.6E-08	-1.35E-06	-1.61E-07	1.29992	7.68E-08	1.49E-06	1.91E-07	-2.27E-08	-1.9E-06	-2.16E-07
	(0.000)**	(0.425)	(0.434)	(0.023)*	(0.689)	(0.322)	(0.046)*	(0.000)**	(0.440)	(0.330)	(0.008)**	(0.835)	(0.519)	(0.000)**

Panel B: Ratio between fortnight variance and daily variance

	c	V_{Nt-1}	V_{At-1}	V_{Gt-1}	V_{Nt-2}	V_{At-2}	V_{Gt-2}	c	V_{Nt-1}	V_{At-1}	V_{Gt-1}	V_{Nt-10}	V_{At-10}	V_{Gt-10}
VR^{10}_{Nt}	0.798688	1.51E-07	-1.32E-07	-2.77E-08	-6.19E-08	-1.23E-06	1.78E-08	0.83862	8.67E-08	-5.53E-07	1.26E-09	1.31E-08	-6.55E-07	-4E-08
	(0.000)**	(0.011)*	(0.765)	(0.030)*	(0.249)	(0.001)**	(0.589)	(0.000)**	(0.227)	(0.192)	(0.969)	(0.873)	(0.023)*	(0.658)
VR^{10}_{At}	0.484982	-3.27E-08	9.74E-07	-1.07E-08	6.58E-08	4.92E-07	1.14E-08	0.39431	-2.75E-08	1.58E-06	-1.12E-08	8.17E-08	-3.76E-07	4.73E-08
	(0.000)**	(0.427)	(0.147)	(0.678)	(0.245)	(0.349)	(0.678)	(0.000)**	(0.237)	(0.021)*	(0.513)	(0.697)	(0.443)	(0.043)*
VR^{10}_{Gt}	0.757591	1.91E-07	-5.58E-08	1.04E-07	-1.04E-07	-2.58E-07	-6.91E-08	0.84987	4.93E-08	-1.03E-07	9.73E-08	5.96E-08	-1.08E-07	-1.18E-07
	(0.000)**	(0.235)	(0.956)	(0.050)*	(0.508)	(0.786)	(0.205)	(0.000)**	(0.421)	(0.900)	(0.014)*	(0.370)	(0.873)	(0.002)**

[a] p-values in parentheses
**: Significant at 1% level
*: Significant at 5% level

Table 11: Tri-variate Full BEKK-GARCH (1,1) estimation results

Panel A: BEKK-GARCH coefficient estimates

ϕ_{N0}	θ_N	c_{11}	c_{12}	c_{13}	a_{11}	a_{12}	a_{13}	g_{11}	g_{12}	g_{13}	*LogL*
ϕ_{A0}	θ_A		c_{22}	c_{23}	a_{21}	a_{22}	a_{23}	g_{21}	g_{22}	g_{23}	15906.13
ϕ_{G0}	θ_G			c_{33}	a_{31}	a_{32}	a_{33}	g_{31}	g_{32}	g_{33}	
0.0007	0.00253	0.002945	0.000143	-0.00046	0.23298	-0.01327	0.054124	0.957261	0.006383	-0.02561	
(0.084)[a]	(0.022)*	(0.000)**	(0.619)	(0.555)	(0.000)**	(0.152)	(0.041)*	(0.000)**	(0.0486)*	(0.095)	
0.00014	0.00066	~	0.000616	-0.00242	0.088529	0.10705	-0.013248	-0.015763	0.99018	0.038446	
(0.529)	(0.268)	~	(0.0634)	(0.139)	(0.012)*	(0.000)**	(0.241)	(0.106)	(0.000)**	(0.002)**	
0.00046	0.0022	~	~	0.001311	-0.02445	0.09573	0.25154	0.010459	-0.00165	0.94823	
(0.182)	(0.022)*	~	~	(0.656)	(0.163)	(0.004)**	(0.000)**	(0.131)	(0.6839)	(0.000)**	

Panel B: Composite coefficient values and significance for each ARCH and GARCH term

	c	ε^2_{Nt-1}	ε^2_{At-1}	ε^2_{Gt-1}	$\varepsilon_{Nt-1}\varepsilon_{At-1}$	$\varepsilon_{Nt-1}\varepsilon_{Gt-1}$	$\varepsilon_{At-1}\varepsilon_{Gt-1}$	h_{NNt-1}	h_{AAt-1}	h_{GGt-1}	h_{NAt-1}	h_{NGt-1}	h_{AGt-1}
h_{NNt}	0.00001[b] *c	0.05428 *	0.00784	0.00060 *	0.04125 *	-0.01139	-0.00433	0.91635 *	0.00025	0.00011	-0.03018	0.02002	-0.00033
h_{AAt}	0.00000	0.00018	0.01146 *	0.00018 *	-0.00284 *	-0.00035	0.00284 *	0.00004 *	0.98045 *	0.00148 *	0.01264 *	-0.00002	-0.04857 *
h_{GGt}	0.00001	0.00293 *	0.00916	0.06327 *	-0.01036	0.02723 *	-0.04816 *	0.00066	0.00000	0.89914 *	-0.00197	-0.00328	0.07291 *
h_{NAt}	0.00000	-0.00309	0.00948	-0.00032	0.02377 *	0.00341	-0.00144	0.00611 *	-0.01561	-0.00002	0.94776 *	-0.00152	0.01038
h_{NGt}	0.00000	-0.00570	-0.00848	-0.00615 *	-0.01751 *	0.05728 *	0.02461 *	0.01001	-0.00061	0.00992	0.03721 *	0.90744 *	-0.01454
h_{AGt}	0.00000	-0.00072	-0.01025	0.00333 *	0.00706 *	-0.00262	0.02566 *	-0.00016	0.03807 *	-0.00157	-0.02511 *	0.00609 *	0.93885 *

[a] p-values in parentheses; **: Significant at 1% level; *: Significant at 5% level

[a]: The coefficients in each of the six equations are functions of the coefficient estimates reported in Panel A. As such, the composite coefficient values are calculated from values of the corresponding estimates reported in Panel A.

[b]: A composite coefficient is deemed significant if and only if all its individual coefficients are significantly different from zero. E.g. The coefficient for the variable $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ in h_{GGt} is $2a_{13}a_{33}$. Since a_{13} and a_{33} are both significant, $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ is also significant. These composite coefficients are denoted with *.

Table 12: VAR (2) estimation results

Panel A: Natural rubber and silver

	c	σ_{Nt-1}	σ_{Nt-2}	V_{Nt-1}	V_{Nt-2}	σ_{St-1}	σ_{St-2}	V_{St-1}	V_{St-2}
σ_{Nt}	0.0105	0.0886	0.1223	0.0000	0.0000	-0.0035	0.0403	0.0000	0.0000
	(0.000)[a]**	(0.000)**	(0.000)**	(0.007)**	(0.000)**	(0.908)	(0.185)	(0.350)	(0.451)
V_{Nt}	94341.6500	8966968	-8649994	0.6630	0.2238	-1594790	638625	0.1393	-0.0534
	(0.012)*	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.358)	(0.000)**	(0.225)	(0.636)
σ_{St}	0.0066	-0.0468	-0.0045	0.0000	0.0000	0.1474	0.1015	0.0000	0.0000
	(0.000)**	(0.102)	(0.802)	(0.110)	(0.408)	(0.000)**	(0.000)**	(0.297)	(0.000)**
V_{St}	21015.9500	-292767	-269647	-0.0016	0.0050	2223103	-549636	0.5156	0.2135
	(0.005)**	(0.281)	(0.315)	(0.726)	(0.269)	(0.000)**	(0.114)	(0.000)**	(0.000)**

Panel B: Aluminum and silver

	c	σ_{At-1}	σ_{At-2}	V_{At-1}	V_{At-2}	σ_{St-1}	σ_{St-2}	V_{St-1}	V_{St-2}
σ_{At}	0.0047	0.1165	0.1139	0.0000	0.0000	0.0425	0.0657	0.0000	0.0000
	(0.000)**	(0.000)**	(0.000)**	(0.564)	(0.064)	(0.012)*	(0.000)**	(0.381)	(0.128)
V_{At}	25533.9400	705601	-528436	0.4000	0.3341	-130067	-220744	-0.0086	0.0005
	(0.000)**	(0.001)**	(0.014)*	(0.000)**	(0.000)**	(0.390)	(0.149)	(0.387)	(0.963)
σ_{St}	0.0067	0.0635	0.1097	0.0000	0.0000	0.1458	0.0942	0.0000	0.0000
	(0.000)**	(0.061)	(0.001)**	(0.178)	(0.059)	(0.000)**	(0.000)**	(0.427)	(0.000)**
V_{St}	13499.6300	937983	595920	0.0663	-0.1393	2056432	-668046	0.5120	0.2238
	(0.065)	(0.060)	(0.230)	(0.209)	(0.008)**	(0.000)**	(0.050)*	(0.000)**	(0.000)**

Panel C: Gasoline and silver

	c	σ_{Gt-1}	σ_{Gt-2}	V_{Gt-1}	V_{Gt-2}	σ_{St-1}	σ_{St-2}	V_{St-1}	V_{St-2}
σ_{Gt}	0.0088	0.0912	0.0912	0.0000	0.0000	0.0626	0.0140	0.0000	0.0000
	(0.000)**	(0.000)**	(0.000)**	(0.810)	(0.008)**	(0.114)	(0.586)	(0.131)	(0.673)
V_{Gt}	513637	19933962	-2049215	0.4182	0.2526	74642	576195	0.1134	0.0985
	(0.000)**	(0.000)**	(0.493)	(0.000)**	(0.000)**	(0.982)	(0.860)	(0.600)	(0.643)
σ_{St}	0.0062	-0.0156	0.0154	0.0000	0.0000	0.1660	0.1191	0.0000	0.0000
	(0.000)**	(0.466)	(0.474)	(0.494)	(0.400)	(0.000)**	(0.000)**	(0.338)	(0.000)**
V_{St}	6955.4740	630877	-595967	0.0031	0.0010	2211607	-493817	0.5132	0.2178
	(0.398)	(0.440)	(0.059)	(0.201)	(0.678)	(0.000)**	(0.152)	(0.000)**	(0.000)**

[a] p-values in parentheses; **: Significant at 1% level; *: Significant at 5% level

Table 13: Bivariate Full BEKK-GARCH (1,1) estimation results

Panel A: BEKK-GARCH coefficient estimates							*Panel B: Composite coefficients and significance of ARCH and GARCH term*							
ϕ_{N0}	c_{11}	c_{12}	a_{11}	a_{12}	g_{11}	g_{12}								
ϕ_{S0}	~	c_{22}	a_{21}	a_{22}	g_{21}	g_{22}		c	ε^2_{Nt-1}	ε^2_{St-1}	$\varepsilon_{Nt-1}\varepsilon_{St-1}$	h_{NNt-1}	h_{SSt-1}	h_{NSt-1}
Panel A: Natural rubber and silver (Log-likelihood = 10292.1)														
0.0005	0.0036	0.0000	0.2686	0.0228	0.9409	-0.0067	h_{NNt}	0.0000[b]	0.0722	0.0004	0.0112	0.8853	0.0001	0.0141
(0.188)[a]	(0.000)**		(0.000)**	(0.216)	(0.000)**	(0.120)		*[c]	*			*		
0.0002		-0.0001	0.0208	0.1755	0.0075	0.9854	h_{SSt}	0.0000	0.0005	0.0308	0.0080	0.0000	0.9710	-0.0133
(0.399)		(0.719)	(0.466)	(0.000)**	(0.284)	(0.000)**				*			*	
							h_{NSt}	0.0000	0.0061	0.0036	0.0476	-0.0063	0.0074	0.9271
											*			*
Panel B: Aluminum and silver (Log-likelihood = 11501.4)														
0.0002	0.0009	0.0000	0.1586	-0.0527	0.9820	0.0273	h_{AAt}	0.0000	0.0251	0.0003	0.0056	0.9642	0.0000	-0.0013
(0.459)	(0.000)**		(0.000)**	(0.031)*	(0.000)**	(0.000)**		*	*			*		
0.0003		-0.0015	0.0176	0.2713	-0.0007	0.9529	h_{SSt}	0.0000	0.0028	0.0736	-0.0286	0.0007	0.9080	0.0520
(0.302)		(0.000)**	(0.179)	(0.000)**	(0.885)	(0.000)**		*	*	*	*	*	*	*
							h_{ASt}	0.0000	-0.0084	0.0048	0.0421	0.0268	-0.0006	0.9357
									*		*	*		*
Panel C: Gasoline and silver (Log-likelihood = 10583.6)														
0.0005	0.0036	0.0000	0.2686	0.0228	0.9409	-0.0067	h_{GGt}	0.0000	0.0722	0.0004	0.0112	0.8853	0.0001	0.0141
(0.188)	(0.000)**		(0.000)**	(0.216)	(0.000)**	(0.120)		*	*			*		
0.0002		-0.0001	0.0208	0.1755	0.0075	0.9854	h_{SSt}	0.0000	0.0005	0.0308	0.0080	0.0000	0.9710	-0.0133
(0.399)		(0.719)	(0.466)	(0.000)**	(0.284)	(0.000)**				*			*	
							h_{GSt}	0.0000	0.0061	0.0036	0.0476	-0.0063	0.0074	0.9271
											*			*

[a] p-values in parentheses; **: Significant at 1% level; *: Significant at 5% level

[b]: The coefficients in each of the three equations in Panel B are functions of the coefficient estimates reported in Panel A. As such, the composite coefficient values are calculated from values of the corresponding estimates reported in Panel A.

[c]: A composite coefficient is deemed significant if and only if all its individual coefficients are significantly different from zero. E.g. The coefficient for the variable h_{ASt-1} in the h_{SSt} equation is $2g_{12}g_{22}$. While g_{22} is significant, g_{12} is not significant, such that h_{ASt-1} is insignificant in the h_{SSt} equation. The composite coefficients that are significant are denoted with a *.

Table 14: Results from principal components analysis based on sample correlation matrix

Round 1: NR, AL and GA

	Component 1	Component 2	Component 3	Variable	Eigen-vector 1	Eigen-vector 2	Eigen-vector 3
Eigen-value	2.9612	0.0388	0.00029	r_{Nt}	-0.5735	-0.8189	-0.0194
Variance Proportion	0.9871	0.0129	0.00001	r_{At}	-0.5791	0.4221	-0.6975
Cumulative Proportion	0.9871	0.9999	1	r_{Gt}	-0.5794	0.3888	0.7163

Round 2: NR, AL, GA and SL

	Component 1	Component 2	Component 3	Component 4	Variable	Eigen-vector 1	Eigen-vector 2	Eigen-vector 3	Eigen-vector 4
Eigen-value	2.9662	0.997	0.0364	0.0002	r_{Nt}	-0.5722	0.0701	-0.817	0.0199
Variance Proportion	0.7415	0.2494	0.0091	0.0000	r_{At}	-0.5787	0.0083	0.4229	0.6972
Cumulative Proportion	0.7415	0.9909	0.9999	1	r_{Gt}	-0.5790	0.0094	0.3888	-0.7166
					r_{St}	0.0505	0.9975	0.0503	-0.0004

Table 15: System estimation of common exposure adjusted returns

Panel A: Adjustment for commodity market factor

	υ_{Mit}	υ_{MNt-1}	υ_{MNt-2}	υ_{MAt-1}	υ_{MAt-2}	υ_{MGt-1}	υ_{MGt-2}
r_{Nt}	1.0003	0.0252	-0.0207	-0.0149	0.0009	-0.0527	0.0177
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.721)	(0.000)**	(0.000)**
r_{At}	1.0013	0.0026	-0.0007	-0.0086	0.0403	0.0300	-0.0193
	(0.000)**	(0.005)**	(0.471)	(0.000)**	(0.000)**	(0.000)**	(0.000)**
r_{Gt}	1.0017	0.0191	0.0139	0.0567	0.0351	0.0021	0.0309
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.503)	(0.000)**

Panel B: Adjustment for industry exposure

	υ_{Iit}	υ_{INt-1}	υ_{INt-2}	υ_{IAt-1}	υ_{IAt-2}	υ_{IGt-1}	υ_{IGt-2}
r_{Nt}	1.0000	0.0126	-0.0174	-0.0007	0.0023	0.0002	-0.0002
	(0.000)**	(0.000)**	(0.000)**	(0.766)	(0.301)	(0.910)	(0.914)
r_{At}	0.9999	0.0021	-0.0005	0.0039	0.0332	-0.0021	-0.0019
	(0.000)**	(0.211)	(0.731)	(0.152)**	(0.000)**	(0.283)	(0.316)
r_{Gt}	0.9999	0.0013	0.0001	0.0083	-0.0006	0.0179	0.0385
	(0.000)**	(0.370)	(0.970)	(0.001)**	(0.809)	(0.000)**	(0.000)**

[a] p-values in parentheses; **: Significant at 1% level; *: Significant at 5% level

Figure 1: Categorization of the existing literature on cross-market studies

Fundamental linkage		**Empirical linkage**	
Close-substitutes	Arbitrage forces	Equities and currencies	Commodities
Cross-listed stocks	*Spot-futures*	*International equity spillover*	*Gold and silver*
Miller & Morey (1996) Hauser et al (1998) Eun & Sabherwal (2003)	Garbade & Silber (1983) Kawaller et al (1987) Stoll & Whaley (1990) Chan (1992)	Hamao, Masulis &Ng (1990) Karolyi (1995) Kwan, Sim &Cotsomitis (1995) Liu, Wei, Yang & Chaung (1995) Liu and Pan (1997) Ghosh, Johnson & Saidi (1999) Ng (2000) Baur &Jung (2006)	Escribano & Granger (1996) Ciner (2001) Liu & Chou (2003) Lucey & Tully (2006) Gerolimetto et al (2006)
Competing derivative markets	*Spot-option*	*Major cross-rate currency spillover*	*Crude oil and equity*
Booth, Brockman & Tse (1998) Holder, Tomas & Webb (1999) Holder, Pace & Tomas (2002) Fung, Leung & Xu (2003) Chng (2004) Huang (2004)	Chan, Chung & Johnson (1993) Sun & Sutcliffe (2003) Chen & Lee (2005) Charlebois & Sapp (2007)	Engle, Ito &Lin (1990) Black &McMillan (2004) Doong & Yang (2004)	Ciner (2001) Maghyereh (2004) Aleisa et al (2004) Hammoudeh & Li (2005) Choi & Hammoudeh (2007) Hammoudeh & Malik (2007)
	Futures-option	*Regional currency spillover*	*Currency-crisis*
	Chan, Cheng & Fung (2000) Chiang & Fong (2001) He & Jang (2004) Fung (2007)	Kanas & Kouretas (2002) McMillan & Speight (2001) Caramazza, Ricci, & Salgado (2004) Rashed & Samanta (2004)	Tai (2003): ERM crisis of 1992 Jager, Klaassen & van Horen (2006): Asian currency crisis of 1997

Figure 2: Top 20 motor vehicle producing countries in 2006 (million units)

Country	1 2 3 4 5 6 7 8 9 10 11 12
Japan	11.48m
United States	11.26m
PR China	7.19m
Germany	5.82m
S.Korea	3.84m
France	3.17m
Spain	2.78m
Brazil	2.61m
Canada	2.57m
Mexico	2.05m
India	1.94m
UK	1.65m
Russia	1.51m
Thailand	1.306m
Italy	1.21m
Turkey	0.99m
Belgium	0.88m
Czech. Rep	0.86m
Iran	0.82m
Poland	0.72m

Reference: World motor vehicle production by country 2005-2006 OICA