Common industry exposure in seemingly unrelated commodities

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Abstract

We investigate cross-market trading dynamics in futures contracts written on seemingly unrelated commodities that are consumed by a common industry. On the Tokyo Commodity Exchange, we find such evidence in natural rubber (NR), palladium (PA) and gasoline (GA) futures markets. The automobile industry is responsible for more than 50% of global demand for each of these commodities. VAR estimation reveals short-run cross-market interaction between NR and GA, and from NR to PA. Cross-market influence exerted by PA is felt in longer dynamics, with PA volatility (volume) affecting NR (GA) volume (volatility). Our findings are robust to lag-specification, volatility measure, and consistent with full BEKK-GARCH estimation results. Further analysis, which benchmarks against silver futures market, TOCOM index and TOPIX transportation index, confirms that our results are driven by a common industry exposure, and not a commodity market factor. A simple trading rule that incorporates short-run GA and long-run PA dynamics to predict NR return yields positive economic profit. Our study offers new insights into how commodity and equity markets relate at an industry level, and implications for multi-commodity hedging.

JEL classification: G14, G15.

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

1 Introduction

Cross-market information flow is well-documented. 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 financial markets linkages to formulate investment strategies and portfolio formation. Firms incorporate covariation in relevant markets for hedging strategies.

Interestingly, existing cross-market studies generally fall into one of two categories. The first constitutes a conceptually clear linkage between markets that are either fundamentally identical e.g. cross-listed stocks, competing derivative contracts, or technically distinct but linked by arbitrage e.g. spot-futures-options. While the strong empirical support is not surprising, it is paramount to provide detailed scholarly evidence for specific applications. 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 a lack of fundamental justification, the careful empirical examination of such linkages is relevant to practitioners since, if they persist in the data, they would need to be acknowledged and documented. We present a non-exhaustive list of studies from both categories in Figure 1.

INSERT FIGURE 1

We have two related objectives. First, we propose a simple structural system to demon-

[1] This case was highlighted to us in the 2000 CBOT futures research symposium. Professor Bill Fung asked the motivation behind testing fractional 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.

strate cross-elasticity among seemingly unrelated commodities that share a common exposure. Price-quantity interactions within the system can be triggered by either an industry-level shock that transmits across complementary commodity inputs[2] or a supply-shock in commodity i that, by affecting the common industry, spills over to other complementary commodities[3]. Second, we empirically test for the presence of cross-market volatility (price) and volume (quantity) interactions across seemingly unrelated commodities.

Specifically, we examine Tokyo Commodity Exchange (TOCOM) futures contracts written on commodities that are exposed to the automobile industry: natural rubber (NR) for making tires; palladium (PA) for making auto-catalyst converters[4] and hybrid integrated circuits.[5]; gasoline (GA) to power internal-combustion engines. More than 50% of global production in NR, PA and GA is consumed by the automobile industry. We choose TOCOM since Japan is the top automobile manufacturing country in the world, and it is home to world-class automobile companies[6]. In addition, TOCOM offers futures trading in all three underlying commodities. Ideally, a cross-market study should be restricted to very similar market microstructure environment to avoid any technically-induced lead-lag dynamics.[7]

Our primary motivation stems from the literature's focus on markets that are either fundamentally similar or empirically linked without a clear economic justification. Our study of interactions among soft, precious metal and fuel-based futures contracts is based on a basic economic argument. If these commodities constitute essential inputs pertaining to a com-

[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]Auto-catalytic converters are used to convert up to 90% of harmful gases from auto-exhaust fumes (hydrocarbons, carbon monoxide and nitrogen oxide) into less harmful substances (nitrogen, carbon dioxide and water vapor). Indeed, as car makers around the world lift emission standards, so will the demand for PA. This is particularly the case for China, the world's third largest car-manufacturing country.

[5]The largest usage of hybrid integrated circuits is in automobile electronics.

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

[7]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.

mon output, then despite of physical dissimilarities, idiosyncratic seasonality and production cycles, they share a common automobile industry exposure. If the common exposure is non-trivial, then information flow which affects the automobile industry would also transmit across these commodities. This is empirically manifested in volume-volatility transmission across futures contracts written on seemingly unrelated commodities. Two recent studies establish cross-trading dynamics that are driven by economic linkages. Cohen and Frazzini (2008) document cross-return predictability among firms that are economically linked in customer-supplier relationships. Menzly and Ozban (2006) identify cross-momentum effects among industries that are economically linked in supply chains i.e. vertical industries.[8]

In addition, most studies examine NYMEX, CBOT and/or LME commodity contracts. 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 the largest commodity exchange in Japan, handling 83% of all commodity futures trading volume. Most relevant is the fact that TOCOM is the third largest in fuel-base futures trading, second largest in metal-base futures trading and hosts the world's largest NR futures market.

Our main results show that in short-run dynamics (lag-1 and lag-2), there is evident two-way interaction between NR and GA. There is also strong evidence of lag-1 NR volume affecting trading volume in PA. In contrast, there is no evidence of PA short-run dynamics affecting either NR or GA. Instead, the cross-market influence exerted by the PA is felt in longer dynamics. Specifically, PA lag-7 volatility affects NR trading volume, while PA lag-7 volume affects GA volatility. These results are robust to lag-specifications, volatility measures and are consistent with findings based on price reversals and variance ratios. We find significant short-term cross-market dynamics between NR and GA, and from NR to PA. There is also evidence of feedback effects from PA to both NR and GA. Interestingly,

[8]We thank an anonymous referee for bringing both papers to our attention.

PA volume has no impact on PA volatility whatsoever. The latter is instead influenced by lag-7 GA volatility. An array of subsequent analysis to ascertain the nature of the common exposure confirms that evident cross-market interaction among NR, PA and GA is attributed to their common non-trivial industry exposure, and not a commodity market factor.

The preceding findings offer implications for multi-commodity hedging and trading. In Section 4, we conceptually demonstrate multi-commodity hedging errors if inherent co-variations are not formally considered. In addition, we empirically examine five variant prediction models pertaining to a simple trading strategy for predicting NR return. We find that the two prediction models which separately incorporate GA short-run volume dynamics and PA long-run volatility dynamics to predict NR returns yield positive economic profit.

Our results are generated from a three-stage empirical analysis. First, we estimate a six-equation VAR to test for own-market and cross-market volatility-volume dynamics among NR, PA and GA. We focus on results that are robust to different lag specifications and volatility measures. Second, we check if our VAR results are consistent across sub-samples and with tri-variate full BEKK-GARCH (1,1) estimation.[9] Third, we conduct a series of tests to ascertain the nature of the common exposure. These tests, which involve comparisons with the silver (SL) futures market[10], TOPIX Transportation Equipment (TE) index (proxy for industry exposure) and TOCOM index (proxy for commodity market factor), confirm that our findings are driven by a common industry exposure, and not a commodity market factor.

The paper proceeds as follow. Model and methodology are outlined in section 2. Results are discussed in section 3. Implications are discussed in section 4. Section 5 concludes.

[9]Since volume is not included, GARCH estimates are not considered main results. Schwert (1989) identifies fluctuations in trading activity as a key explanation for time varying volatility. Lamoureux and Lastrapes (1990) report that volume variables are relevant in modeling GARCH effects. Wu and Xu (2000) argue that information processing by capital markets is manifested in volatility and trading volume.

[10]Here, we assume that SL has a trivial exposure to the automobile industry. While Audi made headlines a few years ago for delivering to a prince of the UAE an Audi A8 whose outer-pressing is made from pure silver, suffice to say, pure silver-bodied cars are not in the production lines of any Japanese car manufacturers.

2 Model and estimation

We present our conceptual argument for trading interactions among seemingly unrelated commodities that share a common industry exposure. 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

Consider a structural system that entails price-quantity interactions between commodity inputs $i = N, P, G$ for NR, PA and GA respectively, and automobile output y. Equation (1) contains three input prices P_i with corresponding global stockpiles Q_i. Faced with P_i, automobile manufacturers exhibit a set of cost-minimizing input demand q_i to produce output level Q_y. Assume an exogenous production technology 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 producers are affected by automobile output. The quantity of each commodity consumed depends on output level. The latter, in turn, is influenced by selling price P_y and commodity input costs. Due to unknown interactions within the system, the equations are specified with unknown functional forms $\{f_i, g_i, h\}$. Denote $\{\xi_{P_i}, \xi_{q_i}, \xi_y\}$ as the corresponding residuals to indicate that i) natural rubber, palladium 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.

Equation (1) conveys the idea of automobile output and production technology as common factors that induce price-quantity interactions among seemingly unrelated soft, precious metal and fuel futures contracts. 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 and 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 input commodity q_i is affected, through Q_y, by the price and quantity of related commodities $P_j, q_{j \neq i}, Q_j$.

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

Equation (2) demonstrates interactions among the price-quantity parameters of commodities that share a common industry exposure. 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 commodity data on Q_i. 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.

The discussion of equation (2) demonstrates how NR, PA and GA can be conceptually perceived as related commodities sharing a common industry exposure. In economic terms, a common yet dominant industry exposure implies non-trivial cross-elasticity that induces price-quantity interactions among related commodities. In finance terms, a common industry exposure implies non-zero return-volatility-volume cross-covariance structures in related commodities. 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 translates to cross-market volatility-volume dynamics, which can be examined from a multivariate time-series systems estimation.

2.2 Empirical methodology

Denote p_{it} as commodity i daily closing price and $r_{it} = Ln(\frac{p_{it}}{p_{it-1}})$ as daily return. Our main variables are volatility $\sigma_{it} = |r_{it}|$ and Yen-volume v_{it}, which facilitate a standardized comparison across markets.[11]

VAR estimation: Volatility-volume relations are well-documented in the literature, both theoretically[12] and empirically[13]. In commodities, Clark (1973) identifies a positive volume-volatility relation in cotton futures. Cornell (1981) finds positive contemporaneous volume-volatility relations in a study of 17 commodities futures contracts. Bessembinder and Seguin (1993) report similar findings across currency, metal, agriculture and financial contracts. Malliaris and Urrutia (1998) empirically document price-volume relationships for various agricultural contracts. Ciner (2002) reports that lagged volume is relevant for predicting absolute return for TOCOM platinium, gold and rubber futures contracts.

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

We estimate a six-equation VAR in equation (3) to test for cross-market volume-volatility transmission effects among NR, PA and GA. The presence of common exposure implies heteroscedasticity and contemporaneous covariance in the cross-equation residuals u_{1it}, u_{2it}. Accordingly, we estimate equation (3) using seemingly unrelated regression (SUR) procedure.[14]

Robustness checks: Our robustness checks include sub-sample analysis, different volatil-

[11] Descriptive statistics as well as a series of preliminary tests on stationarity, autocorrelation and causality features of the sample variables, are excluded from the current draft. They are available upon request.

[12] See Admati and Pfleiderer (1988), Foster and Viswanathan (1990, 1993), Wang (1994).

[13] See Gallant, Rossi and Tauchen (1992), Gannon (1994).

[14] The SUR or Zellner's method, estimates the parameters of the system, accounting for heteroscedasticity 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 between SUR and full-information maximum likelihood estimation.

ity measures and an alternative multivariate system estimation. Our sub-sample analysis addresses potential structural changes from alterations to TOCOM's NR and PA contracts. The NR market underwent two alterations in Jan 2005: i) the contract was moved from the Itayose batch system[15] 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.

On 24 Feb 2000, TOCOM suspended PA trading in response to heavy losses accumulated by several institutional investors on short positions.[16] The suspension was lifted on 15 Mar 2000 with TOCOM issuing Feb and Apr 2001 contracts under stringent margin requirements and price limits. Both contracts were illiquid, with traders focusing on the Dec 2000 contract throughout the first half of 2000.[17] Accordingly, we start our sample from July 2000. The PA contract was subsequently downsized from 1,500g to 500g from the Oct 2003 contract onwards. We examine pre- and post-Jan 2005 sub-samples as well as pre- and post-Oct 2003 sub-samples to test whether structural changes in the NR and PA markets affect our main results on cross-market information flow. In both cases, our main results are consistent.[18]

Second, 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 $\sigma_{it} = |r_{it}|$ rests on the intuition that opening p^o_{it} and/or closing price p_{it} are snapshots of the return generating process. They introduce extreme-value measures using continuously-monitored daily high and low prices p^h_{it}, p^l_{it}. Garman and Klass (2007) refine both measures to derive

[15]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. As such, only five market-clearing trade prices are generated in a given trading day.

[16]Towards the end of 1999, PA was trading at around \$350/oz. Its price jumped to \$433/oz in Jan 2000, and by 24 Feb 2000, it was trading at \$785/oz i.e. the price doubled within three months. The price surge was due to unreliable Russian production and shipments as well as automobile companies replenishing stockpile of the precious metal.

[17]In Jan 2001, when the Russian State Treasury announced an indefinite suspension of palladium export to the rest of the year, this drove PA prices to as high as \$1090/oz. At the same time, platinum was trading at around \$600/oz.

[18]Due to space constraint, we leave them out of the paper. They are available upon request.

an analytical scale-invariant[19] volatility estimator σ_{it}^{GK} that incorporates four daily prices $\{p_{it}^{o}, p_{it}^{h}, p_{it}^{l}, p_{it}\}$. They show that a composite volatility measure σ_{it}^{*} in equation (4), which is a weighted-average of the overnight price change and σ_{it}^{GK}, is eight times more efficient than σ_{it}. The parameter f denotes the proportion of a day when the market is closed.[20]

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

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

We apply both σ_{it} and σ_{it}^{*} in our estimation. Given that the NR contract migrated to continuous 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 $\sigma_{\mathrm{N}t}^{*}$ in cross-market dynamics, particularly in the post Jan 2005 sub-sample.

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

$$H_t = \begin{pmatrix} h_{NNt} & h_{NPt} & h_{NGt} \\ h_{PNt} & h_{PPt} & h_{PGt} \\ h_{GNt} & h_{GPt} & h_{GGt} \end{pmatrix}; \; \epsilon_t = \begin{pmatrix} \varepsilon_{Nt}^2 & \varepsilon_{Nt}\varepsilon_{Pt} & \varepsilon_{Nt}\varepsilon_{Gt} \\ \varepsilon_{Pt}\varepsilon_{Nt} & \varepsilon_{Pt}^2 & \varepsilon_{Pt}\varepsilon_{Gt} \\ \varepsilon_{Gt}\varepsilon_{Nt} & \varepsilon_{Gt}\varepsilon_{Pt} & \varepsilon_{Gt}^2 \end{pmatrix}$$

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

$$H_t = C_0' C_0 + A'\epsilon_{t-1}A + G'H_{t-1}G \tag{5}$$

Third, we estimate a tri-variate full BEKK-GARCH (1,1) to analyze the underlying commodities' conditional covariance structures. The model is presented in equation (5).[21]

[19] 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.

[20] 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.

[21] Engle and Kroner (1995) propose the BEKK-GARCH as an empirically convenient representation to estimate system of equations. They show that by construction, the BEKK-GARCH guarantees a positive definite conditional variance-covariance matrix H_t under weak conditions. This is desirable for addressing convergence problems in maximum likelihood estimation (MLE).

The estimation involves extracting a set of i zero-mean residuals ε_{it} from the mean 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. C_0 is a 3x3 upper triangular matrix of constants; coefficient matrices A and G are affiliated correspondingly with the residual variance-covariance matrix of ARCH terms ϵ_t, and lag-1 conditional variance-covariance matrix of GARCH terms H_{t-1}. Both H_t and ϵ_t are symmetric.

The full BEKK-GARCH provides a richer interaction among ARCH and GARCH terms in each of the six conditional variance and covariance equations of H_t. The estimation of H_t allows covariance terms to enter the conditional variance equations. This is paramount to our investigation of cross-market interaction in related commodity markets. Despite the computational challenges, incorporating NR, PA and GA in a full BEKK-GARCH estimation facilitates a consistent comparison with VAR estimation results.

Industry exposure or commodity market factor: Soaring prices and increasing volatility have elevated commodity to a stand-alone asset class. We address the possibility that any trading interaction among NR, PA and GA is simply due to some latent commodity market factor. We conduct two sets of tests to ascertain the nature of the latent common exposure (if any). The first set involves TOCOM's silver (SL) futures market, while the second set involves the TOCOM Index [22] and TOPIX TE index[23] to proxy for exposures to the commodity market portfolio (M) and automobile industry (I) respectively.

First, we undertake VAR and BEKK-GARCH estimations for pairwise comparison between each of NR, PA and GA against SL. Here, we assume that silver has a trivial (if

[22]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.

[23]In brief, the TOPIX Sector 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.

any) exposure to Japan's automobile industry. If a non-trivial commodity market factor exists, then we should find cross-market interactions among all commodities. But if volume-volatility interaction is driven mainly by a common industry exposure, then the various pairwise comparisons should not yield significant cross-market trading dynamics.

To follow, we conduct two rounds of principle component analysis (PCA), which confirms a dominant first component explains return variability across $\{r_{Nt}, r_{Pt}, r_{Gt}\}$. In the second round PCA, r_{St} is included to examine its impact on the first principal component. If the latter reflects a common industry exposure, then adding SL to the second round PCA will cause the variance explained by the first principal component to drop. The value corresponding to silver in the first eigenvector will be trivial. To follow, the variance explained by another principle component will increase, and silver's weight in the corresponding eigenvector will be significantly larger than those of NA, PA or GA.

$$
\begin{aligned}
\sigma_{it} &= \alpha_0 + \sum_{k=1}^{K}(\alpha_k \sigma_{it-k} + \beta_{kI}\sigma_{It-k}) + v_{Iit} \; \forall i = N, P, G \\
\sigma_{Nt} &= v_{INt} + \sum_{s=1}^{S}(\phi_{1s} v_{INt-s} + \gamma_{1s} v_{IPt-s} + \delta_{1s} v_{IGt-s}) \\
\sigma_{Pt} &= v_{IPt} + \sum_{s=1}^{S}(\phi_{2s} v_{INt-s} + \gamma_{2s} v_{IPt-s} + \delta_{2s} v_{IGt-s}) \\
\sigma_{Gt} &= v_{IGt} + \sum_{s=1}^{S}(\phi_{3s} v_{INt-s} + \gamma_{3s} v_{IPt-s} + \delta_{3s} v_{IGt-s}) \qquad (6)
\end{aligned}
$$

Second, we perform a quasi vector-moving-average (VMA) estimation[24] on the residual volatility of NR, PA and GA after adjustments for a common exposure. Consider an industry exposure σ_{It} and a VAR specification for $\{\sigma_{\mathrm{Nt}}, \sigma_{\mathrm{Pt}}, \sigma_{\mathrm{Gt}}\}$. The idea is to substitute the lagged volatilities of other markets in each commodity's volatility equation (e.g. σ_{Pt-1} and σ_{Gt-1} in σ_{Nt}) with σ_{It-1}, assuming the industry exposure is driving cross-market interactions. As there are no links between the volatility equations, they are estimated as

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

single equations. Outlined in equation (6), the industry-adjusted residual volatility series $\{v_{INt}, v_{IPt}, v_{IGt}\}$ are subsequently estimated as a VMA. The process is repeated to estimate a VMA of $\{v_{MNt}, v_{MPt}, v_{MGt}\}$ after adjusting for a commodity market factor σ_{Mt}.

The two VMA estimations allows us to ascertain which of industry exposure or commodity market factor is more relevant at explaining interactions among NA, PA and GA. If industry exposure is more relevant, then the VMA estimation of $\{v_{INt}, v_{IPt}, v_{IGt}\}$ based on σ_{It} as the filter should reveal limited cross-market interactions among $\{v_{INt}, v_{IPt}, v_{IGt}\}$. To follow, as the commodity market factor is less relevant, this implies σ_{Mt} is a less adequate filter, and a common exposure remains in $\{v_{MNt}, v_{MPt}, v_{MGt}\}$. This is manifested in more evident cross-market interactions from the subsequent VMA estimation. Conversely, if commodity market factor is more relevant than industry exposure, then we would find limited interactions among $\{v_{MNt}, v_{MPt}, v_{MGt}\}$ and more evident interactions among $\{v_{INt}, v_{IPt}, v_{IGt}\}$. For robustness, we consider both return and volatility in our VMA estimation.

3 Background, data and results

3.1 Institutional details, data and sampling

Our daily data is downloaded from the TOCOM website. The files contain 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 markets. Earlier, we highlighted the suspension of PA trading during Feb-Mar 2000. Normal trading in the PA contract in the first half of 2000 is considerably subdued. Our sample starts from 3-Jul-2000 until 31-Mar-2008, which is the latest data available.

INSERT TABLE 1

NR, PA and GA 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.[25] Our sample closing price is from the afternoon session. Unlike most futures markets, trading in Japanese commodity futures is concentrated on the most deferred contract.[26] Based on open interest data, TOCOM traders 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 over the sample period and across NR, PA and GA. We construct our sample from data of the most deferred contract. At month end, we switch to the next contract's data.

3.2 VAR estimation results

As our main results are derived from VAR estimation, the appropriate lag specification is a pertinent consideration. In conjunction with two volatility measures, the estimation spans across alternative VAR specifications. To note, our focus is only on results that are significant and robust across dissimilar specifications. With daily futures data, we conjecture it is unlikely for volume and volatility dynamics to extend beyond 10 lags i.e. two weeks.[28]

For each of σ_{it} and σ^*_{it}, we apply a 4-step diagnostic check.[29] First, we examine an array of information criteria[30] to identify optimal lag specifications. As different information criteria indicate different lags, we cross reference the lags by sequentially back-testing an unrestricted

[25]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.

[26]Webb (1995) suggests this is due to Japanese speculators allowing more time for their longer maturity futures positions to become profitable.

[27]For example, trading interest in NR during Feb 2001 centers on the Jul 2001 contract. Towards the end of 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]Indeed, the PACF results reveal that autocorrelation coefficients for all volatility and volume variables beyond the 7^{th} lag are insignificant. As such, we specify a maximum lag length of 12 in our diagnostic tests, which involves sequentially trimming back the lag specification.

[29]Due to space constraint, we drop the tables of results and corresponding detailed discussion from the current draft.

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

VAR(12) at each lag based on the Chi-square and Wald test statistics for individual variable and joint variables significance respectively. Our two diagnostic tests highlight lag-2 and lag-7 specifications. The third step is a likelihood ratio (LR) test[31] between the restricted VAR(2) and unrestricted VAR(7). For both σ_{it} and σ^*_{it}, the LR-test rejects the null in favor of a VAR(7) specification. Lastly, perform a Lagrange Multiplier (LM) test for serial correlation in the residuals from both VAR specifications. A lag-7 specification removes most of the residual serial correlation. While our 4-step diagnostic check supports a VAR(7) specification, we are mindful of model over-fitting.[32] Furthermore, when we sequentially back-test an unrestrictd VAR(12), we find that most of the significant variables cluster around lags 1, 2 and 7.

INSERT TABLE 2

For each of σ_{it} and σ^*_{it}, we consider three alternative VAR specifications: VAR(2), VAR(7) and VAR(2-7). The latter is a VAR(2) that includes only lag-7 variables. We present and discuss only VAR(2-7) estimation in Table 2, the results of which are representative of those of VAR(2) and VAR(7).[33] $\sigma_{Nt-1}, \sigma_{Pt-1}, \sigma_{Gt-1}$ are significant in both their own volume and volatility equations in both panels, except σ^*_{Pt-1} in the v_{Pt} equation. Both v_{Pt-1} and v_{Gt-1} are significant only in their own volume equation, while v_{Nt-1} is significant in both $\sigma_{\mathrm{N}t}$ and v_{Nt} equations. This is consistent in both panels. $\sigma_{Nt-2}, \sigma_{Pt-2}, \sigma_{Gt-2}$ are significant in only their own-market volatility equations, except σ_{Nt-2} in the v_{Nt} equation. For the three markets, lag-2 volume dynamics is significant in their own-volume equation across both panels. v_{Gt-2} is significant in both its own-market volume and volatility equations. The addition of lag-7

[31]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.

[32]To note, a six-equation VAR(7) on volume-volatility interactions across three markets generates 252 estimated coefficients, excluding constants and dummy variables.

[33]The results and detailed discussions of other VAR specifications were included in a previous draft. They are available upon request.

variables is important, particularly volume. $v_{Nt-7}, v_{Pt-7}, v_{Gt-7}$ are significant in both own-market equations in Panel A, and in their own-volume equations in Panel B. Lag-7 volatility are significant as well, but mostly in Panel B, and is limited to own-volatility equations.

For cross-market effects, there is evidence of two-way interaction between NR and GA. Specifically, v_{Gt-1} affects $\sigma_{\mathrm{N}t}$ and $v_{\mathrm{N}t}$ in both panels, and v_{Gt-2} is significant in both panels' v_{Nt} equation. Similarly, v_{Nt-1} and $\sigma_{\mathrm{N}t}$ are both significant in the $v_{\mathrm{G}t}$ equation of both panels. Evidence of cross-market influence on the PA market remains limited to Panel B. At lag-1, the influence is felt mainly from the NR market, with σ^*_{Nt-1} significant in both σ^*_{Pt} and $v_{\mathrm{P}t}$ equations, and v_{Nt-1} significant in the $v_{\mathrm{P}t}$ equation. The inclusion of lag-7 dynamics reveal some interesting result. Lag-7 volume and volatility variables for GA are significant in the PA volatility equation across both panels. The influence of PA variables on the other two markets are similar to those from the VAR(2) estimation i.e. σ_{Pt-1} in the $\sigma_{\mathrm{G}t}$ equation and v_{Pt-2} in the $v_{\mathrm{N}t}$ equation in Panel A. The lag-7 PA variables exerts some influence on NR and GA, with σ_{Pt-7} significant in the $v_{\mathrm{N}t}$ equation and v_{Pt-7} significant in the $\sigma_{\mathrm{G}t}$ equation.

A comparison across six VAR estimations is awkward given the sheer quantity of results. As we are interested only in the significance or otherwise of variables, we propose a simplified approach in Table 3, which we label a VAR significance score-board. The values in the table indicate the number of times that a variable is significant in the six VAR estimations. Panel A reports the significance scores of lag-1 and lag-2 variables, which are present in all six VAR estimations. Hence the maximum (minimum) score is 6(0).[34] We regard a variable that obtain a significance score of 5 or 6 (0 or 1) as robustly (in)significant. Panel B reports the significance scores for lag-7 variables from VAR(2-7) and VAR(7) specifications.[35]

INSERT TABLE 3

[34]For example, σ_{Nt-1} scored 6 in both the $\sigma_{\mathrm{N}t}$ and $v_{\mathrm{N}t}$ 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.

[35]Accordingly, the maximum attainable score in Panel B is 4, not 6.

Table 3 shows that lag-1 volatility is significant in both own-market σ_{it} and v_{it} equations. This result is similar for all except σ_{Pt-1} in the $v_{\mathrm{P}t}$ equation, which scored 3. Conversely, lag-1 volume is robustly significant only in its own-volume equations. Interestingly, v_{Pt-1} is completely irrelevant in the PA volatility equation. While v_{Gt-1} is significant in its own-volume equation, the result is not robust. Lag-2 volatility variables are robustly significant in their own-volatility equations. However, they are not significant in their own-volume equations. σ_{Nt-2}, σ_{Pt-2} and σ_{Gt-2} achieve corresponding scores of 3, 2, and 0 in the $v_{\mathrm{N}t}$, $v_{\mathrm{P}t}$ and $v_{\mathrm{G}t}$ equations. Lag-2 volume variables scored 5 and 6 in their own-volume equations. As with lag-2 volatility variables, the significance of lag-2 volume variables in their own-volatility equations is not robust: v_{Nt-2} scored 2; v_{Pt-2} scored 1; v_{Gt-2} scored 4.

For cross-market dynamics, Table 3 confirms an evident two-way interaction between NR and GA. Specifically, v_{Nt-1} and σ_{Nt-2} both exhibit a robust and significant influence in the v_{Gt} equation, scoring 6 and 5 respectively. The influence of GA on both $\sigma_{\mathrm{N}t}$ and $v_{\mathrm{N}t}$ is felt mainly through volume effects. v_{Gt-1} scored 5 and 6 in the $\sigma_{\mathrm{N}t}$ and $v_{\mathrm{N}t}$ equations, while v_{Gt-2} scored 6 in the $v_{\mathrm{N}t}$ equation. Lastly, NR volume spill over to PA volume, with v_{Nt-1} scoring 5 in the $v_{\mathrm{P}t}$ equation. In contrast, PA does not exert any evident influence on NR and GA, with lagged PA volatility and volume insignificant in the volatility-volume equations of the NR and GA markets. Panel B shows that any cross-market interaction with PA is manifested in longer-term dynamics. Specifically, σ_{Pt-7} is significant in the $v_{\mathrm{N}t}$ equation and v_{Pt-7} significant in the $\sigma_{\mathrm{G}t}$ equation. Given the reduced significance of own-market lag-7 variables, the support for a VAR(7) specification is likely driven by lag-7 PA variables in cross-market interaction. Another interesting observation is the influence of σ_{Gt-7} in the $\sigma_{\mathrm{P}t}$ equation. To note, v_{Pt-1}, v_{Pt-2} have no influence whatsoever in the $\sigma_{\mathrm{P}t}$ equation.

In sum, VAR estimation reveals some interesting cross-market trading dynamics among NR, PA and GA. Surprisingly, v_{Pt-1} has no influence whatsoever on PA volatility and v_{Gt-1}

has limited impact on its own-volatility equation.[36] Instead, PA volatility is influenced by GA volatility in longer dynamics. Similarly, for $\sigma_{\mathrm{G}t}$, while own-volume plays a limited role, cross-market influence is felt from both NR volatility and PA volume in longer dynamics. Taken together, the results support the presence of cross-market interaction across the three commodities. To note, the interaction between NR and GA is felt in shorter trading dynamics while the interaction between PA and its two counterparts is felt in longer trading dynamics.

3.3 Results from robustness checks

Sub-sample analysis: We generate VAR significance score-boards for pre- and post-Jan 2005 sub-samples to see if results are affected by the NR contract's downsizing and migration to electronic trading.[37] The corresponding VAR score-boards are similar to Table 3. Specifically, NR lag-1 volume remain influential in the $v_{\mathrm{P}t}$ equation; v_{Gt-1} plays an important role in $\sigma_{\mathrm{N}t}$ and $v_{\mathrm{N}t}$ for both sub-samples. Interestingly, there is stronger cross-market volume effects in the post Jan 2005 sub-sample. Since NR, PA and GA are traded on the same computerized platform, this facilitates common information flow, which is manifested in cross-market volatility-volume interactions. We also examine pre- and post-Oct 2003 sub-samples to check if the main finding is affected by the PA contract downsizing. Both sub-samples give a similar finding of PA's influence on NR and GA being felt in longer dynamics.

Full BEKK-GARCH results: $r_{\mathrm{P}t}$ has a significant lag-1 serial correlation, but $r_{\mathrm{N}t}$ and $r_{\mathrm{G}t}$ are serially uncorrelated. All returns exhibit a significant Monday effect. Hence, the GARCH mean-equations for NR and GA include only a constant ϕ_{i0} and Monday dummy with coefficient θ_i. [38] The results are reported in Table 4.[39]. Panel A reports individual

[36]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.

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

[38]We have also tested for a Friday dummy variable, but it is not significant. We did not report the coefficient for r_{Pt-1} so as not to create an extra column in Panel A.

[39]The maximum likelihood estimation algorithm for the full BEKK-GARCH model is programmed in

coefficients and p-values. The results in Panel B are the composite coefficients of ARCH and GARCH variables in each variance or covariance equation. These coefficients are functions of the individual coefficients reported in Panel A. As such, their values are calculated from values of the corresponding estimates. A composite coefficient is deemed significant if and only if all its individual coefficients are significant.[40] All own-equation ARCH and GARCH terms are significant in each of the six equations.

INSERT TABLE 4

GARCH and VAR are consistent in finding short-run dynamics between the NR and GA markets. Both ε^2_{Gt-1} and h_{GGt-1} are significant in the h_{NNt} equation. h_{NGt-1} is also relevant to the h_{NNt} equation. Likewise, ε^2_{Nt-1} and $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ are both significant in the h_{GGt} equation. $\varepsilon_{Nt-1}\varepsilon_{Gt-1}$ plays an important role in the covariance equations. Second, GARCH results support the finding that PA has limited impact on both NR and GA in the short-run. The significance of both ε^2_{Pt-1} and h_{PPt-1} are limited to their own h_{PPt} equation. In contrast, the h_{PPt} equation is influenced by the conditional covariances with NR and GA.

Industry exposure or commodity market factor: In Table 5, we report bivariate BEKK-GARCH results from comparisons against SL.[41] In Tables 5a and 5c, only own-lag ARCH and GARCH terms are significant in their corresponding equations. But the estimation of PA and SL in Table 5b shows that every single variable is significant across the three equations i.e. two-way cross-market interaction. Bivariate BEKK-GARCH estimations do not reveal any evident cross-market interaction between NR-SL and between GA-SL. However, they reveal a substantial interaction between the the two metal-based futures

Eviews and cross-checked against estimates from Matlab. We are unable to consider the first lag in a three market full BEKK-GARCH estimation due to convergence problems.

[40] 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 *.

[41] Comparisons based on VAR estimation and discussions are available upon request.

contracts. We shall comment on this after our discussion on PCA results. Thus far, there is no evident support for a commodity market factor driving cross-market interactions.

INSERT TABLE 5

PCA results are reported in Table 6. In the three-market PCA, the first component explains 60% of variability across $\{r_{\mathrm{N}t}, r_{\mathrm{P}t}, r_{\mathrm{G}t}\}$, with similar weights across commodities. When SL is included in the second round PCA, variance explained by the first component dropped to 45%, with similar weights for $\{r_{\mathrm{N}t}, r_{\mathrm{P}t}, r_{\mathrm{G}t}\}$ in the first eigenvector. The weight attributed to SL is much smaller and has the opposite sign. Thus, it is unlikely that the first component is a commodity factor. To follow, the fourth component explains 14% of variability across $\{r_{\mathrm{N}t}, r_{\mathrm{P}t}, r_{\mathrm{G}t}, r_{St}\}$, which corresponds to the drop in variance explained by the first component. The weights for PA and SL stand out in the fourth eigenvector. This is consistent with BEKK-GARCH results suggesting some interaction between PA and SL.

INSERT TABLE 6

To note, a systematic PA-SL interaction is not surprising. In Japan, silver-palladium alloys[42] are heavily used i) in dentistry for bridges and crowns[43], and ii) by electronics companies for multi-layer ceramic capacitors (MLCC). While the investigation of an 'alloy' exposure is beyond the scope of this paper, evident cross-market interactions between PA and SL reaffirm our argument that commodity market co-movement is likely to be driven by their common industry exposure rather than some commodity market factor.

Finally, we discuss VMA results in Table 7 based on return.[44] To note, we consider lag-1 and lag-2 variables single equation estimations. To follow, the results in Table 7 are

[42]Adding PA to SL increases hardness, melting point and resistance to tarnishing.

[43]Japan is the world's largest palladium consumer for dental applications

[44]While the results based on volatility are not as clear-cut, they are consistent with the results in Table 15, hence are not presented. We could not perform a similar VMA analysis based on volumes since we do not have turnover data for the TOPIX index.

based on a VMA(2) specification.[45] In Panel A, the VMA estimates are based on residuals $\{v_{MNt}, v_{MPt}, v_{MGt}\}$ extracted using TOCOM index as the filter. The results in Panel B are based on residuals $\{v_{INt}, v_{IPt}, v_{IGt}\}$ extracted using TOPIX TE index as the filter.

INSERT TABLE 7

When r_{Mt-1}, r_{Mt-2} are used to extract $\{v_{MNt}, v_{MPt}, v_{MGt}\}$, cross-market interaction remains evident in the VMA estimation e.g. v_{MGt-1}, v_{MGt-2} and v_{MPt-1} are significant in the v_{MNt} equation, while v_{MNt-1} and v_{MNt-2} are significant in the v_{MGt} equation. In fact, except v_{MPt-2} in the r_{Nt} equation and v_{MNt-2} in the r_{Pt} equation, all cross-market variables are significant. All own-market lagged residual returns are also significant, which is surprising given that own-market lagged returns were included in the first round regressions. In stark contrast, Panel B shows that when r_{It-1}, r_{It-2} are used to extract $\{v_{INt}, v_{IPt}, v_{IGt}\}$, all cross-market variables that are significant in Panel A are insignificant in Panel B. However, all own-market lagged returns remain significant. What Table 7 shows is that the TOPIX index is more relevant at explaining cross-commodity return interactions than the TOCOM index.

4 Implications for hedging and trading

We discuss two implications. First, we show in the appendix that when a firm is exposed to complementary commodities, modeling optimal hedge ratio (OHR) on a commodity-by-commodity basis produce hedging errors. Whether the conceptual hedging errors are economically relevant is an empirical question. Second, we implement a simple trading strategy to see if evidence of cross-market interaction among related commodities translates into economic profits. Consider five prediction models in equation (7) to generate a series of 1-step ahead forecasts of r_{Nt}. To note, Model (1), or M(1), is a naive model nested in M(2) to M(5).

[45] We check against results from the same procedure adding lag-7 variables. The overall finding across the two panels remain consistent.

The objective is to see if the more comprehensive models are able to outperform M(1). M(2) and M(3) test for incremental value from adding lagged GA and PA returns respectively. M(4) and M(5) separately test the economic relevance of (v_{Gt-1}, v_{Gt-2}) and σ_{Pt-7} on NR.

$$
\begin{aligned}
M1 :& r_{Nt+1} = a + b_1 r_{\mathrm{N}t} + b_2 r_{Nt-1} + \epsilon_{Nt+1} \\
M2 :& r_{Nt+1} = a + b_1 r_{\mathrm{N}t} + b_2 r_{Nt-1} + g_1 r_{\mathrm{G}t} + g_2 r_{Gt-1} + \epsilon_{Nt+1} \\
M3 :& r_{Nt+1} = a + b_1 r_{\mathrm{N}t} + b_2 r_{Nt-1} + g_1 r_{Pt} + g_2 r_{Pt-1} + g_3 r_{Pt-6} + \epsilon_{Nt+1} \\
M4 :& r_{Nt+1} = a + b_1 r_{\mathrm{N}t} + b_2 r_{Nt-1} + g_1 v_{Gt} + g_2 v_{Gt-1} + \epsilon_{Nt+1} \\
M5 :& r_{Nt+1} = a + b_1 r_{\mathrm{N}t} + b_2 r_{Nt-1} + g_1 \sigma_{Pt} + g_2 \sigma_{Pt-1} + g_3 \sigma_{Pt-6} + \epsilon_{Nt+1}
\end{aligned} \tag{7}
$$

For each model, we apply the following procedure. The estimation sample consists of the first 1,400 observations. A series of 1-step ahead daily forecasts r_{Nt+1} is generated by sequentially updating coefficients one observation at a time into the test sample of 500 observations i.e. two years. Our simple trading rule involves setting up \$1 in a NR futures contract according to the sign of r_{Nt+1}. If the sign for the next period is the same, we keep the position intact. But when the sign changes, we close out the existing position, then take up an opposite position. Based on this, we calculate the cumulative daily return. At the end of the test sample, we compare the cumulative returns from competing models.

INSERT FIGURE 2

Figure 2 shows the cumulative value of \$1 invested over a two-year horizon. We discuss two main findings. First, only M(4) and M(5) manage positive returns. For M(4), the cumulative value of \$1 is \$1.21 in two years, or around 10% pa. For M(5), \$1 becomes \$1.18 or around 9% pa. Assuming that transaction cost is no larger than 9%, M(4) and M(5) give positive economic profit. Second, M(1) to M(3) generate losses. M(3), which included lagged PA return, is near zero profit. M(1) is second-last. These profit results are consistent with key findings in Table 3. The influence of GA on NR is felt in short-run volume dynamics, while the influence of PA on NR is in long-run volatility dynamics. M(4) and M(5) separately harness these cross-market effects in return prediction, yielding positive economic profit.

5 Concluding remarks

We present a basic economic argument of cross-elasticity in complementary commodities consumed by a common industry. Non-trivial cross-elasticity and slow information flow are empirically manifested in cross-market volume-volatility interactions among seemingly unrelated commodities. Based on a reduced-form price-quantity system, we investigate cross-market volatility-volume transmission effects in TOCOM's NR, PA and GA futures markets. The underlying commodities share a common exposure to Japan's automobile industry.

Our main results, which survive stringent diagnostic checks and robustness tests, document short-run cross-market dynamics between NR and GA, and from NR to PA. PA short-run trading dynamics does not seem affect either NR or GA. Instead, the cross-market influence exerted by PA is felt in longer dynamics. Specifically, PA lag-7 volatility is influential to NR trading volume, while PA lag-7 trading volume is influential to GA volatility. Interestingly, $\sigma_{\mathrm{P}t}$ is not affected by its own lagged volume at all, but is instead affected by σ_{Gt-7}. We also show that a common industry exposure, and not a commodity market factor, is driving cross-market trading dynamics in these related commodity futures.

A recent paper by Hong, Torous and Valkanov (2007) document strong evidence that some industries, including metal and petroleum, lead the overall stock market by up to two months. In conjunction with findings documented in this paper, an interesting question is whether there is evidence that trading activity in 'leading' industries, such as metal and petroleum, are being influenced by related metal- and fuel-based futures markets, and the implications in terms of a profitable trading strategy. That question is currently being pursued.

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Appendix

We provide an analytical demonstration of possible hedging errors generated from ignoring non-trivial covariance between related commodities. For brevity, we present a two-commodity discussion involving NR and PA, and we suppress all time subscripts. The algebra can be easily expanded to encompass three commodities. An analysis with time-subscripts would imply the consideration of cross-serial covariances among related commodity futures.

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. Let S_N and F_N be the values of the spot and futures positions, and h_N is the spot-futures sensitivity measure. The OHR $h_i^* = \frac{\sigma_{isf}}{\sigma_{if}^2}$, where σ_{isf} is the spot-futures covariance and σ_{if}^2 is the futures variance, is derived by minimizing the variance of the overall position $Var(S_N - h_N F_N)$:

$$\begin{aligned}\sigma_1^2 &= \sigma_{Ns}^2 + h_N^2\sigma_{Nf}^2 - 2h_N\sigma_{Nsf}\\ \frac{\partial\sigma_1^2}{\partial h_N} &= 2h_N\sigma_{Nf}^2 - 2\sigma_{Nsf} = 0\\ h_N^* &= \frac{\sigma_{Nsf}}{\sigma_{Nf}^2} \qquad (8)\end{aligned}$$

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

A car manufacturer trying to minimize the variability of its overall input cost would take up NR and PA futures to hedge against rising commodity prices. The variance of its overall position is $Var(S_N - h_N F_N) + Var(S_P - h_P F_P) + Cov[(S_N - h_N F_N)(S_P - h_P F_P)]$.[46] We show below that multi-commodity hedging on a commodity-by-commodity basis based on h_N^* and h_P^*, is valid only when there is no interaction between NR and PA. E.g. if NR futures and PA spot covariance σ_{NfPs} and NR and PA futures covariance σ_{NPf} are both trivial, h_N reduces to the single-commodity h_N^*. The case for h_P reducing to h_P^* is similarly described.

$$\begin{aligned}\sigma_2^2 = {}&(\sigma_{Ns}^2 + h_N^2\sigma_{Nf}^2 - 2h_N\sigma_{Nsf}) + (\sigma_{Ps}^2 + h_P^2\sigma_{Pf}^2 - 2h_P\sigma_{Psf})\\ &+ \sigma_{NPs} + h_N h_P\sigma_{NPf} - h_N\sigma_{NfPs} - h_P\sigma_{NsPf}\end{aligned}$$

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

$$\begin{aligned}\frac{\partial\sigma_2^2}{\partial h_P} &= 2h_P\sigma_{Pf}^2 - 2\sigma_{Psf} + h_N\sigma_{NPf} - \sigma_{NsPf} = 0\\ h_P &= h_P^* + \frac{\sigma_{NsPf} - h_N\sigma_{NPf}}{2\sigma_{Pf}^2} \qquad (9)\end{aligned}$$

[46] 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)	Palladium (PA)	Gasoline (GA)
Listing date	12th Dec 1952	3rd Aug 1992	5ht July 1999
Underlying asset	Ribbed smoked sheet (RSS) No. 3	Fine palladium of minimum 99.95% purity	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	Even-month cycle up to 12 months 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	Up to Aug 2003 contracts: 1,500g Oct 2003 contracts onwards: 500g	50 kiloliters (kl)
Minimum tick	Price quote: Yen/kg 0.1 Yen/kg	Price quote: Yen/g 1 Yen/g	Price quote: Yen/kl 10 Yen/kl
Price and position limit	Current month: 200 2nd month: 600 3rd month: 1600 Others: 3,000/contract month	Current month: 60 2nd contract month: 240 3rd & 4th contract month: 360 each Others: 600/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 prior to delivery day (last trading day of all even months	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: 120,000 Others: 60,000 yen	Front contract: 202,500 Others: 135,000

Table 2: VAR (2-7) estimation results

Panel A: Absolute return measure of volatility

	c	σ_{Nt-1}	σ_{Pt-1}	σ_{Gt-1}	v_{Nt-1}	v_{Pt-1}	v_{Gt-1}	σ_{Nt-2}	σ_{Pt-2}	σ_{Gt-2}	v_{Nt-2}	v_{Pt-2}	v_{Gt-2}	σ_{Nt-7}	σ_{Pt-7}	σ_{Gt-7}	v_{Nt-7}	v_{Pt-7}	v_{Gt-7}
σ_{Nt}	0.011	0.084	0.010	-0.001	0.000	0.000	0.000	0.101	0.018	-0.001	0.000	0.000	0.000	0.033	-0.006	0.022	0.000	0.000	0.000
	(0.000)**	(0.001)**	(0.596)	(0.969)	(0.002)**	(0.929)	(0.008)**	(0.000)**	(0.352)	(0.969)	(0.000)**	(0.427)	(0.990)	(0.164)	(0.763)	(0.416)	(0.013)*	(0.134)	(0.103)
v_{Nt}	1.E+05	9.E+06	1.E+05	-2E+04	0.623	0.297	0.017	-8E+06	2.E+06	2.E+06	0.169	-0.543	-0.013	-6E+05	-2E+06	-5E+05	0.129	0.360	-0.003
	(0.060)	(0.001)**	(0.906)	(0.989)	(0.000)**	(0.506)	(0.000)**	(0.000)**	(0.175)	(0.224)	(0.000)**	(0.022)*	(0.003)**	(0.686)	(0.036)*	(0.747)	(0.001)**	(0.333)	(0.419)
σ_{Pt}	0.008	0.000	0.210	-0.034	0.000	0.000	0.000	0.033	0.111	-0.031	0.000	0.000	0.000	-0.022	-0.021	0.081	0.000	0.000	0.000
	(0.000)**	(0.989)	(0.000)**	(0.321)	(0.751)	(0.437)	(0.526)	(0.278)	(0.000)**	(0.372)	(0.850)	(0.155)	(0.212)	(0.481)	(0.382)	(0.020)*	(0.134)	(0.000)**	(0.035)*
v_{Pt}	1.E+04	-8E+04	4E+05	-6E+04	0.002	0.467	0.000	-4E+03	-1E+05	-1E+04	-0.001	0.217	0.000	-9E+04	-2E+05	1.E+05	-0.001	0.144	0.000
	(0.001)**	(0.314)	(0.000)**	(0.499)	(0.120)	(0.000)**	(0.209)	(0.958)	(0.072)	(0.875)	(0.371)	(0.000)**	(0.138)	(0.247)	(0.001)**	(0.252)	(0.534)	(0.000)**	(0.400)
σ_{Gt}	0.008	0.002	0.033	0.065	0.000	0.000	0.000	-0.023	-0.015	0.058	0.000	0.000	0.000	0.046	0.004	0.107	0.000	0.000	0.000
	(0.000)**	(0.933)	(0.039)*	(0.005)**	(0.633)	(0.123)	(0.082)	(0.271)	(0.363)	(0.013)*	(0.437)	(0.346)	(0.001)**	(0.024)*	(0.813)	(0.000)**	(0.382)	(0.048)*	(0.017)*
v_{Gt}	2.E+06	-1E+07	3E+06	7.E+07	0.632	-3.507	0.369	-3E+07	6E+06	-5E+05	-0.166	3.064	0.267	-1E+07	8.E+06	5.E+06	-0.140	-1.338	0.037
	(0.000)**	(0.178)	(0.632)	(0.000)**	(0.000)**	(0.138)	(0.000)**	(0.001)**	(0.284)	(0.951)	(0.187)	(0.193)	(0.001)**	(0.046)*	(0.142)	(0.590)	(0.126)	(0.497)	(0.046)*

Panel B: Composite measure of volatility

	c	σ^*_{Nt-1}	σ^*_{Pt-1}	σ^*_{Gt-1}	v_{Nt-1}	v_{Pt-1}	v_{Gt-1}	σ^*_{Nt-2}	σ^*_{Pt-2}	σ^*_{Gt-2}	v_{Nt-2}	v_{Pt-2}	v_{Gt-2}	σ^*_{Nt-7}	σ^*_{Pt-7}	σ^*_{Gt-7}	v_{Nt-7}	v_{Pt-7}	v_{Gt-7}
σ^*_{Nt}	0.005	0.191	0.016	0.064	0.000	0.000	0.000	0.186	-0.030	0.022	0.000	0.000	0.000	0.137	0.012	-0.027	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.517)	(0.030)*	(0.000)**	(0.782)	(0.017)*	(0.000)**	(0.219)	(0.458)	(0.734)	(0.288)	(0.508)	(0.000)**	(0.580)	(0.347)	(0.112)	(0.627)	(0.094)
v_{Nt}	2.E+05	-8E+06	1.E+06	-1E+06	0.686	0.209	0.019	655579	7.E+05	-3E+06	7.E+05	-0.026	-0.016	6.E+06	1.E+06	-1E+06	0.114	-0.019	0.001
	(0.006)**	(0.000)**	(0.581)	(0.560)	(0.000)**	(0.654)	(0.000)**	(0.749)	(0.157)	(0.786)	(0.000)**	(0.956)	(0.001)**	(0.005)**	(0.021)*	(0.570)	(0.000)**	(0.961)	(0.826)
σ^*_{Pt}	0.005	-0.053	0.323	0.044	0.000	0.000	0.000	0.012	0.186	-0.001	0.000	0.000	0.000	-0.013	0.130	-0.051	0.000	0.000	0.000
	(0.000)**	(0.043)*	(0.000)**	(0.143)	(0.879)	(0.082)	(0.736)	(0.654)	(0.000)**	(0.964)	(0.550)	(0.209)	(0.095)	(0.605)	(0.000)**	(0.047)*	(0.422)	(0.308)	(0.020)*
v_{Pt}	1.E+04	-3E+05	-2E+04	-1E+05	0.003	0.509	0.000	-4E+04	-9E+04	1.E+05	-0.001	0.207	0.000	4.E+04	-1E+05	1.E+05	-0.001	0.136	0.000
	(0.000)**	(0.010)*	(0.824)	(0.240)	(0.047)*	(0.000)**	(0.454)	(0.723)	(0.372)	(0.319)	(0.637)	(0.000)**	(0.321)	(0.673)	(0.266)	(0.291)	(0.479)	(0.000)**	(0.585)
σ^*_{Gt}	0.007	0.020	-0.004	0.245	0.000	0.000	0.000	0.059	0.025	0.143	0.000	0.000	0.000	0.050	-0.012	0.134	0.000	0.000	0.000
	(0.000)**	(0.391)	(0.850)	(0.000)**	(0.269)	(0.910)	(0.310)	(0.011)*	(0.254)	(0.000)**	(0.818)	(0.373)	(0.043)*	(0.023)*	(0.554)	(0.000)**	(0.046)*	(0.025)*	(0.859)
v_{Gt}	2.E+06	-4E+07	1.E+07	-5E+07	0.682	-2.750	0.420	2.E+07	8.E+06	-2E+07	-0.324	2.366	0.267	2.E+07	7.E+06	8.E+06	-0.222	-1.615	0.046
	(0.000)**	(0.001)**	(0.214)	(0.000)**	(0.000)**	(0.263)	(0.000)**	(0.047)*	(0.426)	(0.127)	(0.021)*	(0.343)	(0.000)**	(0.104)	(0.475)	(0.493)	(0.031)*	(0.428)	(0.038)*

[a] p-values in parentheses

**: Significant at 1% level

*: Significant at 5% level

Table 3: VAR significance score-board

Panel A: Lag-1 and lag-2 variables

	σ_{Nt-1}	σ_{Pt-1}	σ_{Gt-1}	v_{Nt-1}	v_{Pt-1}	v_{Gt-1}	σ_{Nt-2}	σ_{Pt-2}	σ_{Gt-2}	v_{Nt-2}	v_{Pt-2}	v_{Gt-2}
σ_{Nt}	**6**^	**0**	2	**6**	**0**	**5**	**6**	0	**0**	**2**	**0**	**0**
v_{Nt}	**6**	**0**	**0**	**6**	**0**	**6**	**3**	1	**0**	**5**	2	**6**
σ_{Pt}	3	**6**	**0**	**0**	**0**	**0**	**0**	**6**	**0**	**0**	**1**	2
v_{Pt}	3	**3**	1	**5**	**6**	**0**	**0**	**2**	**0**	**0**	**6**	**1**
σ_{Gt}	**0**	2	**5**	**0**	**1**	**3**	3	**0**	**5**	**0**	**0**	**4**
v_{Gt}	4	**0**	**6**	**6**+	**1**	**6**	**5**	**0**	**0**	3	**0**	**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 max (min) score that a variable can achieve is 6 (0). We consider scores of 5-6 (0-1) as robustly (in)significant results.

+: Blue (Red) denotes cells corresponding to own-market (cross-market) effects. Cross-market cells that achieve scores between 2 and 4 are ignored.

Panel B: Lag-7 variables

	σ_{Nt-7}	σ_{Pt-7}	σ_{Gt-7}	v_{Nt-7}	v_{Pt-7}	v_{Gt-7}
σ_{Nt}	**2**	0	0	**2**	0	0
v_{Nt}	**1**	**3**	0	**4**	1	0
σ_{Pt}	0	**3**	**3**	0	**2**	2
v_{Pt}	0	**2**	0	0	**4**	0
σ_{Gt}	**3**	0	**4**	1	**3**	**1**
v_{Gt}	1	0	**0**	1	0	**2**

The scores are similarly described, except that the max score that a lag-7 variable could achieve is 4, not 6.

Table 4: Trivariate Full BEKK-GARCH (1,1) estimation results

Panel A: BEKK-GARCH coefficient estimates

ϕ_{N0} ϕ_{P0} ϕ_{G0}	θ_N θ_P θ_G	c_{11}	c_{12} c_{22}	c_{13} c_{23} c_{33}	a_{11} a_{21} a_{31}	a_{12} a_{22} a_{32}	a_{13} a_{23} a_{33}	g_{11} g_{21} g_{31}	g_{12} g_{22} g_{32}	g_{13} g_{23} g_{33}	*LogL* 15906.13
0.0007 (0.079)^	0.0025 (0.022)	0.0031 (0.000)**	0.0000 (0.981)	-0.0008 (0.224)	0.2392 (0.000)**	-0.0274 (0.296)	0.0490 (0.003)**	0.9536 (0.000)**	0.0179 (0.140)	-0.0211 (0.188)	
-0.0001 (0.766)	0.0007 (0.268)		0.0053 (0.000)**	0.0003 (0.584)	0.0023 (0.879)	0.3399 (0.000)**	-0.0057 (0.686)	0.0027 (0.729)	0.9057 (0.000)**	0.0074 (0.295)	
0.0006 (0.103)	0.0022 (0.022)			-0.0008 (0.224)	-0.0264 (0.091)	0.0754 (0.002)**	0.1808 (0.000)**	0.0122 (0.045)*	-0.0175 (0.202)	0.9725 (0.000)**	

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

	c	ε^2_{Nt-1}	ε^2_{Pt-1}	ε^2_{Gt-1}	$\varepsilon_{Nt-1}\varepsilon_{Pt-1}$	$\varepsilon_{Nt-1}\varepsilon_{Gt-1}$	$\varepsilon_{Pt-1}\varepsilon_{Gt-1}$	h_{NNt-1}	h_{PPt-1}	h_{GGt-1}	h_{NPt-1}	h_{NGt-1}	h_{PGt-1}
h_{NNt}	0.0000 *	0.0572 *	0.0000	0.0007 *	0.0011	-0.0126	-0.0001	0.9094 *	0.0000	0.0001 *	0.0052	0.0233 *	0.0001
h_{PPt}	0.0000	0.0007	0.1155 *	0.0057 *	-0.0186	-0.0041	0.0513 *	0.0003	0.8203 *	0.0003	0.0324 *	-0.0006	-0.0318
h_{GGt}	0.0000	0.0024 *	0.0000	0.0327 *	-0.0006 *	0.0177 *	-0.0021 *	0.0004	0.0001	0.9457 *	-0.0003	-0.0410	0.0143
h_{NPt}	0.0000	-0.0065	0.0008	-0.0020	0.0812 *	0.0188 *	-0.0088	0.0171 *	0.0024	-0.0002	0.8638 *	-0.0165	0.0110 *
h_{NGt}	0.0000	-0.0063	0.0000	-0.0048	-0.0013 *	0.0420 *	0.0006 *	0.0116 *	0.0000	0.0119 *	0.0070	0.9271 *	0.0027
h_{PGt}	0.0000	-0.0013	-0.0020	0.0136 *	0.0168 *	-0.0013 *	0.0610 *	-0.0004	0.0067	-0.0171	-0.0190	0.0178	0.8807 *

^ 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 5: 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_{i0}	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_{it-1}	ε^2_{St-1}	$\varepsilon_{it-1}\varepsilon_{St-1}$	h_{iit-1}	h_{SSt-1}	h_{iSt-1}
Table 5a: Natural rubber and silver (Log-likelihood = 10274.85)														
0.0006	0.0033	0.0000	0.2618	-0.0010	0.9456	0.0039	h_{NNt}	0.0000	0.0685	0.0006	0.0133	0.8942	0.0000	0.0099
(0.107)	(0.000)**		(0.000)**	(0.941)	(0.000)**	(0.387)		*	*			*		
0.0003		-0.0005	0.0254	0.1993	0.0053	0.9798	h_{SSt}	0.0000	0.0000	0.0397	-0.0004	0.0000	0.9600	0.0076
(0.327)		(0.056)	(0.328)	(0.000)**	(0.427)	(0.000)**				*			*	
							h_{NSt}	0.0000	-0.0003	0.0051	0.0522	0.0036	0.0052	0.9265
											*			*
Table 5b: Palladium and silver (Log-likelihood = 10164.52)														
-0.0006	0.0046	0.0000	0.3665	-0.0208	0.9078	0.0094	h_{PPt}	0.0000	0.1343	0.0125	-0.0819	0.8240	0.0013	0.0652
(0.200)	(0.000)**		(0.000)**	(0.019)*	(0.000)**	(0.021)		*	*	*	*	*	*	*
0.0003		0.0003	-0.1117	0.2058	0.0359	0.9759	h_{SSt}	0.0000	0.0004	0.0424	-0.0086	0.0001	0.9525	0.0183
(0.340)		(0.192)	(0.000)**	(0.000)**	(0.000)**	(0.000)**			*	*	*	*	*	*
							h_{PSt}	0.0000	-0.0076	-0.0230	0.0778	0.0085	0.0350	0.8863
									*	*	*	*	*	*
Table 5c: Gasoline and silver (Log-likelihood = 10510.89)														
0.0003	0.0032	0.0000	0.2373	-0.0314	0.9480	0.0271	h_{GGt}	0.0000	0.0563	0.0001	0.0037	0.8986	0.0002	0.0264
(0.334)	(0.000)**		(0.000)**	(0.058)	(0.000)**	(0.020)		*	*			*		
0.0004		-0.0017	0.0078	0.2625	0.0139	0.9527	h_{SSt}	0.0000	0.0010	0.0689	-0.0165	0.0007	0.9076	0.0515
(0.171)		(0.000)**	(0.778)	(0.000)**	(0.189)	(0.000)**		*		*			*	
							h_{GSt}	0.0000	-0.0075	0.0020	0.0621	0.0256	0.0133	0.9035
											*			*

[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_{PSt-1} in the h_{SSt} equation is $2g_{12}g_{22}$. While g_{22} is significant, g_{12} is not significant, such that h_{PSt-1} is insignificant in the h_{SSt} equation. The composite coefficients that are significant are denoted with a *.

Table 6: Results from principal components analysis based on sample correlation matrix

Round 1: NR, PA and GA

	Component 1	Component 2	Component 3	Variable	Eigenvector 1	Eigenvector 2	Eigenvector 3
Eigen-value	1.3940	0.8192	0.7868	r_{Nt}	-0.5883	0.3076	0.7479
Variance Proportion	0.5715	0.2104	0.2081	r_{Pt}	-0.5820	0.4810	-0.6557
Cumulative Proportion	0.5715	0.7819	1.0000	r_{Gt}	-0.5614	-0.8210	-0.1039

Round 2: NR, PA, GA and SL

	Component 1	Component 2	Component 3	Component 4	Variable	Eigenvector 1	Eigenvector 2	Eigenvector 3	Eigenvector 4
Eigen-value	1.7837	0.8494	0.8131	0.5538	r_{Nt}	-0.4253	-0.5584	0.7122	0.0059
Variance Proportion	0.4459	0.2124	0.2033	0.1384	r_{Pt}	-0.5382	-0.5393	0.6867	-0.6391
Cumulative Proportion	0.4459	0.6583	0.8616	1.0000	r_{Gt}	-0.4385	-0.5438	-0.1052	-0.2010
					r_{St}	0.1205	-0.5796	-0.1010	0.7424

Table 7: System estimation of the common exposure adjusted residual returns

Panel A: Adjustment for commodity market factor

	υ_{Mit}	υ_{MNt-1}	υ_{MNt-2}	υ_{MPt-1}	υ_{MPt-2}	υ_{MGt-1}	υ_{MGt-2}
r_{Nt}	1.000	0.025	-0.021	-0.015	0.001	-0.053	0.018
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.721)	(0.000)**	(0.000)**
r_{Pt}	1.001	0.003	-0.001	-0.009	0.040	0.030	-0.019
	(0.000)**	(0.005)**	(0.471)	(0.000)**	(0.000)**	(0.000)**	(0.000)**
r_{Gt}	1.002	0.019	0.014	0.057	0.035	0.002	0.031
	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.000)**	(0.035)*	(0.000)**

Panel B: Adjustment for industry exposure

	υ_{Iit}	υ_{INt-1}	υ_{INt-2}	υ_{IPt-1}	υ_{IPt-2}	υ_{IGt-1}	υ_{IGt-2}
r_{Nt}	1.000	0.013	-0.017	-0.001	0.002	0.000	0.000
	(0.000)**	(0.000)**	(0.000)**	(0.764)	(0.297)	(0.909)	(0.913)
r_{Pt}	1.000	0.002	-0.001	0.004	0.033	-0.002	-0.002
	(0.000)**	(0.201)	(0.746)	(0.001)**	(0.000)**	(0.249)	(0.292)
r_{Gt}	1.000	0.001	0.000	0.008	-0.001	0.018	0.038
	(0.000)**	(0.366)	(0.969)	(0.159)	(0.807)	(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) Ghosh, Johnson & Saidi (1999) Ng (2000)	Escribano & Granger (1996) Ciner (2001) Liu & Chou (2003)
Competing derivative markets	*Spot-option*	*Major cross-rate currency spillover*	*Crude oil and equity*
Holder, Pace & Tomas (2002) Fung, Leung & Xu (2003) Chng (2004) Huang (2004)	Chan, Chung & Johnson (1993) Sun & Sutcliffe (2003) Charlebois & Sapp (2007)	Engle, Ito &Lin (1990) Black &McMillan (2004) Doong & Yang (2004)	Aleisa et al (2004) Choi & Hammoudeh (2007) Hammoudeh & Malik (2007) Driesprong et al (2008)
Intra and Inter Industry Firms	*Futures-option*	*Regional currency spillover*	*Currency-crisis*
Menzly & Ozbas (2006) Hou (2007) Cohen & Frazzini (2008)	Chiang & Fong (2001) He & Jang (2004) Fung (2007)	Kanas & Kouretas (2002) McMillan & Speight (2001) Caramazza, Ricci, & Salgado (2004)	Tai (2003): ERM crisis of 1992 Jager, Klaassen & van Horen (2006): Asian currency crisis of 1997

Figure 2: Economic profits from competing models