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Median Response to Shocks: A Model for VaR Spillovers in East Asia

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Median Response to Shocks: A Model for VaR Spillovers in East Asia

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Abstract

We propose a procedure for analyzing financial interdependencies within an area of interest, interpreting a negative daily return in an Originator market as a VaR (i.e. the product of a volatility level and the corresponding α–quantile of a time independent probability distribution), and measuring the Median Response in the Destination market through its volatility associated with the one in the Originator and the reconstruction of the correlation structure between the two (through copula functions). We apply our methodology to nine Asian markets, varying the choice of the Originator and deriving a number of indicators which represent the importance of each market as a provider or a receiver of turbulence. Over a 1996-2015 period we confirm the role of traditionally important markets (e.g. Hong Kong or Singapore), while over a rolling three–year estimation period, we can detect rises and declines, the explosion of turbulence in the occasion of the Great Recession and the magnified role of China in the recent years.

1 Introduction

Recent crises have highlighted the vulnerability of the global financial system to interdependence: this is reflected in the complex network of interconnectedness across various segments of each market ((Billio *et al.*, 2012) identify hedge funds, banks, brokers and insurance companies as separate actors with strong links across). The buzzword in public debates be they academic or policy–oriented is *resilience*, a characteristic to be analyzed (and possibly regulated or built) in the various components of a system to withstand shocks that may propagate very quickly to other segments.

Regulatory authorities in particular have had a growing concern for deriving measures of systemic risk, meant to represent the accumulation of adverse events affecting the financial system as a whole, with a possible cascade and amplification of the negative outcomes, including losses, credit freeze, lack of trust and decrease in liquidity. There is a vast literature on the subject: Rogantini Picco (2015) develops a survey of the indicators followed by major regulatory institutions, including the ECB and the IMF, pointing out the need for the regulatory relevance and the timeliness of systemic risk indicators.

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A class of indicators focuses on the transmission of extreme events from one system component to another: to be clear, in this context either component can be a single institution or a market. Thus, some studies have analyzed how to measure a spillover from a single institution to the market or an indicator of distress for the single institution from a market movement. In the distinction suggested by Zhou (2010), the former would be called *systemic impact index*, while the latter is called a *vulnerability index*. As pointed out by Girardi and Ergün (2013), the first type of methodology falls within the CoVaR approach suggested initially by Adrian and Brunnermeier (2011) where the attention is on the VaR measurable in one component conditional upon the other component being at its own VaR. Girardi and Ergün (2013) themselves change the definition of CoVaR by enlarging the set for the conditioning component to mean that it is at or below its own VaR. Within the second type of methodology, vulnerability is measured by the reaction by a single institution by a large negative market movement. Brownlees and Engle (2011) develop a way to measure the *Marginal Expected Shortfall*, that is the expected value in the tail of returns which will occur when the market is in its right tail; this is an estimate of the actual exposure of a single institution to the market turbulence and, correspondingly, a regulatory indicator of capital requirements. In a number of papers, Diebold and Yilmaz (e.g. Diebold and Yilmaz (2009), Diebold and Yilmaz (2015)) suggest a methodology to measure volatility spillovers within a Vector Autoregression framework based on forecast error variance decomposition, isolating relative importance of markets. Engle *et al.* (2012) devised a Vector Multiplicative Error Model (vMEM – cf. (Cipollini *et al.*, 2013)) to measure dynamic market interconnectedness and the impact of the East Asian Crisis of 1997-98 (cf. the references thereof).

In this paper, we design a measure of interconnectedness between two system components in the line of the quantile dependence approach (Bouyé and Salmon (2009) and Jing *et al.* (2008) adopt quantile regressions, not used here). We consider the effect of a large negative price movement in one component (the *Originator* being at or below the VaR) on the other (the *Destination*). Even if this is reminiscent of the definition of a CoVaR, according to Girardi and Ergün (2013), we part from that approach since we are not interested in estimating distributions at a given time t conditional on the information available one period before. Since daily returns[1] are the product of a scale factor (the volatility, usually a conditional measure, but it may be an end–of–day measure) and of an i.i.d. random variable (a standardized innovation), one can compute the quantiles of interest from the latter. A sizeable shock to daily returns (e.g. -3%) can be assumed to be a VaR at a given level α (e.g 0.05): dividing it by the α quantile of the distribution of standardized innovations we derive the corresponding level of volatility which we call VaR(α)-*derived* volatility (as such, not related to a specific t). The interconnectedness follows two separate channels: the first is the bivariate distribution of standardized innovations (which we model with a copula function approach); the second is the estimation of a relationship between volatilities, with the aim of reconstructing the *average* level of volatility in the Destination associated to the VaR(α)-*derived* volatility in the Originator (which we model as a log–log IV regression).

We introduce a measure of *Median Response* in the Destination to a left tail shock in the Originator: this is a level – generally negative – which is higher than 50% of the returns in the Destination associated with the Originator having experienced a drop in returns interpretable as a $VaR(\alpha)$. It is the product of the 50–th percentile in the marginal distribution of the Destination standardized innovations corresponding to the α quantile in the Originator times the *average* level of volatility in the Destination associated to the VaR(α)-*derived* volatility in the Originator. By so doing, we consider events (the VaR and the Median Response) with a high enough joint probability: for example if $\alpha = 0.05$, the joint probability under the bivariate distribution would be 0.025, lending itself to standard validation techniques (in– and out–of

[1] We are assuming a mean return of zero for simplicity.

sample; e.g. Christoffersen (1998)).

In the empirical application, we have chosen nine markets from East Asia which will be alternated in the role of Originator and Destination of the shock. By repeating the approach across the nine markets, and alternating the role of Originator and Destination, we are able to associate each bilateral link with a measure of an *integrated* Median Response over a meaningful range of negative returns (each interpretable as VaR's at a given α) and adjusting the VaR–derived volatilities accordingly. We can focus on several indicators: the first, called *Bilateral Median Responses*, are Destination– and Originator–specific; if we aggregate across Originators we obtain a Destination–specific *Market Median Response*; aggregating the latter across Destinations, we obtain an overall *Area Median Response*. As a by–product, we can represent each Bilateral Median Response as a share of the Area Median Response: mimicking (admittedly with some abuse) indicators of international trade, we can treat bilateral shares as if the Area Median Response were equivalent to total trade within the area, and each share represented the relative importance of bilateral trade in one direction. By aggregating across markets considered as Originators, respectively, Destinations, we gather measures similar to a country's export and import shares, deriving in turn a measure of balance on the net transmission of shocks, and a ranking of markets as of their relative importance in the area.

The paper is organized as follows: in Section 2 we lay out our definitions and methodology, detailing the estimation procedures and the measures that can be derived from our approach. In Section 3 we introduce the nine markets and we discuss the various issues arising with empirical estimation, the derivation of the results and the interpretation of the measures suggested. Concluding remarks follow in Section 4.

2 A Median Response to VaR between Markets

In this section, we suggest an innovative approach to measure the impact of a shock originating in a market (the Originator) on several other markets (the Destination). Such a shock is expressed in terms of market movement in one day, r^*, and is interpreted as a Value at Risk at a given coverage level α. As noted elsewhere (Christoffersen, 2003), the calculation of the Value at Risk amounts to the derivation of a quantile of the distribution of returns. Typically, one considers a conditional distribution where it is recognized that

$$r_t = \mu_t + \sigma_t \eta_t \tag{1}$$

where $\mu_t = E(r_t|\mathcal{I}_{t-1})$, $\sigma_t = \sqrt{V(r_t|\mathcal{I}_{t-1})}$ and η_t is an i.i.d. innovation with mean zero and unit variance. Therefore, the VaR at level α, denoted $r_t(\alpha)$, is such that

$$\Pr(r_t \leq r_t(\alpha)|\mathcal{I}_{t-1}) = \alpha. \tag{2}$$

From the definition (1), $r_t(\alpha) = \mu_t + \sigma_t\eta(\alpha)$, so that the influence of the information set $\mathcal{I}_{t-1}$ lies in the calculation of the scale factor σ_t, whereas the relevant quantile $\eta(\alpha)$ (irrespective of t) pertains to the distribution of the η's. Following the GARCH literature, the customary procedure is one where μ_t is negligible and can be assumed equal to zero, σ_t is the square root of the GARCH conditional variance and η_t is derived as a byproduct of the estimation and can be used as diagnostics for the correct specification of the dynamics of σ_t. The way that σ_t is calculated can differ: for example, in a risk management framework, Brownlees and Gallo (2010) use a Multiplicative Error Model (MEM) to forecast volatility σ_t based on realized volatility measures (Andersen *et al.*, 2006) and the daily range (Parkinson, 1980), showing that there is an improvement over the standard GARCH and that the daily range is a good alternative to ultra-high frequency based estimators of volatility, especially when intradaily data are not easily available. When forecasting is not of direct interest, the previous discussion holds with the idea that the distribution providing the quantiles is the results of a standardization of the returns by some suitable measure of volatility. From an end-of-day perspective, we can safely assume that the use of an estimator of volatility (either realized volatility or daily range) will provide a more accurate definition of the distribution of the η's, leading therefore to an improved estimate of the quantile $\eta(\alpha)$. To summarize, we have three main options for σ_t:

1. In a forecasting perspective $\sigma_{t|t-1}$:
   (a) GARCH for the conditional variance of returns;
   (b) MEM for a realized measure of volatility or for the daily range (cf. Chou (2005));
2. In an end-of-day perspective σ_t: a realized measure or the daily range.

As per the distribution of η_t, even if option 1a implies, for estimation purposes, a parametric choice (usually the standard Normal or the Student's t, symmetric or asymmetric), for the calculation of the quantile it is customary to make reference either to the empirical distribution of the standardized returns or to a parametric distribution fitted to them, both of which are independent of t.

In general, we can notice that for a given generic value of a return $r^* < 0$ (interpreted as a VaR), the quantile $\eta(\alpha) < 0$ maps it into a corresponding VaR(α)-*derived* level of volatility

$$\sigma(r^*, \alpha) = \frac{r^*}{\eta(\alpha)}. \tag{3}$$

The same r^*, therefore, can be associated with different VaR-derived volatilities, noting that $\eta(\alpha_2) < \eta(\alpha_1) < 0$ leads to $\sigma(r^*, \alpha_1) < \sigma(r^*, \alpha_2)$.

In evaluating the reaction of the Destination (d) to a market drop in the Originator (o), we have to consider two components:

1. the link between the volatility in the Originator, σ_o, and the volatility in the Destination, σ_d;
2. the dependence between the two markets, so that we can analyze what quantile in the marginal distribution of the Destination should be associated with $\eta(\alpha)$ in the Originator.

For the first component, we adopt a simple (static) log-log relation

$$\ln \sigma_d = \beta_0^* + \beta_1 \ln \sigma_o + \varepsilon \tag{4}$$

with β_1 conveniently representing the average elasticity of response in the volatility of the Destination to a one percent impulse in the volatility of the Originator. On the basis of the time series $(\sigma_{o,t}, \sigma_{d,t})$ over a suitable sample period, the parameters β_0^* and β_1 are better estimated by Instrumental Variables (IV) in order to account for the possible correlation between ε and $\ln \sigma_o$; inference can then be carried out with robust standard errors (Bollerslev and Wooldridge, 1992). Such a relationship is used to map a given level of VaR-derived volatility, $\sigma_o(r^*, \alpha)$ for the originating market, into the corresponding level of volatility in the destination market according to

$$\sigma_d(r^*, \alpha) = \beta_0 \sigma_o(r^*, \alpha)^{\beta_1} \tag{5}$$

where $\beta_0 = \exp(\beta_0^*)$.

For the second component, we model the joint distribution of the standardized returns, η_o and η_d, resorting to copula functions (Cherubini *et al.*, 2004). Using this approach, the joint c.d.f. of (η_o, η_d) can be represented as

$$F(\eta_o, \eta_d) = C(F_o(\eta_o), F_d(\eta_d)),$$

where $F_o(\cdot)$ and $F_d(\cdot)$ denote the c.d.f.'s of the standardized Originator and Destination returns, respectively, and $C(\cdot,\cdot)$ is a suitable copula. $F_o(\cdot)$ and $F_d(\cdot)$ can be fitted either empirically or parametrically; $C(\cdot,\cdot)$ can be estimated separately on the given dataset by the Probability Integral Transformations (PIT's) $(u_{o,t} = F_o(\eta_{o,t}), u_{d,t} = F_d(\eta_{d,t}))$. A flexible choice adopted in the application is the Student's t Copula, whose density is given by

$$c^t_{\nu\rho}(u,v) = \rho^{\frac{1}{2}} \frac{\Gamma\left(\frac{\nu+2}{2}\right)\Gamma\left(\frac{\nu}{2}\right)}{\Gamma\left(\frac{\nu+1}{2}\right)^2} \frac{\left(1+\frac{\zeta_1^2\zeta_2^2 - 2\rho\zeta_1\zeta_2}{\nu\,(1-\rho^2)}\right)^{-(\nu+2)/2}}{\prod_{j=1}^2 \left(1+\frac{\zeta_j^2}{\nu}\right)^{-(\nu+2)/2}} \tag{6}$$

where $\zeta_1 = t_\nu^{-1}(u)$, $\zeta_2 = t_\nu^{-1}(v)$, t_ν^{-1} is the inverse of the c.d.f. of the univariate Student's t with ν degrees of freedom, and ρ is a correlation parameter.

The related measure of association between the two markets is chosen to be the median of the conditional distribution of η_d given $\eta_o \leq \eta_o(\alpha)$, denoted as $\eta_{d|o}(50|\alpha)$ and defined by

$$\Pr\left(\eta_d \leq \eta_{d|o}(50|\alpha) \middle|\, \eta_o \leq \eta_o(\alpha)\right) = 0.5. \tag{7}$$

An estimate of such a measure can be computed easily from the estimated $F_o(\cdot)$, $F_d(\cdot)$ and $C(\cdot,\cdot)$. Correspondingly, we define the *Median Response* to r^*, as

$$\text{MeRes}_{d|o}(r^*,\alpha) = \eta_{d|o}(50|\alpha)\ \sigma_d(r^*,\alpha), \tag{8}$$

which highlights the presence of two components: one tied to the copula function and the other to the association between volatilities. As we will see later, it may be instructive to isolate the joint behavior of two important sources in the Response, one related to the correlation between standardized returns and the other which pertains to the relationship between volatilities.

Using Equations (3) and (5), the Median Response can be expressed as

$$\text{MeRes}_{d|o}(r^*,\alpha) = \frac{\eta_d(50|\alpha)\beta_0}{|\eta_o(\alpha)|^{\beta_1}}|r^*|^{\beta_1} \equiv k_{d|o}(\alpha)\ |r^*|^{\beta_1} \tag{9}$$

which is a negative valued function of r^* because of the sign of $k_{d|o}(\alpha)$. For a given α, the calculation of MeRes over a reasonable range for r^*, say $l^* \leq r^* \leq u^* \leq 0$, gives a *Median Response Function*, an outcome similar to what is depicted in Figure 1 where $l^* = -5\%$ and $u^* = -1\%$ (the profile – in solid line – is borrowed from actual values estimated in the empirical application). We can superimpose a benchmark profile (dashed line) where one could assume a theoretical one–to–one response in the Destination for each r^* in the Originator.

We can calculate the area below the Median Response Function, defined as the *Bilateral Median Response*, as

$$\text{BMeRes}_{d|o}(\alpha) = \int_{l^*}^{u^*} \text{MeRes}_{d|o}(r^*,\alpha)dr^* = \frac{k_{d|o}(\alpha)}{\beta_1+1}\left(|l^*|^{\beta_1+1} - |u^*|^{\beta_1+1}\right). \tag{10}$$

Correspondingly, the theoretical benchmark (area of the trapeze in 1) is $(u^2 - l^2)/2$; in our example $(1-25)/2 = -12$.

As noted in the Introduction, the Bilateral Median Response is Destination– and Originator–specific. A *Market Median Response* aggregates the Bilateral Median Responses across originating markets and indicates the response of a single market to shocks originating elsewhere

$$\text{MMeRes}_d(\alpha) = \sum_o \text{BMeRes}_{d|o}(\alpha). \tag{11}$$

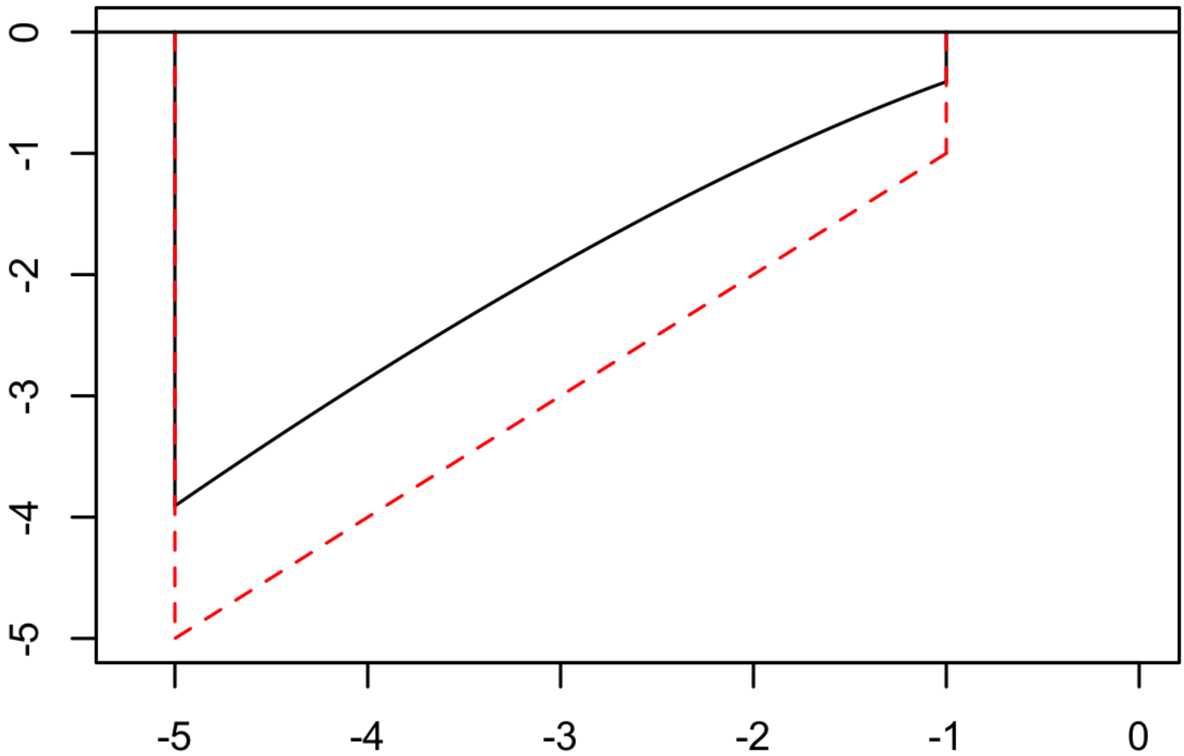

Figure 1: Example of an estimated Median Response Function (solid line based on the response of PH to MY, cf. the empirical application) for r^* between -5% and -1%, depicted together a theoretical one-to-one response (dashed line).

By extension, having reconstructed the effects of r^* spanning the range between l^* and u^*, we can aggregate these values across originating markets, coming up with a measure of the relative importance of that market as source of spillovers, a *Market Spillover Effect*,

$$\mathrm{MSEff}_o(\alpha) = \sum_d \mathrm{BMeRes}_{d|o}(\alpha). \tag{12}$$

As these are not derived as net effects, there is some sort of double counting which, however, is mitigated by the use of the IV estimator. Moreover, if we aggregate the Market Median Responses (Market Spillover Effects) across destination (originating) markets, we obtain an index called *Area Median Response*

$$\mathrm{AMeRes}(\alpha) = \sum_d \mathrm{MMeRes}_d(\alpha) = \sum_o \mathrm{MSEff}_o(\alpha). \tag{13}$$

The interest of these measures lies in the possibility of expressing the BMeRes's as a share of AMeRes, giving an idea of the relative importance of bilateral links, and, as we will see in the empirical application, in the comparability of both the relative BMeRes's, the MMeRes's, the MSEff and the AMeRes estimated over subsamples in order to check the evolution of market interdependencies.

3 Market Interdependence in East Asia

We apply our methodology to an area of nine East Asian markets: we cover Malaysia (Kuala Lumpur Composite Index, MY), Singapore (Straits Times Index, SG), Hong Kong (Hang Seng Index, HK), Indonesia (Jakarta Stock Exchange Composite Index, ID), South Korea (Korea Stock Exchange Index, KR), The Philippines (Philippines Stock Exchange, PH), Thailand (Stock Exchange of Thailand, TH), China (Shanghai Stock Exchange Composite Index, CN) and Taiwan (Taiwan Stock Exchange Weighted Index, TW). All data were taken from Bloomberg, with the exception of Singapore which was taken from Finance Yahoo. The period covered spans from February 2, 1996 to December 18, 2015, a total of 5386 observations.[2] For the purposes of this paper, we deem as negligible any market opening time differences and the two hour time zone difference between Thailand and South Korea: we thus consider data as synchronous.

During this interval, the financial markets considered have gone through some periods of severe turbulence/crisis. In the graphs representing the indices (in semi–log scale, Figure 2) we have superimposed some shaded areas corresponding to July 2, 1997 to Dec. 31, 1998 (Asian crisis triggered by the Baht devaluation), and the dates of the US Great Recession (Dec. 1, 2007 to June 30, 2009), superimposing a darker shade of gray in correspondence to the turmoil following the bankruptcy of Lehman Brothers (Sep. 15, 2008 to October 10, 2008).

In Figure 3, for the same markets we have reported the graphs of the daily Garman–Klass volatility (Garman and Klass, 1980)

$$\sigma_t = \sqrt{0.511(h_t - l_t)^2 - 0.019(c_t(h_t + l_t) - 2h_t l_t) - 0.383c_t^2} \tag{14}$$

[2] These markets feature even long periods of closure for holidays: for example, during the Chinese New Year, China and Taiwan are closed for five days, South Korea and Hong Kong for three, and so on. As closures are not necessarily always synchronous, we have a problem of missing observations. For days in which at least one market is open, we take returns and volatility by single market, we calculate the standardized returns η, and we block–bootstrap the missing observations for η, completing the available calendar. Correspondingly, the volatility is linearly interpolated. Finally, pseudo returns are inserted when missing, by multiplying the interpolated volatility by the block–bootstrapped η's. Other schemes were attempted which resulted in undesirable outcomes: deleting all days with at least one market closed makes us lose too many observations; linear interpolation of returns or repetition of the last available value leads to artificial serial correlation.

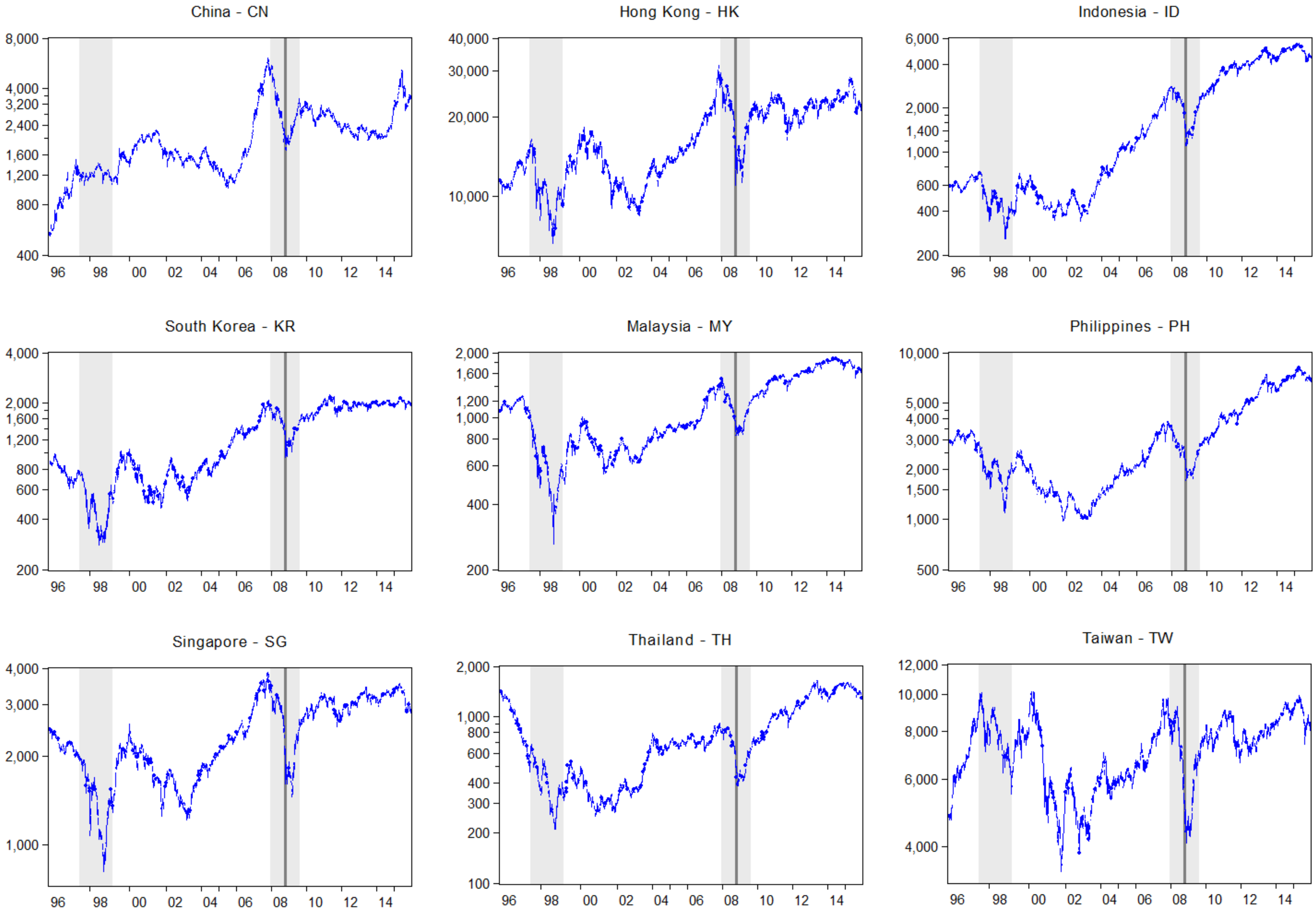

Figure 2: Indices of the nine markets in semi–log scale. Sample period: Feb. 2, 1996 – Dec. 18, 2015. Shaded areas represent respectively, the Asian crisis of 1997–1998, the Great Recession of 2007–2009 and (in a darker shade of grey) the turmoil originating from the bankruptcy of Lehman Brothers.

where $h_t = \ln(H_t/O_t)$, $l_t = \ln(L_t/O_t)$, $c_t = \ln(C_t/O_t)$ and O_t, H_t, L_t, C_t denote the opening, highest, lowest and closing prices of day t. Note that (14) has been rescaled to have the same unconditional quadratic mean as the daily returns to adjust for overnight effects.

The volatility estimator is used to standardize the daily returns assuming $\mu_t = 0$: as mentioned before, if we take an end–of–day stance we use the daily Garman–Klass volatility as an easily available volatility estimator. Not to burden the presentation with an excess of descriptive results, we can succintly say that the resulting distributions are by and large platikurtic, mainly because large returns in market scale are usually associated with very high daily Garman–Klass volatilities (the same is true for daily ranges). The autocorrelation properties of the standardized returns are generally satisfactory.

3.1 The Estimation of the Copula Functions

We used the standardized returns with pairs of markets to estimate the parameters of a bivariate Student's t copula function, namely the correlation ρ and the degrees of freedom ν. For the large sample period between 1996 and 2015, the results are reported in Table 1 and show as significant all correlation coefficients, with a group of four markets exhibiting values greater than 0.4 (SG, HK, KR and TW), three less connected markets (ID, MY and TH) with The Philippines, but mostly China being the least connected markets. Most degrees of freedom are between 10 and 30, showing some tail dependence features of the joint distribution. Other copula functions were tried but the evaluation based on standard information criteria suggests this as the best choice.

Table 1: Estimated parameters of a Student's t Bivariate Copula function calculated on standardized returns. Sample period: Feb. 1996 – Dec. 2015. Standard errors for $\widehat{\rho}$ (all smaller than 0.02) not reported. Based on Garman-Klass volatility.

		HK	ID	KR	MY	PH	SG	TH	TW
CN	ρ	0.242	0.114	0.134	0.111	0.091	0.140	0.116	0.156
	ν	13.052	37.653	23.502	28.858	25.276	25.326	20.667	16.729
HK	ρ		0.377	0.466	0.363	0.290	0.521	0.374	0.413
	ν		23.570	9.834	18.451	51.306	9.976	18.866	9.450
ID	ρ			0.306	0.345	0.292	0.370	0.321	0.298
	ν			17.732	29.009	36.444	10.353	31.988	20.897
KR	ρ				0.300	0.251	0.381	0.313	0.444
	ν				22.752	65.991	14.234	24.372	7.913
MY	ρ					0.278	0.369	0.302	0.296
	ν					87.491	20.006	29.044	56.970
PH	ρ						0.264	0.243	0.261
	ν						59.890	95.839	58.338
SG	ρ							0.377	0.359
	ν							12.156	22.098
TH	ρ								0.279
	ν								14.325

Once the results of the estimated copula functions are remapped in terms of the standardized returns, we can visually check the estimated correlations with a scatterplot of the bivariate data by pairs of market with superimposed level curves of the corresponding bivariate density function.

The main ingredient for subsequent analysis that comes out of this bivariate copula function estimation is $\eta_{d|o}(50|\alpha)$, the median of the conditional distribution of η_d for the Destination given

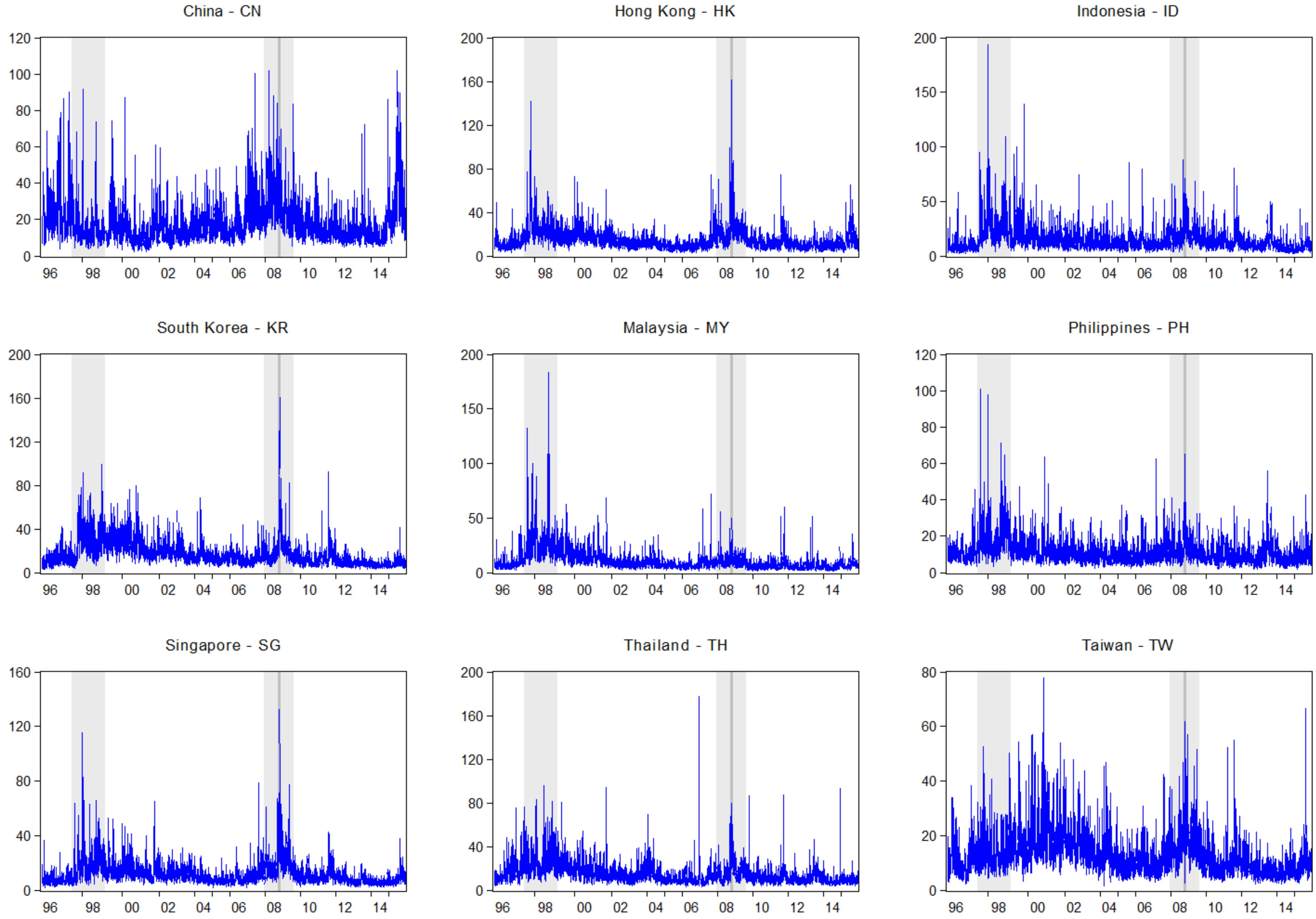

Figure 3: Annualized percentage Garman–Klass volatilities $\sigma_t \cdot \sqrt{252} \cdot 100$. Sample period: Feb. 2, 1996 – Dec. 18, 2015. Shaded areas represent respectively, the Asian crisis of 1997–1998, the Great Recession of 2007–2009 and (in a darker shade of grey) the turmoil originating from the bankruptcy of Lehman Brothers.

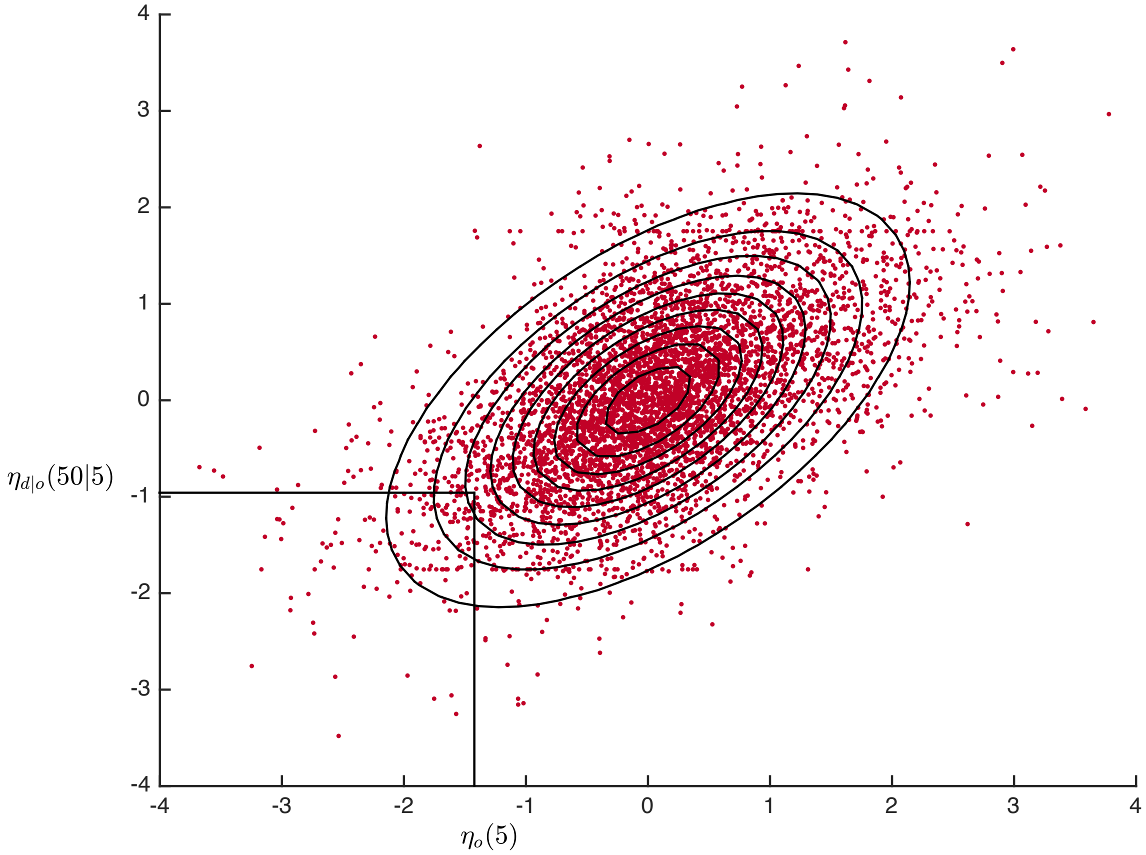

Figure 4: Example of $\eta_o(5)$ and the corresponding $\eta_{d|o}(50|5)$ calculated for Hong Kong as Originator and Singapore as a Destination (cf. Equation (7)). Contour lines from the Student's t bivariate density fitted on the data. Sample period: Feb. 2, 1996 – Dec. 18, 2015. Based on Garman-Klass volatility.

$\eta_o \leq \eta_o(\alpha)$ for the Originator, i.e. the chosen measure of association between the two markets. Tables 2 report the results for $\alpha = 0.05$ (values of $\eta_o(\alpha)$ on the main diagonal).

Table 2: $\eta_{d|o}(50|\alpha)$ for $\alpha = 5\%$: Median of the conditional distribution of η_d for the Destination (by column) given $\eta_o \leq \eta_o(\alpha)$ for the Originator, estimated from the bivariate copula. The main diagonal reports in boldface the value of $\eta_o(\alpha)$. Sample period: Feb. 2, 1996 – Dec. 18, 2015. Based on Garman-Klass volatility.

		Destination								
		CN	HK	ID	KR	MY	PH	SG	TH	TW
Originator	CN	**-1.348**	-0.379	-0.130	-0.173	-0.133	-0.137	-0.226	-0.194	-0.234
	HK	-0.390	**-1.417**	-0.531	-0.824	-0.483	-0.474	-0.924	-0.615	-0.745
	ID	-0.138	-0.610	**-1.051**	-0.497	-0.448	-0.478	-0.656	-0.513	-0.500
	KR	-0.175	-0.813	-0.443	**-1.510**	-0.396	-0.399	-0.660	-0.509	-0.810
	MY	-0.131	-0.595	-0.487	-0.479	**-1.087**	-0.448	-0.630	-0.486	-0.478
	PH	-0.099	-0.438	-0.412	-0.383	-0.351	**-1.241**	-0.428	-0.394	-0.412
	SG	-0.183	-0.895	-0.547	-0.648	-0.490	-0.422	**-1.375**	-0.637	-0.618
	TH	-0.148	-0.612	-0.453	-0.503	-0.395	-0.387	-0.660	**-1.253**	-0.475
	TW	-0.210	-0.712	-0.428	-0.803	-0.381	-0.415	-0.611	-0.467	**-1.416**

3.2 Volatility Elasticity Responses

We used the Garman Klass volatility measures in Equation 14 to estimate the bivariate relationship between the Destination and the Originator volatilities (cf. Equation (4)). We use an IV estimator, choosing current VIX and lagged volatilities, both in the Destination and in the Originator, as instruments. Table 3 reports the estimates of $\beta_0 = \exp(\beta_0^*)$ while Table 4 shows the corresponding elasticities. The links between volatilities show a variety of features. We detect a generalized asymmetric response across markets: for example, Hong Kong has values around 1 as a destination while around 0.7 as Originator, while the opposite is true for South Korea. China has very low (and a few non significant) $\widehat{\beta}_1$.

Table 3: Estimates of $\beta_0 = \exp(\beta_0^*)$ in the bivariate market volatility relationship. Sample period: Feb. 1996 – Dec. 2015. Coefficients in italics are not significant, those in boldface are not significantly different from 1 (both at 5% with robust standard errors) Based on Garman-Klass volatility.

		Destination								
		CN	HK	ID	KR	MY	PH	SG	TH	TW
Originator	CN		0.019	0.010	0.009	0.011	0.035	0.018	0.013	0.011
	HK	0.016		0.267	0.188	0.182	*1.099*	0.442	0.285	0.392
	ID	0.009	0.662		0.219	0.194	1.991	0.514	0.334	0.344
	KR	0.008	*1.180*	0.497		0.365	1.859	0.767	0.728	1.626
	MY	0.007	1.414	0.495	0.399		6.537	0.632	*1.034*	0.710
	PH	0.014	0.115	0.081	0.046	0.067		0.088	0.120	0.061
	SG	0.015	*1.114*	0.445	0.262	0.197	2.132		0.317	0.742
	TH	0.011	0.356	0.182	0.165	0.185	1.514	0.202		0.166
	TW	0.008	0.277	0.113	0.174	0.089	0.286	0.223	0.102	

We calculate the generalized R^2 between σ_d and $\widehat{\sigma}_d$ (Table 5), which shows the strength of these links on this sample period even more poignantly: the strongest link is between HK and

Table 4: Estimated elasticity β_1 in the bivariate market volatility relationship. Sample period: Feb. 1996 – Dec. 2015. Coefficients in italics are not significant, those in boldface are not significantly different from 1 (both at 5% with robust standard errors). Based on Garman-Klass volatility.

	Destination								
Originator	CN	HK	ID	KR	MY	PH	SG	TH	TW
CN		0.142	*0.013*	*-0.016*	*0.027*	0.257	0.123	0.059	*0.025*
HK	0.153		0.727	0.672	0.599	**0.973**	0.794	0.745	0.788
ID	*0.018*	0.916		0.705	0.612	1.091	0.825	0.779	0.763
KR	*-0.026*	**1.009**	0.830		0.709	**1.052**	0.879	0.915	1.050
MY	0.058	1.153	0.936	0.915		1.402	0.942	1.095	**0.987**
PH	0.168	0.601	0.528	0.423	0.454		0.522	0.614	0.459
SG	0.181	1.069	0.879	0.790	0.658	1.148		0.814	**0.962**
TH	0.068	0.781	0.641	0.637	0.597	**1.030**	0.634		0.609
TW	*0.025*	0.759	0.574	0.680	0.484	0.731	0.682	0.555	

SG (above 0.4), higher values (between 0.2 and 0.3) generally involve HK, KR, MY and SG while there appears a second group (values between 0.1 and 0.2) with ID, PH, TH, TW. CN is somewhat disconnected.

Table 5: Generalized R^2 in the bivariate market volatility relationship. Sample period: Feb. 1996 – Dec. 2015. Based on Garman-Klass volatility.

	Destination								
Originator	CN	HK	ID	KR	MY	PH	SG	TH	TW
CN		0.038	0.001	0.000	0.002	0.009	0.011	0.004	0.004
HK	0.030		0.225	0.268	0.268	0.167	0.427	0.191	0.147
ID	0.001	0.220		0.174	0.223	0.171	0.281	0.163	0.072
KR	0.000	0.270	0.180		0.216	0.101	0.275	0.178	0.211
MY	0.000	0.224	0.191	0.173		0.163	0.227	0.177	0.067
PH	0.006	0.160	0.169	0.099	0.189		0.190	0.144	0.048
SG	0.013	0.428	0.278	0.267	0.258	0.202		0.185	0.145
TH	0.004	0.187	0.160	0.177	0.224	0.133	0.181		0.056
TW	0.001	0.155	0.086	0.232	0.108	0.050	0.165	0.070	

3.3 VaR(α)-*derived* Volatilities

The next step is to calculate the VaR(α)-*derived* levels of volatility in correspondence to a given VaR(α) $= r^*$. From the estimated value of $\eta_o(\alpha)$, we can find the *derived* volatility in the originating market as (cf. Equation (3))

$$\sigma_o(r^*, \alpha) = \frac{r^*}{\eta_o(\alpha)}$$

and then, as an effect of the estimated log–log relationship, the related volatility for the destination market as

$$\sigma_d(r^*, \alpha) = \widehat{\beta}_0 \sigma_o(r^*, \alpha)^{\widehat{\beta}_1}$$

according to Equation (5). As an illustrative example, the results are reported in Table 6 for a choice of $r^* = -0.03$ as a daily movement and the $\eta_o(\alpha)$'s taken from the main diagonal of Table 2. On its main diagonal, we report the VaR(α)-*derived* volatility in the originating market.[3] The numbers on the diagonal represent reasonable medium–high levels of volatility spanning from about 31% (KR) to 45% (ID). Off–diagonal, the corresponding volatility values of the Destination parallel the results on the estimated β_0 and β_1 confirming the presence of asymmetric effects: take the example of PH where its volatility as an originator (38.4%) carries effects which are lower than 20% in other markets, whereas the volatilities to PH induced by other markets are much higher, well above 40%, and in two cases (from ID and MY) above 60%.

Table 6: VaR(α)-*derived* level of volatility in annualized terms. For a given VaR(α) $= r^*$ (expressed as a daily movement), we report the VaR(α)-*derived* volatility in the originating market $\sigma_o(r^*, \alpha) = r^*/\eta_o(\alpha)$ (main diagonal), and the related $\sigma_d(r^*, \alpha) = \widehat{\beta}_0 \sigma_o(r^*, \alpha)^{\widehat{\beta}_1}$ (off–diagonal) where the originator market is by row and the destination market is by column. Here $r^* = -0.03$ and $\alpha = 5\%$. Sample period: Feb. 1996 – Dec. 2015. Based on Garman-Klass volatility.

		Destination								
		CN	HK	ID	KR	MY	PH	SG	TH	TW
Originator	CN	**0.353**	0.175	0.153	0.149	0.157	0.209	0.176	0.160	0.155
	HK	0.142	**0.336**	0.257	0.224	0.286	0.410	0.328	0.256	0.299
	ID	0.127	0.405	**0.453**	0.283	0.349	0.653	0.434	0.332	0.363
	KR	0.139	0.359	0.305	**0.315**	0.360	0.478	0.389	0.321	0.421
	MY	0.090	0.358	0.274	0.238	**0.438**	0.677	0.340	0.322	0.326
	PH	0.116	0.195	0.180	0.151	0.197	**0.384**	0.200	0.194	0.175
	SG	0.116	0.296	0.245	0.203	0.253	0.419	**0.346**	0.223	0.297
	TH	0.137	0.307	0.263	0.242	0.317	0.514	0.301	**0.380**	0.272
	TW	0.114	0.236	0.197	0.201	0.218	0.272	0.255	0.190	**0.336**

Before venturing into the analysis of the Median Responses, it is interesting to suggest a graph where we have plotted each pair of markets highlighting the role played by the two components as discussed after Equation (8). This is done in Figure 5 where we have plotted the estimated β_1's on the horizontal axis, and the correlation parameter ρ, as estimated in the copula function, on the vertical axis (thus, for each pair of markets, we have one value of ρ and two values of β_1). In the figure we have superimposed two axes corresponding to the means: thus we have isolated four quadrants where we can group pairs of markets according to whether they have values higher (lower) than the mean along one axis, correspondingly, higher (lower) than the mean along the other. It is striking to notice that CN is consistently below the mean by both coordinates (with very similar β_1's close to zero); correlations for ID and PH are around the mean and show average β_1's (for PH slightly higher than that as a Destination); MY and TH have β_1's around the mean and higher than average ρ's. HK and SG have high ρ's accompanied by several high β_1's as well, while KR and TW have higher ρ's and closer to average β_1's.

[3]Volatilities in Table 6 are expressed in annualized terms for ease of interpretation. This means that the diagonal entries are $\sigma_o(r^*, \alpha) \cdot \sqrt{252}$, while off–diagonal entries are obtained modifying the $\widehat{\beta}_0$'s in Table 3 as $\widehat{\beta}_0 \cdot 252^{(1-\widehat{\beta}_1)/2}$.

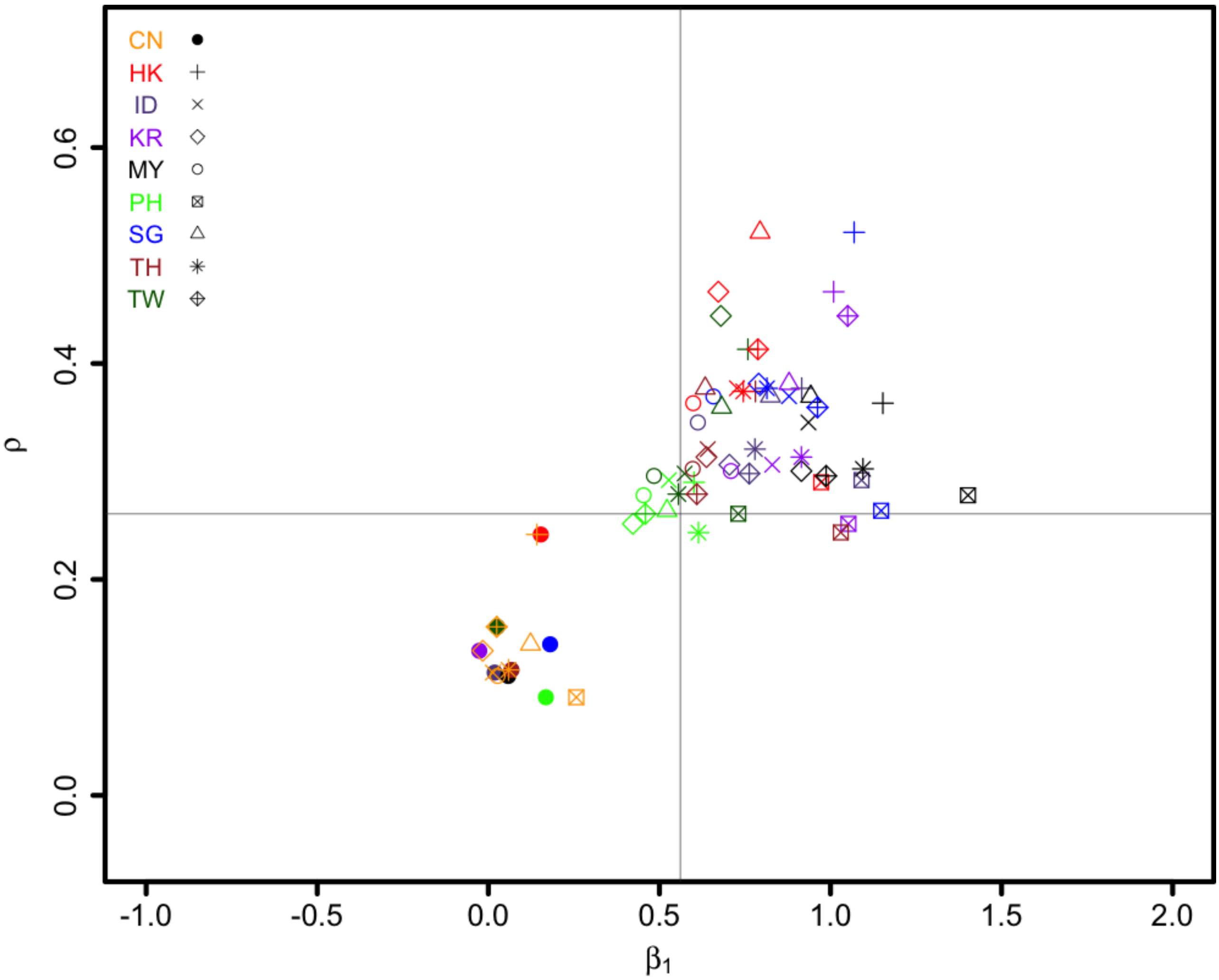

Figure 5: Relationship between correlations (ρ) and volatility elasticities (β_1) (the superimposed axes correspond to the means of the two parameters). The color identifies the Originator market, the symbol indicates the Destination market. Sample period: Feb. 1996 - Dec. 2015. Based on Garman-Klass volatility.

3.4 The Median Response to VaR's

We are now in a position to put all the pieces together and derive some empirical implications of our approach for the response to market movements associated with a $VaR(\alpha)$–drop in one market. We first report the Median Response to a specific choice of $r^* = -0.03$, again for $\alpha = 0.05$, in Table 7.

Here we can notice some asymmetries between the lower and upper triangular portions of the matrices of results. For certain markets, for example Singapore, the effects of a 3% dip in other markets are quite substantial and are larger than the effects of when the dip originates in Singapore.

If one makes r^* vary, the result is the Median Response function in Equation (8), where, we recall, the factor $\eta_{d|o}(50, \alpha)$ depends on the given choice of α in the VaR and the correlation structure from the bivariate distribution, and the remaining terms contain the binding link between originating and destination markets through the estimated coefficients of the log–log relationship (4).

The best way to synthetically represent the results is by way of graphs grouped by originating market showing the profile of the Median Responses by destination market (Figure 6); as usual we choose the α level to be 0.05. We keep the same scale on the y–axis to compare the results

Table 7: Median Response (MeRes ; $\alpha = 5\%$) in the destination market to a dip by a daily 3% in the originating market (main diagonal, in bold) interpreted as a VaR(α). Originating market is by row and destination market is by column. Sample period: Feb. 1996 – Dec. 2015. Based on Garman-Klass volatility. Percentage values throughout.

		Destination								
		CN	HK	ID	KR	MY	PH	SG	TH	TW
Originator	CN	**-3.00**	-0.42	-0.13	-0.16	-0.13	-0.18	-0.25	-0.20	-0.23
	HK	-0.35	**-3.00**	-0.86	-1.16	-0.87	-1.22	-1.91	-0.99	-1.40
	ID	-0.11	-1.55	**-3.00**	-0.89	-0.98	-1.97	-1.79	-1.07	-1.14
	KR	-0.15	-1.84	-0.85	**-3.00**	-0.90	-1.20	-1.62	-1.03	-2.15
	MY	-0.07	-1.34	-0.84	-0.72	**-3.00**	-1.91	-1.35	-0.99	-0.98
	PH	-0.07	-0.54	-0.47	-0.37	-0.44	**-3.00**	-0.54	-0.48	-0.45
	SG	-0.13	-1.67	-0.85	-0.83	-0.78	-1.12	**-3.00**	-0.90	-1.16
	TH	-0.13	-1.18	-0.75	-0.77	-0.79	-1.25	-1.25	**-3.00**	-0.81
	TW	-0.15	-1.06	-0.53	-1.02	-0.52	-0.71	-0.98	-0.56	**-3.00**

across panels. There is a group of 5 originating markets (HK, ID, KR, MY and SG) for which the array of responses is quite varied (the lowest, across the board, are on CN which also does not propagate): among these destination markets we see more frequently among the largest responses HK, PH, SG, TW. The lowest responses come from PH, TH and TW.

3.5 Assessing Market Importance: Bilateral Median Response

The graphs in the previous section can be synthesized, evaluating the flows between markets in the form of a Bilateral Median Response (BMeRes, Equation (10)), from the originating to the destination market, as the integral under the curves seen in the Figures 6. For a pair of markets and a level of α, the value of BMeRes provides a benchmark for the bivariate impact of the shock on the Destination, and allows for a comparison across Destinations for the same Originator and for a given Destination across Originators. We report these values in Table 8: the results highlight the interconnectedness between Hong Kong and Singapore (with high BMeRes in both directions). For other markets, this symmetry is absent: the highest BMeRes (above 7) are had from ID to PH and to SG, from KR to HK and to TW, and from MY to PH; only two of the remainder are above 6, namely, from ID to HK and to KR to SG.

We can aggregate $BMeRes$ into the MMeRes, the Market Median Response of a Destination to drops in other originating markets, adding the values within the Table 8 by column. Apart from CN which has the lowest figure, we see HK, PH, SG and TW clustering toward the high 30's, while ID, KR, MY and TH are grouped in the low 20's. The Area Median Response AMeRes is about 243.

The BMeRes's can also be seen from the point of view of the Originator, invoking the MSEff in Equation (12), shown as the rightmost column in Table 8. Apart from the isolated CN, this time higher values are had by ID and KR (in the upper 30's), followed by MY and HK (mid–30's), SG and TH (upper 20's) and then TW (low 20's) and PH.

We may treat these values as if they were total exports and total imports in international trade. The Area Median Response for our nine markets would be the equivalent of world trade, and, correspondingly, we could calculate the shares by row ("Originator" as if they were exports, MSEff divided by AMeRes) and by column ("Destination" as if they were imports, MMeRes divided by AMeRes). Taking $1/9 = 11.11\%$ as a benchmark, we note that both HK and SG have values above that in both relative indices. ID, KR, MY have values higher than the benchmark for the relative MSEff (and lower for the relative MMeRes), while PH

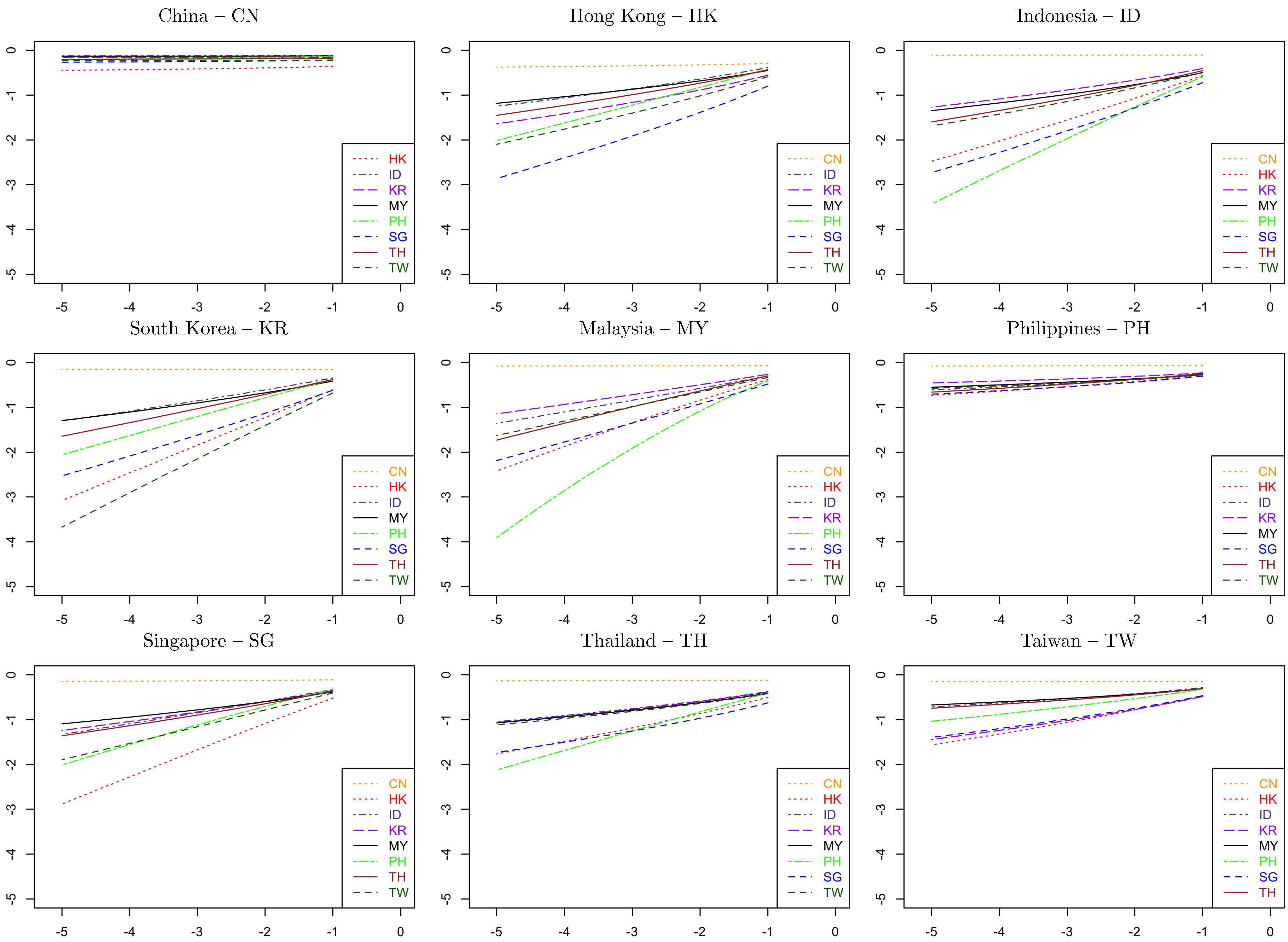

Figure 6: Bilateral Median Responses in the destination market as a function of r^*, considered a $VaR(\alpha)$ in the originating market. $\alpha = 5\%$. Estimates on sample period : Feb. 1996 – Dec. 2015. Based on Garman-Klass volatility.

Table 8: Bilateral Median Response calculated analytically for $\alpha = 5\%$. We report the bilateral impact ("Originator", "Destination"), the sum by row from the originating market (MSEff), the sum by column to the destination market (MMeRes) and the grand total (AMeRes). Sample period: Feb. 1996 – Dec. 2015. All signs are negative. Based on Garman-Klass volatility.

		Destination									
		CN	HK	ID	KR	MY	PH	SG	TH	TW	MSEff
Originator	CN		1.65	0.50	0.65	0.53	0.71	1.00	0.78	0.91	6.73
	HK	1.38		3.39	4.57	3.42	4.89	7.55	3.91	5.53	34.63
	ID	0.44	6.18		3.49	3.86	7.93	7.10	4.23	4.51	37.73
	KR	0.61	7.37	3.37		3.54	4.83	6.41	4.09	8.63	38.85
	MY	0.30	5.44	3.34	2.85		7.96	5.37	3.98	3.92	33.16
	PH	0.29	2.10	1.83	1.43	1.71		2.12	1.89	1.78	13.15
	SG	0.53	6.72	3.35	3.27	3.06	4.52		3.54	4.61	29.60
	TH	0.51	4.66	2.95	3.01	3.09	5.02	4.91		3.19	27.34
	TW	0.60	4.17	2.08	4.00	2.05	2.80	3.86	2.19		21.76
	MMeRes	4.65	38.30	20.82	23.26	21.25	38.66	38.31	24.61	33.09	242.95

Table 9: Relative MSEff and MMeRes by market as a share of the grand total (AMeRes). The Balance indicates the difference between the two: a positive value is to be interpreted as the market being a net provider of impulses. Results from $\alpha = 5\%$. Sample period: Feb. 1996 – Dec. 2015. Based on Garman-Klass volatility.

Market	Relative MSEff	Relative MMeRes	Balance
CN	2.77	1.91	0.85
HK	14.25	15.77	-1.51
ID	15.53	8.57	6.96
KR	15.99	9.58	6.41
MY	13.65	8.75	4.90
PH	5.41	15.91	-10.50
SG	12.19	15.77	-3.58
TH	11.25	10.13	1.13
TW	8.96	13.62	-4.66

and TW have the opposite. TH is in a neutral position, while the unconnectedness of CN is confirmed also here. The evaluation of whether each market is a net provider or receiver of impulses (looking at the difference as a sort of trade balance in percentage) is a complementary indication to what we just discussed. The last column of Table 9 shows the extent by which PH is particularly vulnerable (SG and TW somewhat less so), and ID, KR and, to a lesser extent, MY net providers of impulses.

3.6 Dynamic Analysis

The turmoil affecting the financial markets in different occasions makes the previous analysis open to the issue of the stability of the estimated relationships across subperiods. In this Section, we address some of these concerns in reference to the evolution of the interconnectedness between markets. We take a three–year rolling estimation window, in which we add one month at the time and re–estimate all indices involved: the results are assigned to the last month of the window. For the sake of space we defer the details to the supplemental web material, limiting ourselves to some major comments here.

Let us start from the AMeRes seen as a measure of areawide response, i.e. a synthesis of the total interconnectedness, although its unit of measurement does not have an interpretation *per se*. If we reformulate it as an index which takes the value 100 in the first month, corresponding to the three-year period straddling the East Asian crisis which followed the devaluation of the Thai Baht in 1997, the outcome is useful in a comparative sense. Figure 7 conveys the idea that subsequent periods had a lower or higher interconnectedness than the one that was had during a major crisis in the area. Unsurprisingly, until 2007 the index hovers around 100: a local peak is had as a consequence of the burst of the dot com bubble, with the later years of low volatility and low interest rates providing lower values. Starting toward the end of 2007, we have a sudden and generalized increase of the index until the beginning of 2009, after which it starts to decline back toward the value estimated on the whole period (as seen before, cf. Table 8). A sudden burst is had at the end of the time span, as a consequence of the events occurred in August 2015, surrounding the uncertainty about the Chinese economy and the devaluation of the Renminbi. Acknowledging that with a monthly rolling window, dating these events may be tricky, for the ease of reference we will refer to vertical lines drawn in correspondence to a selection of local peaks: Sep. 2000, labeled the “Dot Com Bubble” with the aftermath of a major stock market reversal; May 2005, labeled the “Global Savings Glut” according to Bernanke’s definition of a major period of low interest rates; Apr. 2009, labeled the “Great Recession” in reference to the effects of the global financial crisis (the trough in the S&P500 was had in Feb. 2009); and, finally, Aug. 2015 labeled the “Renminbi devaluation”, with the major reverberation on neighboring countries and the overall uncertainty about the perspectives of economic growth in the area.

Having established the time–varying pattern of the responses and having isolated some meaningful dates, it is interesting to examine how the various components analyzed before behave in the face of a restricted sample estimation. We start from the link between the standardized returns, summarized by the copula correlation ρ, and the elasticity between volatilities, expressed by β_1. Figure 8, which parallels Figure 5, illustrates the relationship between such two estimated parameters in correspondence to the four local peaks marked in Figure 7 (to ensure comparability, the superimposed axes correspond to the same means of the two parameters on the whole sample as before).

Without going into too much detail, we notice that the scatterplot moves around substantially, highlighting the dynamics of interdependence in the area: generally speaking, the points tend to move from bottom left to top right, with the highest level of interdependence in Apr. 2009. In particular, the panel (a) (Sep. 2000 – the “Dot Com Bubble”) is characterized by values generally below the overall means (the sample specific means are SW of the overall ones) and negative correlations just for CN; in the panel (b) (May 2005 – the “Global Savings Glut”) the values are more spread out (with some negative β_1’s, just involving CN); in the panel (c) (Apr. 2009 – the “Great Recession”) most points are above the overall means with many elasticities that go above 1 (for CN the increase in volatility interdependence seems to be stronger than the increase in correlation; PH shows a large dependence in volatility); finally the panel (d) (Aug. 2015 – the “Renminbi Devaluation”) highlights a generalized reduction in interdependence but a stronger role of China as an Originator limited to the volatility channel (correlations stay low). It is interesting to note that Hong Kong has experienced a generalized reduction of its position as an Originator in the last years and that South Korea (and to a lesser extent Singapore) shows a lot of dependence in volatility as a Destination.

We can tie these comments to the detection of specific changes in the bilateral relationships as reflected by the synthetic BMeRes. This is done in Figure 9 where we have selected the

Figure 7: AMeRes(α = 5%) estimated by a 3-year rolling window on the sample period Feb. 1996 – Dec. 2015 as a percentage to the value of Jan. 1999. The horizontal line is drawn at the value corresponding to the whole period. The vertical lines correspond to a selection of local peaks (cf. dates in the text). Based on Garman-Klass volatility.

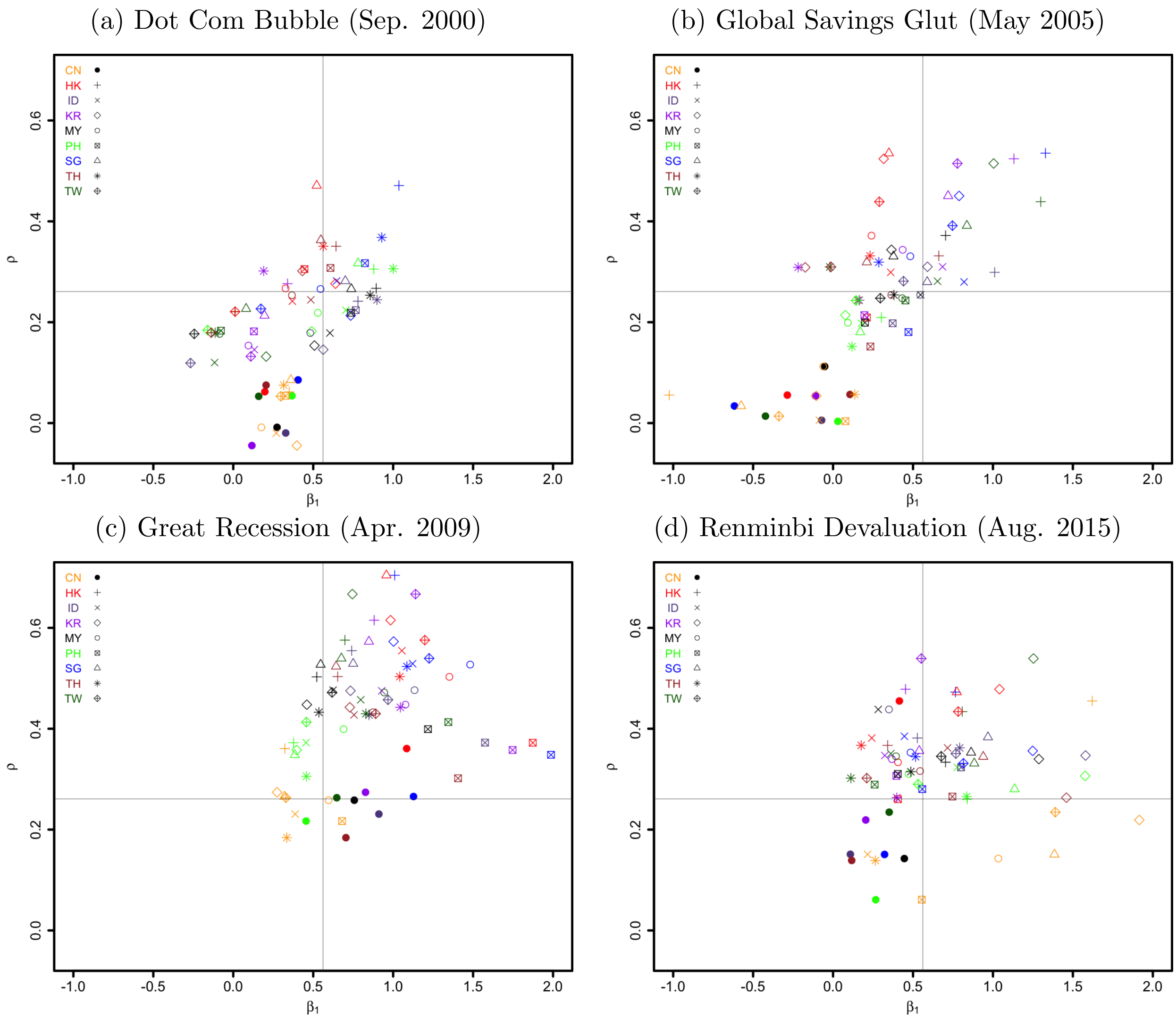

Figure 8: Relationship between correlations (ρ) and volatility elasticities (β_1) estimated by a 3-years windows ending on the specific data (the superimposed axes correspond to the whole sample means of the two parameters). The color identifies the Originator market, the symbol indicates the Destination market. Based on Garman-Klass volatility.

four major markets (HK, KR, SG and TW) and have inserted CN next to them, in view of its increased importance in the area: as an Originator, CN confirms to gain importance only in the very last part of the sample; as shown in panel (d) of Figure 8, we can attribute that to volatility spillovers more than an increase in correlation. By the same token, as a Destination, CN has become temporarily more vulnerable to other markets in the years following the 2008 global crisis: this is also reflected in panel (c) of Figure 8, where we notice that the points corresponding to CN as a Destination are present on the right side of the scatter, once again as a reflection of its increased volatility response to other markets. By contrast, HK experiences a decline in response from KR and SG in the last period, after having experienced a steady increase especially post 2008 (a similar declining pattern is shown for HK as an Originator, this time toward SG and TW, while a moderate increase is had toward KR). TW as a Destination appears to have had an increased Bilateral Median Response to KR and SG until 2013 and a sharp decrease thereafter. All the others seem fairly stable across time.

To complement the analysis, we can calculate the Relative MSEff and Relative MMeRes as a share of the AMeRes ($\alpha = 5\%$) estimated on the same three-year rolling window. Figure 10 gives us a feeling about the importance of each market as an Originator of responses (dashed

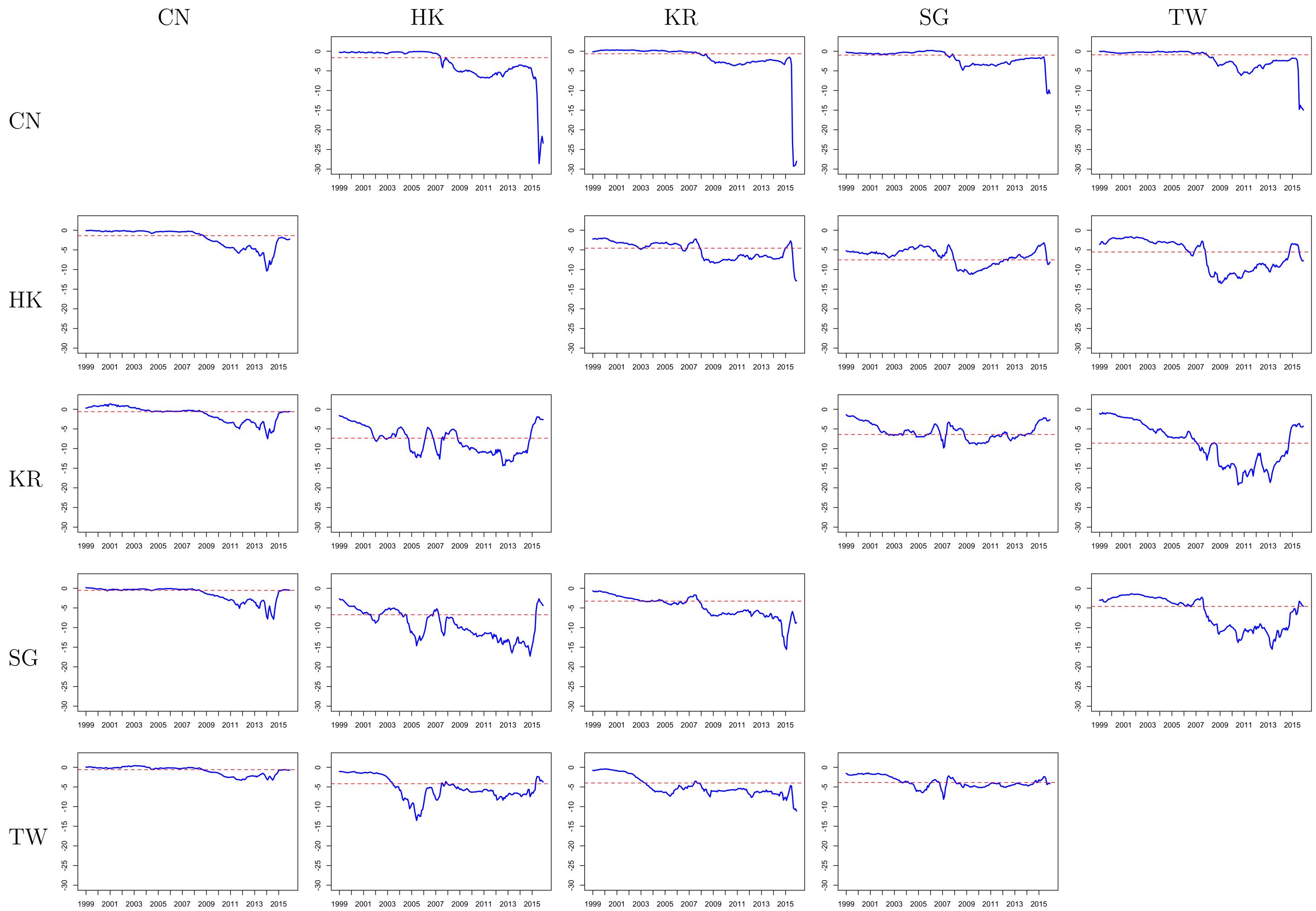

Figure 9: Selected Markets. BMeRes(α = 5%) estimated by a 3-year rolling window on the sample period Feb. 1996 – Dec. 2015. The horizontal lines are drawn at the values estimated on the whole period. Based on Garman-Klass volatility.

line) and as a Destination (solid line). These measures are important because they sterilize the evolving behavior of AMeRes, allowing to concentrate on the relative importance of each market, and on whether the shares are stable with respect to the whole sample estimates (horizontal lines). We confirm the previous comment that CN has affirmed its presence in the area past 2007 with a sharp increase toward the end of the sample as an Originator and a steady increase and then a sharp decrease of the responses as a Destination. HK has more stable shares as Originator with a fairly erratic behavior as a Destination market even if the last couple of months are very close to the whole period estimates; the opposite is true for ID. KR has stable estimates until 2014, after which there is an abrupt reversal of importance, showing a large share as a Destination market, while a sharp decline as an Originator. For MY we notice a generalized loss of role as an Originator and a temporary surge between 2008 and 2013 as a Destination. The PH gained some importance in the recent past as Originator (but seem to have had a decline since), while having a more pronounced hump as a Destination between 2007 and 2013. SG is relatively stable, though with mirrorlike movements in its importance as Originator and Destination. Apart from a temporary surge as an Originator, TH has had a fairly stable share, and the same can be said for TW, at least for the period post 2007.

The results about the dynamic evolution of the interconnectedness find a good synthesis in Figure 11 where we reconstruct a graphical network (for a general approach and references cf. Barigozzi and Brownlees (2014)), in which each node is a market, and it is made proportional to the sum of MSEff (Originator, in red – darker) and of MMeRes (Destination, in green – lighter). The thickness of the arcs connecting the nodes is drawn on the basis the values of BMeRes relative to the benchmark (depicted in Figure 1, in our case equal to 12), grouped in four classes. Arcs with relative importance below a certain threshold were not reported. The visual impression is that both the importance of markets and the strength of the links first increased (peak after the global financial crisis, panel (c)) and then they declined (panel (d)), showing how important CN has grown (first as Originator), how HK has lost its leading role and how KR has maintained its size (but it has reverted the roles from Originator to Destination).

4 Conclusions

In this paper we have suggested a novel methodology to reconstruct the network of financial interdependencies within an area of interest. We focus on a negative daily movement in an Originator market return r^*, and interpret it as a VaR associated with a certain probability α; as customary, such a return can be seen as the product of a derived volatility level and the corresponding α–quantile of a time independent probability distribution (of standardized returns). The effect on the Destination market is accordingly defined as the product of the volatility level associated with the one in the Originator (through a volatility link) times (through a copula function) the median of the distribution of the Destination standardized returns, conditional on the α–quantile. Such an effect is defined as the Median Response of the Destination market to r^* in the Originator.

By making r^* vary within a meaningful interval, an array of responses is derived, which can be synthesized into a Bilateral Median Response, and, by successive aggregation, an Area Median Response. These can be interpreted as indicators of the bilateral, respectively, overall turbulence associated (not at any given moment) with potential extreme returns. To be clear, although the concept is reminiscent of CoVaR, we are eschewing time conditionality: by definition, the standardized return distributions are independent of time; the volatility link is a static one (log–log relationship between volatility measures estimated by IV), and aims at reconstructing possibly asymmetric associations between volatilities. By adopting bivariate relationships we are not seeking partial effects (identifiable in a Granger–causal sense) but a mere association between volatilities, as in the question “on a 27% volatility day in Hong Kong,

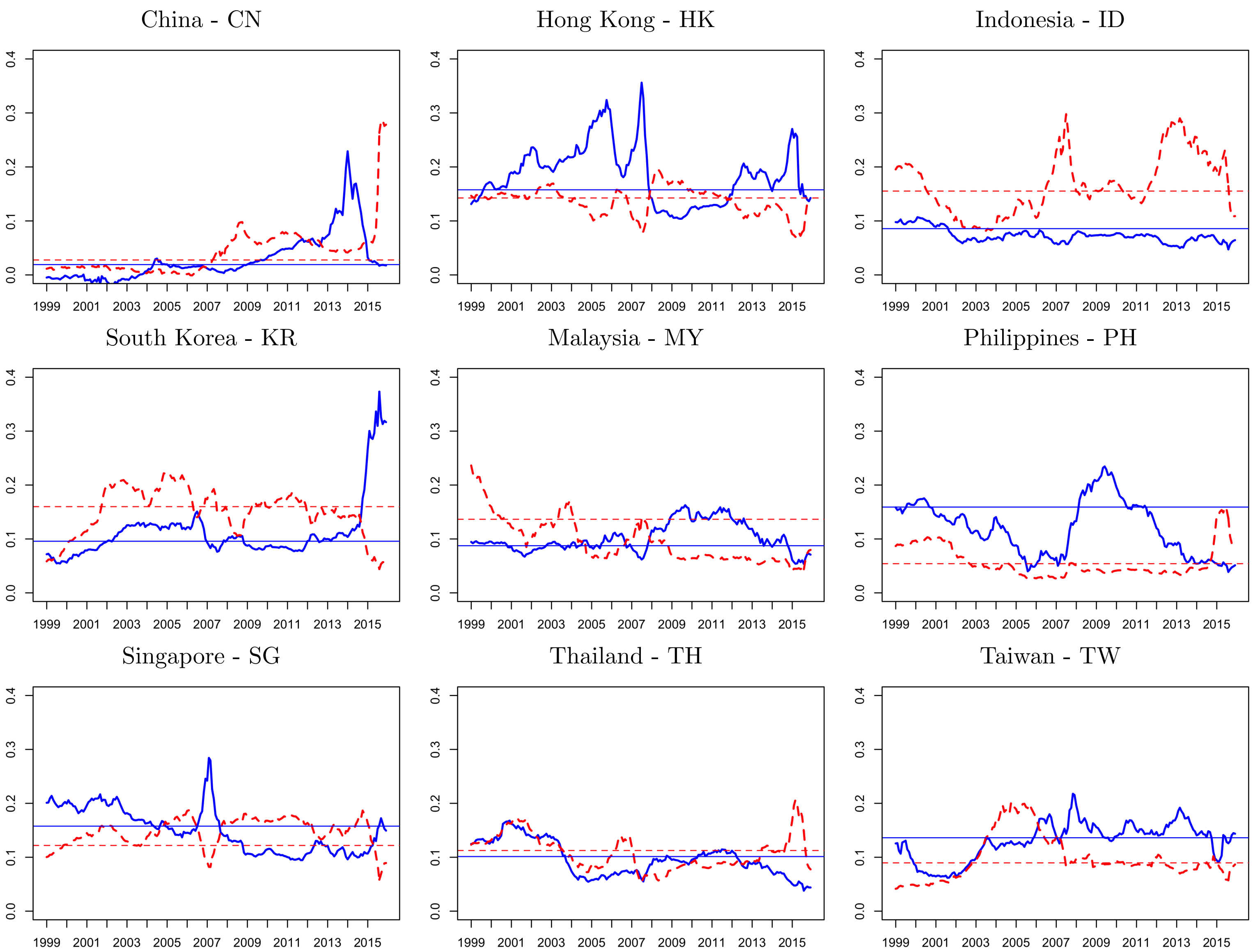

Figure 10: Relative MSEff of each market as Originator (dashed line) and Relative MMeRes as Destination (solid line) as a share of the AMeRes ($\alpha = 5\%$) estimated by a 3-year rolling window on the sample period Feb. 1996 – Dec. 2015. The horizontal lines are drawn at the values estimated on the whole period. Based on Garman-Klass volatility.

what is the associated average volatility in Singapore?"; by avoiding a causal interpretation, such a choice is independent of which other markets are included.

We have applied the methodology to nine East Asian markets over a sample spanning 1996 to 2015. Over the whole period, the result which emerges is one which sees Hong Kong, Singapore, South Korea and Taiwan as the main markets (both as Originators and as Destinations). Further investigation, though, reveals that the responses are sample specific, and that the role played by individual markets changes through time. By reestimating our relationships on a three year rolling period (adding and eliminating a month at a time), we show that the Area Median Response follows an expected pattern of stable and low level until 2007, a sharp increase on or around the global financial crisis of 2008, a subsequent decline past 2009, and a sudden peak in August 2015 as a consequence of the Renminbi devaluation. Moreover, there is a decrease in the importance of the role played by traditional, so–to–speak, players (especially by Hong Kong and Singapore) in favor of a strong emergence of China first responding to other markets, and then propagating shocks to the area in the occasion of its currency devaluation. By contrast, there is less evidence of a strongly time-varying behavior of the correlations.

The approach can be seen as a modular one. In the current application, we have taken a readily available measure of range–based volatility (Garman and Klass, 1980); other choices are possible, of course: as an end–of–day measure, any of the variants of realized volatility; as a one-step ahead measure we could take a GARCH– or a MEM–based time series of conditional volatilities to be inserted in the static log–log equation. Both approaches could be extended in the direction of Engle *et al.* (2012) where the past information set is enlarged to include lagged returns and/or past observed measures of volatility. To reconstruct the conditional Median, alternatives to using a copula function are available: for one, a dynamic copula function, but also any variant of a parametric bivariate distribution with an appropriate specification for the (dynamic, e.g. DCC) correlation.

The application presented here is built on an area represented by stock markets. The methodology can easily be applied to a larger number of variables representing individual stocks within a sector, for example, a network of financial institutions to be analyzed in their systemic importance.

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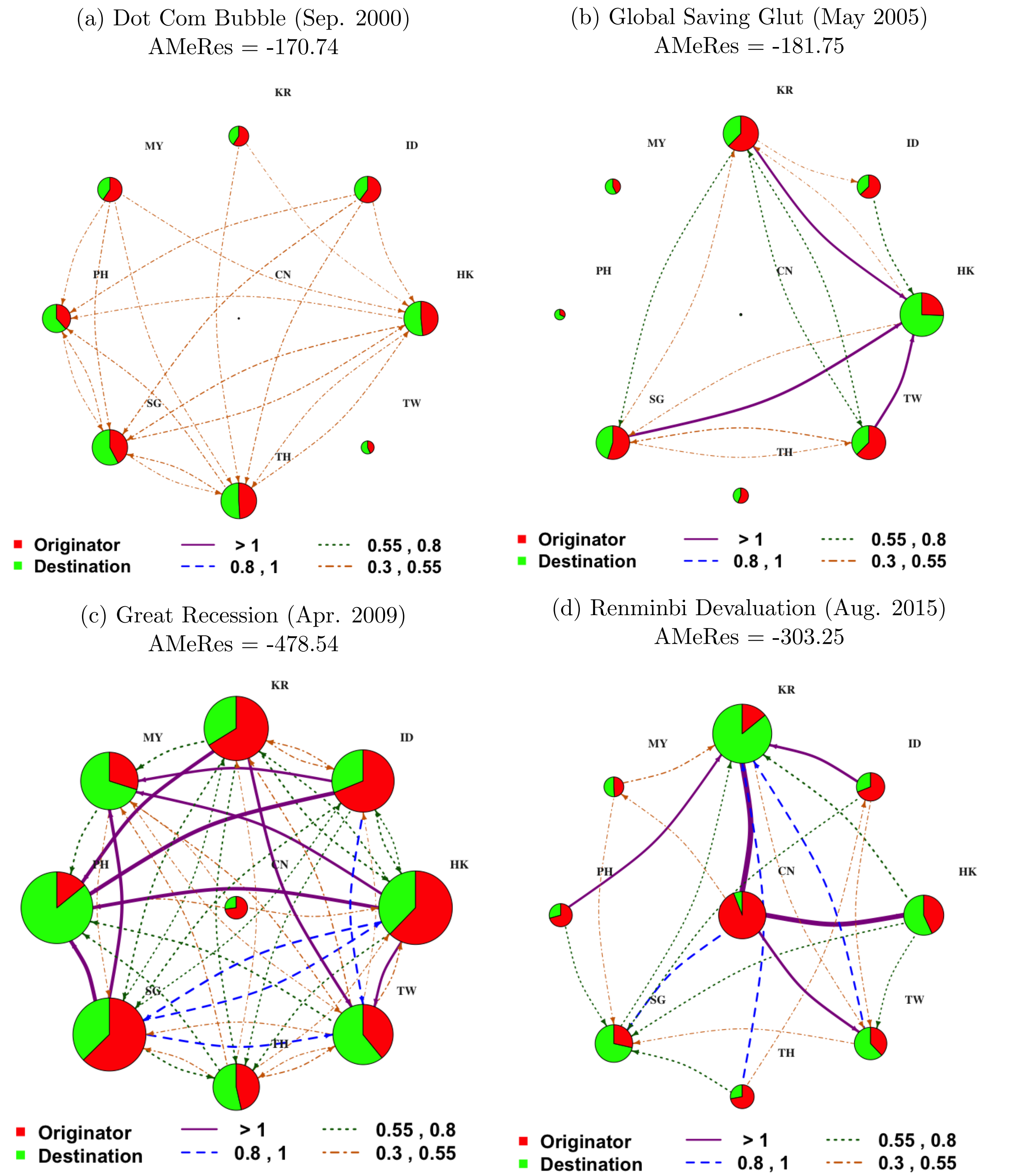

Figure 11: Network relationship derived from estimates at 5% on a 3-years windows ending on the specific data. Based on Garman-Klass volatility.