Beyond the "Asian Flu". "Asia-vu"[1]? Internal and External Risks for The Economy of Indonesia. Asset Price Bubbles and Contagion

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ABSTRACT

Asset price bubbles and cross-country contagion, embodying an economy's domestic and foreign risks respectively, are two topical issues in finance. Indonesia, a fast-growing emerging market economy, and one of the world's volatile "Fragile Five", is a prime suspect for a country that is likely to exhibit vulnerabilities to both bubbles and contagion. Even more so, in the light of the massive money flows, induced by the Fed's quantitative easing operations and their subsequent "tapering". To test for bubbles, we apply decomposition of Indonesian stock, property, and foreign-exchange prices, based on Kalman filter estimation and unobserved components modeling. In the measurement of cross-country contagion we employ four well-known contagion tests (DFGM, FR, FG, and BKS) to evaluate equity spillover effects for Indonesia during the Lehman bankruptcy crisis, the Greek sovereign-debt crisis, and the Tapering scare of 2013. Ultimately, the paper comes up with a unified conceptual framework for joint testing of a country's resilience to both external and internal financial shocks. By defining and quantifying an innovative indicator of a country-specific risks level, dubbed the "bubbagion index", we provide a flexible blueprint for systematic global economic-threats reporting in the context of that framework. In particular, the empirical application of our combined methodology to the case of Indonesia indicates much greater susceptibility of this Southeast Asian country to contagion risks than to domestic asset-price bubble formations. The main findings of this new approach explicitly take into account the specificities of the economic-history, current macroeconomic-performance, foreign-trade, and global-imbalances/coordination conjuncture, when critically assessing the overall sustainability of the Indonesian economy.

Keywords: Bubbles; Contagion; Indonesia; Kalman filter; "Bubbagion index".

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[1] The paronymic term "Asia-vu" stands for a déjà vu of the "Asian flu". It was coined by DBS, a Singapore-based bank.

INTRODUCTION

Financial historians have argued that huge historical mistakes, including economic disasters, usually repeat themselves because, as a rule of thumb, people tend to forget the negative episodes rather quickly and learn slowly from history's lessons (Ahamed, 2009; Fergusson, 2008). Indonesia, currently the largest Southeast Asian economy, was the far worst affected country in the Asian financial crisis ("Asian flu") of the late 90s. This was quite counterintuitive and unanticipated, since prior to the crisis Indonesia was irrefutably believed to have the soundest fundamentals in the region. It enjoyed the highest economic growth in Southeast Asia, low inflation, a relatively modest current account deficit, rapid export growth and growing international currency reserves (Iriana and Sjöholm, 2002).

However, in those days there existed a few ”negligible” macroeconomic glitches or macroeconomic imbalances within the Indonesian economy. In conjunction with, and amplified by the economic turbulence hitting its neighbours, they subsequently managed to produce a financial tsunami and investor scare of massive proportions. Some of these glitches were the relatively small current account deficit, at around 2.5% of GDP between 1990 and 1996, financed nonetheless predominantly by dollar-denominated short-term debt ("original sin"), as well as the insufficient foreign-currency reserves. Others were the lurking and ready-to-burst asset price bubbles[2] within Indonesia's stock, Forex and property markets, caused by ”hot money” inundating Southeast Asia en masse at the time. Suddenly, the Thai baht devaluation in July 1997 was allegedly that trigger which made the foreign investors wary of any hitherto neglected macroeconomic fragility in the region. Currency devaluation deepens financial crises, if debt is denominated in foreign currency (both Thailand's and Indonesia's case in 1997), something often referred to as the "original sin" of emerging markets (Brunnermeier and Oehmke, 2012). As a result of the devaluation, the ostensibly healthy Indonesian economy was sent into a tailspin. Once again economists began talking of contagion (”Asian flu”), or the rapid spread of similar economic difficulties across countries within the same region (Iriana and Sjöholm, 2002).

Those days of apocalyptic turmoil are long gone now. Over the last 17 years Indonesia, through prudent fiscal and monetary policies, has experienced impressive long-term macroeconomic stability and resilience. This has translated into a steady above-region-

[2] The concept of asset price bubble is defined in the Empirical Methodology section of the paper.

average GDP growth, consistent current account surpluses, moderated inflation, well-capitalized banking system, and significantly increased foreign reserves buffers.

And yet, Indonesia ranks nowadays among the ”Fragile Five”. The term was first introduced by Morgan Stanley’s currency analyst James K. Lord in August 2013 to describe the fast-growing emerging-market economies of Turkey, Brazil, South Africa, India and Indonesia. These are five countries, heavily reliant on foreign capital to fund their current account deficits. Therefore, they are particularly vulnerable to fickle money, Fed “tapering” of its post-Lehman-era massive quantitative easing (QE) operations, and a swift loss of investor confidence[3] (Lord, 2013). On top of that, most recently the Indonesian economy has imperceptibly commenced exhibiting the recognizable ”minor” macroeconomic glitches, which characterized its pre-“Asian flu” performance. They include a sharp widening of the current account deficit (up to 4.4% of GDP in 2013), accelerating inflation and a GDP slowdown (Melka, 2013).

Moreover, just as in the late 90s Indonesia shared economic similarities and was heavily susceptible to tremors within Thailand, nowadays it is not less prone to major fluctuations of the Chinese or Indian economic growth. After all, Indonesia is a major exporter of coal, rubber and palm oil, so a slowdown in China severely hurts the global demand for these commodities. India, on the other hand, shares a lot of similarities with Indonesia in terms of geographic location, current account deficits and significant reliance on foreign capital (drying up, as a result of the Fed’s QE “tapering”). Thus, investor scare in the Indian markets seems highly likely to quickly spill over to Indonesia. Indeed, Indonesia must be more susceptible than most of its neighbours to global investor sentiment, since 34% of its government debt is owned by foreigners (to put things into perspective, only Malaysia exhibits similar level of foreign-owned local debt - 28%; the figures for Thailand, Korea, and Japan stand at 17%, 9%, and 8% respectively) (Asian Development Bank, 2014). In May 2013, when Ben Bernanke, then Federal Reserve chairman, first uttered the word “tapering”, yields on 10-year Indonesian bonds jumped from 5.66 per cent to 8.41 per cent, the highest level since early 2011 (ATR KimEng Overview, 2013).

The picture of imminent threat for Indonesia becomes even more palpable, if just one more fact is added to the above coincidence list. This is the fact that since the Lehman crisis enormous QE operations have flooded with ”hot money” Southeast Asia in a

[3] The terms “quantitative easing” and “tapering” are both formally defined later in the study.

way, only seen in the pre-“Asian flu” heydays. Indeed, disparagers may speciously argue that, as US and European equity largely shrugged off the 1997 “Asian flu” due to its relatively significant geographical distance, we should not worry that nowadays Indonesian equity may react any differently to far-off shocks. However, these critics conveniently fail to mention the mounting pile of statistical evidence, categorically revealing that global economic and capital-market links have become so much closer since the distant 1997.

Thus, the natural empirical question which springs to one’s mind, when observing these recurring patterns, is: Is it a foregone conclusion that the market extrapolates financial disaster out of this familiar set of co-existing risks, and that history repeats itself all over again for Indonesia 17 years later? If this so-called “Asia-vu” is really transpiring, can we do something about it or not?

In order to satisfactorily test and answer this speculative question, we must explore in-depth the combined effects of any additional internal and external risks, facing Indonesia. The former risks comprise potential asset price bubbles, haunting nowadays the Indonesian stock, foreign-exchange and property markets. The latter ones include the likelihood of contagion effects spilling over to Indonesia from other countries during the most recent financial shock events, both regional and global.

Consequently, as a first objective, this paper aims to assess the current domestic risks for the Indonesian economy. This is achieved by means of employing the Kalman filter and unobserved components methodology into decomposing three types of Indonesian asset prices, and into extracting the bubble components. As a second objective, the study attempts to apply four contagion-effects methodologies (DFGM, FR, FG, and BKS)[4] into testing how resilient Indonesia has been to catching contagion via its stock market. The periods of interest are the Lehman debacle, the Greek sovereign-debt crisis and the mid-2013 Tapering scare.

Ultimately, a new economic indicator of a country’s overall financial stability, or vulnerability to bubbles, contagion, and potential feedback loops between them, is presented. It is dubbed ”the bubbagion index” [bə-’bā-jən] = bubble + contagion. The introduction of this index aims to turn the analytical framework of this paper into a conceptual framework for periodic testing/measuring of a country’s domestic and foreign

[4] Dungey, Fry, Gonzalez-Hermosillo, and Martin (2002, 2005; the DFGM test), the correlation approach of Forbes and Rigobon (2002; the FR test), the dummy-variable approach of Favero and Giavazzi (2002; the FG test), and the probability-based measure of Bae, Karolyi, and Stulz (2003; the BKS test).

risks, jointly. After being quantified, the “bubbagion index” is critically juxtaposed against a similar-spirit performance measure, named the “Work/Reward Quotient”.

The notion of “bubbagion” originates from a stylized fact: “In modern economies episodes of financial crises (with cross-country contagion being a special case of an acute financial crisis) are usually precipitated by boom-bust cycles in asset prices, i.e., by bubbles, or vice versa” (Glindro and Delloro, 2010). Indeed, a financial crisis can be a product of excessive credit expansion, too. The feedback loops are intertwined, nevertheless, since loose credit also acts as a catalyst for bubble formations.

Our final results indicate only partial or circumstantial evidence of bubble formations within the analysed Indonesian asset classes, on one hand. On the other, they offer robust corroboration for the existence of massive Indonesian vulnerability to contagion from abroad in at least two of the three tested periods. In a last-minute twist for Indonesia, these country-specific results, along with the “unambiguously one-sided” macroeconomic-policies implications thereof, are critically viewed and challenged. This is done in the larger-picture context of global imbalances, their concomitant beggar-thy-neighbour/currency-wars trade-offs, and risks of nascent carry trade bubbles. Most recent macroeconomic developments (up until April 2014) are analysed and related to the test-results implications.

The paper is organized as follows: Section 1 discusses data and their sources. Section 2 outlines the methodology used. Section 3 analyses the results. Section 4 investigates avenues for future research, then introduces and quantifies a new economic metric of a country’s financial stability, the “bubbagion index.” Section 5 concludes.

LITERATURE REVIEW

Before we proceed with the more analytical sections of this paper, a few paragraphs must be also dedicated to describing the pre-existing contributions in financial economics to developing the separate testing methodologies, applied together/unified here.

In terms of explicitly using the Kalman filter and unobserved components models in discovering asset-price bubbles, we are bound to mention a few influential studies. Firstly, Xiao and Tan (2005) investigate Hong Kong property price bubbles by extracting latent state variables with the Kalman filter. Based on their empirical comparisons, they attribute the large price swings in the Hong Kong property market during the 1980s and 1990s to a periodically collapsing rational speculative bubble. Similarly, Glindro and Delloro

(2010) from the Central Bank of the Philippines explicitly apply the same methodology to examine evidence of asset price bubbles in the Philippine stock, property and foreign-exchange markets. The Kalman filter is used by them to decompose the asset prices into fundamental, cyclical, and bubble components. They find bubble episodes in the Philippine stock and Forex markets, generally coincidental with the major macroeconomic boom-and-bust cycles, but no evidence of bubbles in the property prices.

Another seminal study by Harvey (2002) combines unobserved components with an error correction mechanism, and thus allows a decomposition of time series into trend, cycle and convergence components. The insight from this decomposition enables the current state of the economy to be accurately assessed and gives a procedure for the prediction of future observations. US, Chilean, and Japanese GDP data is used. Alagidede (2009) also employs models cast in "state-space form" (a generic term, which encompasses unobserved components models), and estimated with maximum likelihood and the Kalman filter. The goal is to decompose and predict the behaviour of agricultural raw materials prices and metal price indices through time.

In terms of explicitly using our four contagion-test methodologies jointly, we must acknowledge the pioneer comparative study of Dungey et al. (2005). In it, the DFGM, FR, FG and BKS tests are, for the first time, used together to robustly test for evidence of contagion during the "Tequila crisis" of 1994-95, the "Asian flu" of 1997, and the Argentine crisis of 2001-02. Another, relevant for our study, paper is the one written by Iriana and Sjöholm (2002). The authors examine whether contagion from the Thai baht devaluation during the "Asian flu" triggers the subsequent crisis in Indonesia by means of the FR test. The findings not only show evidence of such a contagion link, but also suggest that the spillover effects are exacerbated by increasing imbalances in the Indonesian economy.

Finally, Fry (2009), similarly to what we do on a macro-level, uses a unified testing methodology on a micro-level for detecting bubbles and contagion in English house prices. The bubbles are modeled by methods originating in statistical physics. The findings reveal the presence of a nationwide housing bubble in the period 2002-2007 and signs of contagious effects, with the bubble in London affecting prices in Yorkshire and the North, for example. Likewise, following a combined methodology in the context of Greek sovereign-debt crisis, Kizys and Pierdzioch (2011) estimate a present-discounted value model of equity valuation, extended to include a speculative bubble component. They find that the speculative bubbles in the Greek equity market may have the potential to spill over contagiously to Portugal, Ireland, Italy, and Spain.

1. DATA

1.1. Data (asset-price decomposition)

The asset prices that we consider for our decomposition analysis are: a) the IDX Composite Stock index (COMPINDEX), which is the main stock index of the Jakarta Stock Exchange and covers all the shares traded for the period 1985 – 2013 (August 14, 1991 = 100); b) the Financial Stock Index (FinStockIndex) and the Property Stock Index (PropStockIndex), which are two of the nine sector-wise indices that comprise the IDX Composite Stock Index for the period 1996 - 2013; c) the Residential Property Index (ResPropIndex), which is based on the prices (in Indonesian Rupiah) of new dwellings in 14 major cities of Indonesia and is available for the period 2002 - 2013; d) the nominal exchange rate between the Indonesian Rupiah and the US Dollar (USDIDR) for the period 1993 - 2013.

Stock market data is collected from the Bank Indonesia due to the availability of observations at longer time horizons and the specific nature of sectoral indices data. Residential Property Index observations are collected from the Bank for International Settlements' database for availability and reliability considerations. Exchange rate data is obtained from financial services provider Oanda since the relatively little popularity of the currency pair does not make it universally available at more conventional data sources.

With the exception of the Residential Property Index, which is reported on a quarterly basis by the Bank for International Settlements, all the other series consist of monthly observations. We decided to work with monthly observations for two reasons: firstly, to make our procedure compatible to that of Glindro and Delloro (2010); secondly, we believe that monthly data provides a reasonable trade-off between allowing larger-scale asset price dynamics development and high frequency of observations. All the series examined are in logarithms in order to reduce the skewness of data, make patterns more interpretable, and to help meet the assumptions of inferential statistics.

Descriptive statistics and correlation matrix for the time series are presented in Tables 1 and 2, respectively. Judging by the standard deviations, the three stock indices are the most volatile variables, and we would expect to see a great susceptibility to rapid and potentially irrational/overextended movements there. On the other hand, the exchange rate and property prices are the least volatile variables. The correlation matrix reveals interesting patterns. The composite stock index is highly positively correlated with the exchange rate and the residential property index. The two sectoral components of the composite index, Finance and Property, also exhibit very strong positive correlation. The exchange rate is also positively correlated with the property index. These findings confirm the important tendency of asset prices to co-move (Borio and Mcguire, 2004).

The time series used in the decomposition are plotted in Figure 1[5]. Visual inspection of the log observations reveals strong uptrends in most of the series in the second half of the sample period, but this is not a sufficient condition to render these increases bubble formations. A notable exception can be observed for the exchange rate series which somewhat flattens from 1999 (a couple of years after the height of the Asian crisis) onwards. A regime of managed float in an inflation targeting framework is the de-facto IMF classification of Indonesia's current exchange rate arrangement. Under this framework, foreign exchange intervention is implemented with the primary motivation of stabilizing the exchange rate along its fundamental path and maintaining financial system stability (Warjiyo, 2013). We suspect that this is the main reason for the prima facie exchange rate stability, but a more detailed discussion on this issue is to be found in the Results section.

A brief analysis of the volatility of the first-difference graphs in Figure 1 might give us some preliminary clues as to the time periods of potential bubble episodes. There are indeed some periods with pronounced volatility that appear in most time series under consideration. These coincide with the Asian crisis of the mid-late 1990s, the early 2000s with the dotcom boom and bust, and the most recent financial crisis of 2008-2009.

1.2 Data (contagion testing)

The conventional approach in the contagion literature usually involves analysis of equity returns or exchange rates. We chose to focus exclusively on the former here. Hence, we compiled stock index daily close prices for seven countries, namely Indonesia (IDX Composite Stock index, the main stock index of the Jakarta Stock Exchange which covers all the shares traded), Malaysia (FTSE Bursa Malaysia Kuala Lumpur Composite Index, a market-value-weighted index which tracks the 30 largest companies on the Bursa Malaysia by market capitalization), Hong Kong (the Hang Seng index, a market-value-weighted index

[5] The sample partial autocorrelation functions (PACFs) of the five time series are presented in Figure 2.

which comprises the 50 largest companies on the Hong Kong Stock Exchange by market capitalization), the US (S&P500, a free-float market-value-weighted index that includes 500 large-cap companies in the United States traded on the New York Stock Exchange and NASDAQ), Greece (The Athex Composite Share Price Index, a market-value-weighted index of 60 large-cap stocks listed on the Athens Stock Exchange), India (S&P Bombay Stock Exchange Sensitive Index, a free-float market-cap-weighted index of 30 component stocks representing large, well-established and financially sound companies across key sectors, traded on the Bombay Stock Exchange), and Brazil (Ibovespa, a free-float market-value-weighted index of 73 of the most actively traded and representative stocks of the Brazilian stock market traded on the Sao Paulo Stock, Mercantile, and Futures Exchange)[6]. The data is obtained from Yahoo Finance, with the decision to pick this data provider largely driven by the wide range of stock market data availability and uniformity.

Two common practical issues need to be addressed here: inconsistent (missing) observations and time zone alignments. Inconsistency in observations arises from differences in public holiday schedules and/or any other external factors in the countries under consideration that may cause a stock exchange in one country to be closed on a certain day while the other exchanges are normally functioning. In dealing with this, several imperfect procedures can be utilized: replacement of a missing observation with the previous one, interpolation between observations, or removal of that data point from the sample (Dungey and Tambakis, 2005). Replacing a missing observation with the previous one does provide a longer and smoother sample, but it is ultimately altering the way in which shocks are presumed to transmit through the different countries. Interpolation invalidates the very purpose of tracking the changes, while deleting a missing data point significantly reduces the dynamics of the process. In most practical applications, only the first and the third options are considered, with a preference towards the third option, which we also adopted in our analysis.[7]

Time zone alignment issues stem from the lack of trading time overlap between countries even if their markets are opened on the same date. Events in Indonesia occurring at time t can be processed by US or Brazilian markets at time t, but not vice versa. Events observed in the US or Brazil cannot be accounted for in Indonesian markets until date t + 1.

[6] The choice of countries is motivated in the Results (contagion testing) section of the paper.
[7] A simple procedure in VBA filtered out all the dates with a missing observation for a given country so that only dates with observations for all countries remained.

Two approaches in overcoming this problem exist. Introducing moving averages of returns can control for the differences in time zones (Forbes and Rigobon, 2002). A disadvantage of the moving-average procedure is that it may smooth some of the movements in asset prices, and possibly introduce spurious dynamics between asset returns. Another technique involves a choice of different lags depending on time zone differences and causal patterns (i.e. the choice of host country) studied (Bae, Karolyi, and Stulz, 2003), and this is the one that we applied in this paper.

The data is divided into two subsamples. The first one covers the period from 3rd January 2005 to 14th March 2014 (2073 observations after VBA filtering). It includes stock index data for Indonesia, Malaysia, Hong Kong, the US (lagged one period and used as a control variable), and Greece. This subsample is used for the tests of contagion during the Lehman panic and the Greek sovereign-debt crisis. The time difference between the Greek and the Asian stock markets is assumed here to be much smaller (than the one between the US and the Asian markets) to warrant any $t + 1$ manipulation of the Greek data (vis-à-vis the Asian indices). The second subsample covers the period from 3rd January 2012 to 14th March 2014 (480 observations after VBA filtering). It incorporates stock index data for Indonesia, India, Brazil (lagged one period), and the US (lagged one period and used as a control variable). Tests of contagion during the Tapering scare are conducted using this subsample.

2. EMPIRICAL METHODOLOGY

2.1 Empirical Methodology (asset-price decomposition)

Since we will be uncovering bubble components, we start off by broadly defining bubbles in asset prices. The definition of *bubble* most often used in economic research is that part of asset price movement that is unexplainable, based on what we call fundamentals (Garber, 2000).

However, it is essential to make a clear distinction between overshooting and bubbles in asset prices, because they may easily be conflated. The overshooting (above fundamental values) may contain both cyclical and bubble components. In this paper we will be interested only in extracting the latter, if indeed they are part of the overvaluation. This distinction is so important to make, since a cyclical component of overvaluation reflects inherent structural frictions and does not require special macroprudential measures. Conversely, a bubble component presents a dangerously disruptive market distortion, which necessitates the implementation of targeted stabilization policies. Furthermore, magnitude, or size of the discovered bubbles, also matters a lot for our ultimate conclusions. After all, if every innocent, short-term price overshoot were dealt with like a major bubble, the unnecessarily harsh restrictive monetary policies would stunt economic growth[8]. To further clarify matters, bubbles can be positive (price movement above what is accounted for by fundamentals and cyclical components, i.e., overvaluation) and negative (price movement below what is accounted for by fundamentals and cyclical components, i.e., undervaluation).

We use the famous Kalman filter and unobserved components/state-space modelling for implementing the asset-price decomposition in this study. Kalman filter is chosen because it is considered the best among the class of linear filters (Pasricha, 2006). Theoretically, the Kalman filter, (Kalman (1960), and Kalman and Bucy (1961)), is a fundamental algorithm for the statistical treatment of state space methods (Grassi, 2010).

The generic linear Gaussian state space model for a T-dimensional observation sequence $y_1, \dots, y_T$ is the statistical framework for the unobserved components models (also known as structural time series). In matrix notation it is made up of a measurement (signal) equation

$$y_t = Z_t X_t + \varepsilon_t, \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2), \qquad t = 1,2, \dots\dots, \mathrm{T}, \tag{1.1}$$

and a state (transition) equation

$$X_{t+1} = T_t X_t + D_t \eta_t,\ \eta_t \sim NID\ (0, V_t). \tag{1.2}$$

The first equation relates the time series y_t to a t×1 vector of unobserved components or state vector, X_t, through Z_t, that is a 1×t vector. The second equation is a dynamic linear model for the state X_t, taking the form of a first order vector autoregression. In this case X_t is a t×1 vector of unobserved states, T_t is a t×t transition matrix, determining the dynamic evolution of the state vector. D_t is a t×l matrix (could be the identity matrix) and η_t is an l×1 vector of random disturbances. The state space form of equation (1.1) and (1.2) can be easily extended to a multivariate setting, in which case y_t is an N×1 vector of time series, Z_t is an N×t matrix and ε_t is an N×1 vector of random disturbances, with $H_t = Var(\varepsilon_t)$ (Pasricha, 2006).

[8] For a more extensive discussion on the nature of bubbles, the reader can consult J.J.Siegel's article "What Is an Asset Price Bubble? An Operational Definition." (2003).

For a detailed, step-by-step illustration of the Kalman filter data fusion algorithm (prediction and measurement update/correction), used to estimate state-space models, in a simplified scalar notation, the reader is encouraged to consult Appendix 1. The appendix also presents the maximum likelihood estimation of the Kalman filter.

Following Glindro and Delloro's (2010) methodology of decomposing univariate asset price time series into fundamental, friction, and bubble components, we expand in scalar form the above-written generic state space equations (1.1) and (1.2). The fundamental asset price level is given by the trend whereas the cyclical component corresponds to the short-run fluctuations in price level. The new measurement equation is:

$$y_t = \mu_t + \psi_t + \gamma_t + \phi_t + \varepsilon_t,\ \ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2),\ t = 1,2, \ldots\ldots, \mathrm{T} \tag{1.3}$$

where: y_t - asset price; μ_t - trend component; ψ_t – cyclical component; γ_t- seasonal component; $\phi_t -$ autoregressive component; ε_t - irregular component.

The state equation for the trend μ_t typically consists of two parts, namely, the level and the slope β_t, in which the latter may not be necessarily present. A level is an actual value of the trend and a slope is a tendency of the trend to grow. A slope β_t is not always present in a model, because some time series move around their level randomly without a tendency to grow.[9] The state μ_t, that we use in the bubble extraction, refers to the estimated trend at all points in the sample using all observations, otherwise known as smoothing or signal extraction. There are also the filtered estimate and the predicted estimate. The former is based only on previous and current observations, whereas the latter is based only on previous observations (Glindro and Delloro, 2010).

As discussed in the beginning of the section, Glindro and Delloro (2010) define asset price overvaluation as a situation wherein asset prices are higher than their fundamental values. The overvaluation is not interpreted as a bubble, because it still contains an intrinsic cyclical component that captures short-run frictions. As such, asset prices can exhibit fluctuations around the equilibrium fundamental values. The other component is the residual or what Glindro and Delloro (2010) interpret as the bubble, because it cannot be explained by

[9] For an illustration, both on the estimation mechanics of two pivotal unobserved components time series models, and on the incorporation of cyclical and seasonal components within these models, the reader is encouraged to consult Appendix 2. Appendix 2 also contains information about STAMP, the programme implementing the asset-price decomposition. STAMP is a proprietary econometric software package of Timberlake Consultants Limited, used in unobserved components model estimations.

long-run and cyclical components. Their ultimate decomposition of asset price overvaluation into cyclical and bubble components is carried out as follows:

1) First, price overvaluation is given by the difference between actual and long-run trend of the asset price:

$$y_{t,long-run}^{excess} = y_t - y_t^{lr}$$

where y_t is the actual asset price and $y_t^{lr} = \mu_t$ is the long-run trend. (μ_t contains β_t) Seasonal factors, γ_t, if present, are added back to the estimated long-run trend to derive a measure of y_t^{lr}.

2) Second, the proportion of price overvaluation that is explained by short-run frictions or cyclical factors is given by:

$$y_{t,short-run}^{excess} = (y_{t-1} + E\Delta y_t) - y_t^{lr}$$

where $y_{t-1} + E\Delta y_t$ is the short-run price that captures short-run frictions and $E\Delta y_t (E\Delta y_t = \psi_t)$ pertains to the values of the short-run cyclical component of the univariate model (to $E\Delta y_t$ are also added the components from any AR(1) and AR(2) processes, or ϕ_t, if present). The difference between the short-run price and long-run price is attributable to short-run frictions.

3) Third, the residual, (i.e., y_t^{bubble}), which is the difference between the price overvaluation and the portion attributable to the short-run frictions is then interpreted as the measure of asset price bubble:

$$y_t^{bubble} = (y_{t,long-run}^{excess} - y_{t,short-run}^{excess}) \text{ (Glindro and Delloro, 2010).}$$

Glindro and Delloro (2010) assume a double-digit 10% as the threshold for irrational bubble, although they admit that the threshold itself is an empirical question. Nonetheless, this approximates the minimum estimated bubble during major crisis episodes.

However, Glindro and Delloro's (2010) estimated y_t^{bubble} is easily found to be inconsistent with their own interpretation of a bubble. If we extend the last three equations, we obtain

$$y_t^{bubble} = y_t - \cancel{y_t^{lr}} - y_{t-1} - E\Delta y_t + \cancel{y_t^{lr}} = y_t - y_{t-1} - E\Delta y_t.$$

This means that their reported bubble components (y_t^{bubble}) for the Philippine asset markets are not what they are supposed to be. Instead, they include both the bubble (residual) and the long-run trend, y_t^{lr}, (this is an obvious contradiction), and only the cyclical components ($E\Delta y_t$) are accounted for (or subtracted from y_t^{bubble}) in the extended equation above. Nonetheless, we choose to follow this inconsistent bubble estimation for two crucial reasons. The first one is the understanding that this is the only way to make our bubble estimates for Indonesia comparable with those, presented by Glindro and Delloro (2010) for the Philippines. The second one is the realization that not subtracting the long-run trend, y_t^{lr}, from y_t^{bubble} introduces an upward bias for the reported y_t^{bubble} (Figures 3 and 4), and that we can easily correct for this bias. Its presence mitigates any evidence of huge bubbles, while reconfirming any no-bubble results. The bias is strictly upward, because for all analysed Indonesian asset prices the estimated long-run trends are invariably positive in value. Therefore, should we discover hardly any traces of bubble episodes in the Indonesian asset prices (in effect, this is our main conclusion in the decomposition results subsection), then, the explicit accounting for this upward bias of y_t^{bubble} will further corroborate the robustness of the subsequent no-bubble findings.

A potential additional weakness of the unobserved components model, used in the paper, arises from our choice of applying this model in a univariate setting. It is believed, after all, that a multivariate framework provides a superior modeling environment for macroeconomic variables. It surpasses the univariate setting in that it also offers important insights in the dynamic relations between variables (Schleicher, 2002)**.** Moreover, the main drawback of our methodology appears to be in the relatively high sensitivity of the solution to the initial parameters (unknown) used for computing, as elucidated in the latter part of Appendix 1 (Dudek and Pachucki, 2011).

On a more positive note, time series models based on unobserved components are particularly efficient, compared to ARIMA type models, for example. Even more so, if irregular features are present in the data, such as missing values, mixed frequencies, outliers, structural breaks and nonlinear non-Gaussian aspects. This is crucially important since our data certainly contains some of these stumbling blocks. Another advantageous feature is that, unlike the Box-Jenkins model (also a linear Gaussian model), for instance, unobserved components do not require the differencing of a time series towards a stationary process (Koopman and Ooms, 2010). On top of this, the superior advantage of being able to provide direct economic interpretation of the separate components of a particular time series (especially of its bubble component) makes structural time series incredibly useful in assessing a country's internal risks.

2.2 Empirical Methodology (contagion testing)

As a consequence of, and in the wake of the 1987 "Black Monday", the Mexican "Tequila crisis", and the 1990s "Asian flu" versatile econometric tests have been propounded for measuring the effects of financial contagion between countries. The first problem with measuring contagion stems from the fact that there does not exist, and will probably never exist, a uniformly accepted definition of the term ”contagion” and its scope among financial economists. Broadly, contagion may be defined as an increase in correlation between asset returns during a crisis period. However, this definition does not tell us anything about the channels of propagation from one country to another, or about the stability of the transmission mechanism through time. Hence, it is such a tough task to estimate something that is so loosely defined in the first place.

For instance, in an influential paper (”No Contagion, Only Interdependence: measuring Stock Market Comovements”) Roberto Rigobon and Kristin Forbes (2002) make a subtle distinction between the terms ”shift contagion” and ”interdependence”. This distinction suggests that previous econometric tests may have discovered utterly spurious contagion, provided that we properly account for the inherently untenable assumptions behind these tests.[10]

In order to partially overcome the definition impediment, Rigobon, in this same seminal contagion-tests-review paper ”Contagion. How to Measure it?” (2002), chooses a different perspective. He decides to shift the focus to merely resolving the measurement issues with the existing tests, as well as to developing an ultimate optimal contagion test (DCC, determinant of the change in covariance). This is itself a Herculean task, since measuring contagion on stock market returns, interest rates, exchange rates, or linear combinations of these, is marred by a plethora of problems. For example, all these time series are plagued by simultaneous equations, omitted variables, conditional and unconditional heteroskedasticity, serial correlation, nonlinearity, and non-normality problems. To make

[10] For a detailed discussion on the impossibility of fully defining all aspects of the term ”contagion” in finance, the reader is advised to read E.G. Mendoza's critical *Comment* within Rigobon's paper ”Contagion. How to Measure it?” (2002).

matters even worse, the entire contagion tests literature is generally permeated by the overarching conclusion that there does not exist a perfect test for measuring contagion effects.

However, our primary objective is not to provide a comprehensive comparative review of all available methodologies, or of their corresponding pros and cons. It is, instead, to test for contagion (external risks) affecting the Indonesian economy. Therefore, we apply Rigobon's (2002) abovementioned measurement-oriented, parsimonious approach of selecting and implementing four influential, but imperfect contagion tests upon the Indonesian daily stock market data. The testing is conducted prior to, and during the Lehman crisis, the Greek sovereign-debt crisis, and the 2013 Fed-induced Tapering scare. In each case a sample of three countries is chosen. Three hypotheses are tested. The first (hypothesis 1) is an overall test of contagion allowing for linkages among all countries during a crisis period. Hypothesis 2 tests for contagion from one country (the host country) to both of the other countries in the sample. Hypothesis 3 tests for contagion between two individual countries. The tests utilized are the latent factor model of Dungey, Fry, Gonzalez-Hermosillo, and Martin (2002, 2005; the DFGM test), the correlation approach of Forbes and Rigobon (2002; the FR test), the dummy-variable approach of Favero and Giavazzi (2002; the FG test), and the probability-based measure of Bae, Karolyi, and Stulz (2003; the BKS test).

The generic two-factor-model representation of any asset returns, presented by Dungey and Tambakis (2005) below, serves as an initial common building block of the four contagion methodologies:

Let the return on the i-th asset in a noncrisis period be represented by $x_{i,t}$, while the corresponding return on the asset during a crisis period is given by $y_{i,t}$[11]. The durations of the noncrisis and crisis samples are, respectively, T_x and T_y. During periods of calm a standard two-factor model is assumed, in that the return in each market is a linear function of a set of common shocks (w_t) which affect all asset markets, and an idiosyncratic shock ($u_{i,t}$). For a set of N asset markets, this relationship is represented as:

$$x_{i,t} = \lambda_i w_t + \delta_i u_{i,t},\ i = 1, 2 \dots N, \tag{2.1}$$

[11] Not to be confused with the y_t from the earlier asset decomposition methodology, denoting asset prices.

where λ_i and δ_i are the loadings on the common factor and the idiosyncratic factor, respectively. For certain classes of models the common shocks represent the market fundamentals while the idiosyncratic shocks correspond to periods where actual returns deviate from the market fundamental values.

Crisis periods are commonly characterized as periods of increased volatility in asset returns, whereby the variance of $y_{i,t}$ is greater than the variance of $x_{i,t}$. This may be due to increased volatility in either the common shocks or the idiosyncratic shocks, or the result of additional channels that may arise only during crisis periods. It is this last channel which is commonly referred to as *contagion* (e.g., Kaminsky, Reinhart, and Végh, 2005; Masson, 1999; Forbes and Rigobon, 2002). That is, in the measurement of contagion any increases in volatility would necessarily exclude increases in either the volatility of the common shocks w_t, or increases in the volatility of the idiosyncratic shocks $u_{i,t}$, or both. To allow and test for potentially contagious transmission mechanisms during financial crises, it is necessary to augment equation (2.1) by including additional contagion variables when modelling returns in crisis period $y_{i,t}$. The augmentation produces the four contagion methodologies, used in this study. However, the detailed discussion on the resultant contagion-testing procedures (with their respective additional contagion variables, added to the crisis-mode version of eq. (2.1)) is preserved for Appendix 3. The appendix also elaborates on the underlying theory behind the four tests, as well as on their inherent measurement strengths and weaknesses (Dungey and Tambakis, 2005).

It is important to highlight that before implementing the DFGM, FR and BKS tests, we filter the returns by estimating a VAR with one lag, with US returns as a control variable. The residuals represent the filtered returns in the calculations that follow for these tests. The filtering is not conducted for the FG test, to be commensurate with the FG methodology. After the preliminary filtering, we apply the four chosen tests to our unique Indonesia-related data sets. For a step-by-step guidance on the numerical procedures, employed in the implementation of the four contagion tests, the reader is advised to consult Appendix 4. Subsequently, we comment (in relative, as well as in absolute terms) on both the unilateral and the joint confirmatory merits of our three hypotheses from each test in the Results section. The primary goal will be to determine whether these four alternative methods result in different contagion/no-contagion conclusions by using a common data set, i.e., whether the testing procedures results are robust.[12]

A common problematic feature of all four contagion methodologies, chosen in the paper, is the proper identification of the start and end point of the crisis period. These points have been ad hoc and exogenously assigned for all tests. At least two solutions for endogenising the crisis period have been proposed, which both include Markov-Switching model utilization (Hamilton, 1989). The first one is the MS-VAR DCC model (Pontines and Siregar, 2007), which improves the Rigobon's DCC procedure by applying Markov-Switching to obviate the arbitrary determination of crisis windows. The second approach (Gravelle et al, 2006) is an example of "identification through heteroskedasticity", and again applies Markov-Switching modelling to endogenise the timing of changes in volatility.

Despite its intuitive appeal, it is important to stress that in this study no Markov-Switching has been used. Instead, the determination of the crisis windows is based on an ad hoc sample split via popular news chronology. For instance, the day when Lehman announces bankruptcy, or the day when Greece announces for the first time that it has misreported its fiscal books, practically serve as starting-days for the crisis period observations. The determination of the crisis windows is also based on visual inspection of the stock returns volatility graphs around the days when the investigated shocks are known to have occurred (Figure 5).

Before ultimately proceeding to analysing the Results section, we must also emphasize a crucial discovery of the contagion empirical literature. This is the finding that most contagion tests exhibit poor size properties due to the typically small samples available, and in general, low power. Consequently, the tests could be biased, in that users of the FR model are unlikely to find evidence of contagion when it does exist, while users of the FG and BKS models are more likely to find contagion when it does not exist. These caveats admonish us that we should treat with great care and caution the upcoming analysis of the contagion test results in Section 3.2 (Dungey et al., 2005).

[12] This comparative approach was first implemented by Dungey, Fry, Gonzalez-Hermosillo, and Martin in their paper "A Comparison of Alternative Tests of Contagion with Applications" (2005). The four tests were applied to equity markets during the Mexican peso crisis of 1994-95 ("Tequila effect"), the Hong Kong speculative attack in October 1997 ("Asian flu"), and the Argentine crisis of 2001-2. Our testing procedures draw extensively on the methodology described in that paper.

3. RESULTS

3.1. Results (asset-price decomposition)

Before we present and discuss the estimated bubble components of the log time series, we check their first-differences in Figure 1, in order to ascertain any seasonal components that need to be accounted for in the STAMP specification of the Kalman filter. Such seasonal components can be readily detected via visual inspection, but a formal test procedure is necessary to confirm the validity of it. To that end, we create dummy variables and run regressions of the monthly (quarterly) log time series on a constant and the monthly (quarterly) dummies. The regression model takes the following general form (omitting time subscripts for ease of exposition):

$$y_i = \alpha_i + \gamma_{i,j} D_j + \varepsilon_i \ ,$$

where y_i is the respective log price series of asset i, α_i is a constant term, $\gamma_{i,j}$ is a vector of regression coefficients for asset i in month/quarter j, D_j is the dummy variable for a given month/quarter j, and ε_i is the residual term. The t-statistics of the regression coefficients from the abovementioned regression are summarized in Table 3. The formal regression results confirm our visual-inspection findings of no seasonal components. The t-statistics for the regression coefficients range from (-0.35) to 0.45, and none of them are statistically significant even at 10% significance level. Hence, the inclusion of seasonal components to the Kalman filter model specification does not seem to be warranted.

The next preliminary step of the estimation process consists of identifying autoregressive components in the time series, to be accounted for in the Kalman filter set-up. We can incorporate autoregressive components of order up to two as part of modelling pseudo-cyclical behaviour in STAMP. To that end, we investigate the sample partial autocorrelation functions (PACFs) of the five time series in Figure 2. Visual inspection reveals that the first two lags of all time series exceed the critical limits, which means that they are statistically significant from zero. The remaining lags are within the statistically-significant limits for COMPINDEX, FinStockIndex and PropStockIndex. There are, however, some higher-order lags for ResPropIndex and USDIDR that appear to be outside the significance limits. The mere existence of such autoregressive components compels us to explicitly account for them when modelling the cyclical behaviour of the analysed time series.

Having already been given a definitive answer whether to include any seasonal or autoregressive components when conducting the bubbles estimation, we are ready now to present and analyse our main results for each time series. The estimated bubble components (y_t^{bubble}) reported in Figure 3 correspond to the annual average of the monthly estimates for the respective time series (quarterly estimates for the commercial property prices).[13]

I. Stock Market

Significant estimated bubble components in the Indonesian stock market and their subsequent downward corrections are best and solely exemplified by the events of the late 80s and early 90s (Figure 3). The ensuing memorable financial shocks, nonetheless, such as the Asian financial crisis, the dot-com bubble, the Great Recession, and the QE/"tapering", exert much more subdued, sometimes even totally negligible, bubble effects. Accounting for the inherent upward bias of y_t^{bubble} (all estimated long-run trends, y_t^{lr}, are positive in value and are not subtracted from y_t^{bubble}) only validates these no-bubble findings. For instance, the May 2013 "tapering"-induced selloff is hardly evident in our annual average estimate of the bubble component in Figure 3. Even more strikingly, since the early 90s the magnitude of the Indonesian bubble component is much lower than the comparable magnitude, estimated by Glindro and Delloro (2010) for the Philippine stock market, and especially so, for the downward corrections. What could be the reason behind this incredible long-term resilience and sustainability of the Indonesian stocks (even in relative terms)?

First explanatory factor to pinpoint must be the consistently high GDP growth rate of Indonesia. However, through the years following the Asian crisis the Indonesian economic authorities have systematically demonstrated to investors that they prioritize stable or sustainable over excessive growth policies. Thus, they have never been hesitant in assuming a hawkish stance and tightening the monetary and fiscal taps, should there be any signs of overheating (such as, for instance, inflation being up off-target). This is what they did quite recently in 2013 by increasing the basic interest rate in order to curb rising inflation, which peaked at 9.5% y/y at end-2013 (IMF, 2013). The corollary of these sustainable-growth policies is that the higher interest rates inevitably also cool down the stock market and

[13] All the reported results posted strong to very strong convergence and have the highest log likelihood ratio for which steady states were found.

prevent it from unnecessary overheating. In effect, they preclude any stock market bubbles from inflating.

Secondly, what also pre-empts the painful downward corrections is the favourable fact that Indonesia has managed to significantly reduce its public debt by almost a third from 35% to 24% of GDP between 2007 and 2012 (IMF, 2013). This attainment makes Indonesia practically long-term impervious to any external shocks in terms of their chances to threaten the country's solvency. Then, this is precisely how stock market investors perceive Indonesia, no matter what calamitous, short-term shocks may be coming its way from the Eurozone, from the disorderly unwinding of QE, or from the price fluctuations of export commodities[14].

Finally, the most reasonable explanation may be hiding in the fact that Indonesia has a lower stock market capitalization (including vis-a-vis the Philippines) than many comparable emerging markets (EM) economies. It is a country in the process of financial market deepening. As of end-2012, stock market capitalization was equivalent to 49 percent of GDP, with free floating stocks accounting for only 37 percent of the total (IMF, 2012). IMF's comment about this is the following:

"Deepening financial markets in Indonesia is vital for mobilizing savings to fund investment and providing a wider range of financial products to meet the social needs. In addition, more liquid money and FX markets would enable the economy to better withstand shocks and enhance policy transmission mechanisms. Similarly, more diversified and deeper capital markets would help intermediate capital inflows without large swings in asset prices, therefore supporting financial stability. The availability of derivative instruments would also allow businesses and households to manage their financial risks more effectively. Finally, a broader and more diversified domestic investor base would bolster the resilience of Indonesia's financial markets, currently dominated by foreign investors, to global financial shocks, which could cause market turmoil as witnessed in recent months (IMF, 2013).

Similarly to Glindro and Delloro (2010), we complement the analysis by examining bubble episodes in the Indonesian property and financial stock prices, deemed more susceptible to asset price bubbles than the composite stock price index time series. The property stock index bubble estimates, shown in Figure 3, seem to be a bit larger than those

[14] Indonesia is a leading global exporter of coal, rubber, palm oil, and thus highly dependent on their prices.

of the general stock index in more recent years, but only marginally so. They are certainly not large enough, though, when we also account for the upward bias of these estimates. Again, if we juxtapose the property stock index bubble estimates for Indonesia with those of the Philippines since the early 90s, presented by Glindro and Delloro (2010), we reach the same conclusion, i.e., that the magnitude in Indonesia's bubble estimates is considerably more subdued, especially during crises. We ascribe this fact again to Indonesia's superior relative macroeconomic performance since the Asian financial crisis. After all, the Great Recession was just a temporary blip on the Indonesian GDP growth line, whereas it was a major slowdown on the Philippine one.

On the other hand, the bubble component effects are unsurprisingly most insignificant for the financial stock index. To a great extent this must be the result of the sweeping, IMF-imposed banking reforms that all Southeast Asian economies, affected by the "Asian flu", implemented in the years thereafter. Moreover, Indonesia stands out, regionally and internationally, in strengthening corporate and financial sector balance sheets. Banking system asset quality remains satisfactory and banks are profitable and well-capitalized, with the capital to risk weighted asset ratio at 16 percent (IMF, 2012). The return on assets of Indonesian banks amounted to 2.6% in 2012, comparatively high among major emerging market and ASEAN peers. Non-performing loans at end-June 2013 were 1.8% of total loans, down from 3.3% at end-December 2009 (IMF, 2013). Bank credit is low and this reflects, in part, the continued aversion to debt since the Asian crisis. In particular, most firms, especially in the dynamic resource extraction sector, choose to finance investment through retained earnings (IMF, 2012). What is more, the Indonesian monetary authorities have deployed various macroprudential policies to maintain the stability of the financial system. Measures are varied from setting the Loan-To-Value level for mortgages and downpayments on motor vehicle loans, pursuing supervisory actions and enhancing the liquidity management of banks (IMF, 2013).

II. Residential Property Market

One of the biggest difficulties in analysing the dynamics of residential property prices in Indonesia lies in the paucity of official data. Our dataset starts from 2002 and is limited to only 47 quarterly observations, which might render any conclusive arguments insignificant.

Nevertheless, judging by the plot of quarterly observations in Figure 1, the residential property prices exhibit strong increase, which has recently become even steeper.

In the last three years, residential property prices rose at an annual rate of 30 - 40% in the main urban centres (Bland, 2014). The remarkable growth in residential property prices is accompanied by a concurrent increase in the commercial property segment. Indonesia's booming economy attracts a significant portion of Foreign Direct Investment. The size of FDI nearly quadrupled in the period 2009-2013. The arrival of many international companies drove up the demand in the commercial property sector. The occupancy rate at Jakarta's Central Business District is at its highest level since 1990 (Van der Schaar, 2013).

All these developments and excessive price movements suggest that there might be an evidence of bubble formation in property prices. When applying the Kalman filter to the observations, however, the results in Figure 3 do not confirm this hypothesis. The magnitude of annual estimated bubble components is more than negligible, ranging from 0.08% to 0.4%, even despite the upward bias of these estimations.

What are the fundamental factors that can explain these puzzling findings? Strong economic growth and low interest environment can be identified as the main culprits. The rate of growth of the Indonesian economy was consistently above 4% in the previous decade and went above 6% in the period 2010-2013. Reports by the IMF suggest that this trend is likely to continue in the years ahead. Purchasing power is rising in line with the increase in GDP per capita. Strong consumer spending by Indonesia's rising middle class in the residential segment constituted the largest contribution to the property growth. The Bank Indonesia interest rate stayed below the 7% level from the second half of 2009 until September 2013, and it has only gradually gone up to its 7.5% current reading. This is still low compared to the 12.5% level in the first half of 2006. Another possible explanation of this puzzle is that the steep property price growth comes from a low base. Prices have only recently reached a level similar to the pre-Asian crisis period. Limited supply is yet another explanation. According to some estimates, the country was still short 15mn houses compared to demand in 2013 (Bisara, 2013). This was mainly due to complicated and burdensome administrative procedures for obtaining building permits and basic infrastructure issues.

III. Foreign Exchange Market

The rupiah has had a *de jure* free floating exchange arrangement since August 14, 1997, and the current *de facto* arrangement is managed floating. The market exchange rate was Rp 11,580 per U.S. dollar as of September 2013 (IMF, 2013).

The exchange rate has been modelled as a local linear trend with a short cycle of 5 years and AR(1) and AR(2) components but no seasonal component, following Glindro and Delloro's (2010) methodology. Earlier estimates that we present indicate insignificance of the seasonal component for this time series.

The most remarkable feature of our bubble estimates in Figure 3 is the striking absence of any economically significant spikes or declines, but in the period associated with the Asian financial crisis of the late 90s. Even prior to and in the midst of the recent so-called Great Recession (2008-2009), the bubble effects have been negligible to non-existing, despite their inherent upward bias.

However, the period prior to the Asian crisis was a time when speculative "hot money" would inundate the booming Southeast Asian economies, such as Indonesia, on the lookout for a higher yield. It would appreciate the local currency and stock market far beyond fundamentals in the process, and then would vanish like a monsoon rain (flight to safety), causing abrupt and painful readjustments. Curiously, the real effective exchange rate (REER) in Indonesia was stable between 1990 and 1995. Actually, in spite of a small appreciation in 1996, it is very questionable whether there was any serious exchange rate misalignment or bubble in play. The rupiah appreciation of 5% was certainly lower than that in other ASEAN countries (Iriana and Sjöholm, 2002).

In those days, the gravest issue for Indonesia, which was not confined to this specific Southeast Asian economy alone, was the glaring absence of sufficient foreign currency reserves. Otherwise, their presence would have helped Bank Indonesia (BI) stem the inevitable rapid depreciation of the rupiah against the US dollar, once the scared "hot money" had begun exiting Southeast Asia en masse. Indonesia had a managed exchange rate regime, with BI allowing the rupiah to float within a band around a target, which was set against a basket of major currencies (dominated by the US dollar). This regime necessarily required foreign currency reserves in order to be maintained. The country also had other "harmless" macro weaknesses, such as a modest current account deficit, overreliance on short-term debt, borrowed from foreign banks ("original sin"), and a relatively small share of FDI. Thus, the lack of indispensable reserves buffer, combined with those allegedly "innocent" macroeconomic imbalances, made Indonesia particularly susceptible to regional turbulence, spillovers and contagion, as a result of investors' scepticism (Iriana and Sjöholm, 2002). This transpired despite the fact that at the time the country was enjoying the highest economic growth in Southeast Asia, low inflation, and rapid increase in exports.

Consequently, following the “Asian flu”, Indonesia has learned its lesson well by accumulating substantial emergency foreign currency reserves. These have been at the BI’s disposal whenever the rupiah is under severe market pressure and needs propping. One pertinent example of the utilization of this protective interventionist lever was BI’s recent reaction after the May 2013 Forex and stock market selloff, caused by hints from the Fed for premature “tapering” of its unconventional monetary policies. BI stepped with its foreign currency reserves and moral suasion in the FX market in order to stabilize the rupiah. Not only was this successful intervention, but it also did not dent BI’s reserves excessively (IMF 2013). Official reserves fell from US$113 billion at end-December 2012 to US$93 billion at end-July 2013, before stabilizing.

Taking a step back to analyze the realities that the entire East Asia faces in a more holistic framework, we find another explanation why precisely these exchange rates against the US dollar must have been so bubble-free since the ”Asian flu”. This explanation is ”Bretton Woods 2”, and the above-mentioned BI foreign-reserves accumulation/interventions are part of it, too. Dollar dominance in East Asia has always created financial fragility for countries with both ”original sin” (debtors, such as Indonesia, that cannot borrow in their own currency and are unable to hedge their net dollar liabilities, leading to currency and maturity mismatch), and ”conflicted virtue” (creditors, such as China, that cannot lend in their own currency and hedge their net dollar assets). Therefore, the imperfect solution for the East Asian countries has been to keep their dollar exchange rates as stable as they possibly can since 1997. This, in turn, has reduced risk, as perceived by either unhedged dollar debtors or unhedged dollar creditors within these economies. Hence, these countries’ favoured resort to ”soft” dollar pegging, which we observe in non-crisis periods, an arrangement dubbed ”Bretton Woods 2” by some economists (McKinnon, 2005). It is this unofficial monetary management system that may well explain the absence of substantial bubble components within the exchange rate time series of both Indonesia and the Philippines since the ”Asian flu” (Figure 3).

Thus, since the Asian crisis, the effects from the combined benign policies of foreign currency reserves accumulation, successful inflation targeting/moderating and steady current account surpluses for Indonesia have ushered in a 17-year-long era of bubble-free exchange rate dynamics under ”Bretton Woods 2”. This is an impressive period of moderation, not perturbed even by such tumultuous shocks as the post-Lehman tsunami or the 2013 ”tapering” jitters.

However, all these achievements should not lead to self-complacency among the Indonesian economic decision-makers, because at the end of 2013 three particular macroeconomic problems emerged there – a slowing growth rate, a current account deficit and accelerating inflation. The trio is vaguely reminiscent of those “tiny” impediments prior to the “Asian flu”, proven to be so lethal, in conjunction with other unforeseen shocks (an abrupt GDP slowdown in China, “tapering” by the FED, or a Eurozone meltdown).

Ultimately, the conspicuous absence of bubble-loaded episodes in the exchange rate within the last 17 years perhaps may be partially ascribed also to the size and liquidity of the Indonesian FX market. An excerpt from the most recent IMF report on Indonesia reads:

“*Despite the increasing importance of external flows in the Indonesian economy, the local FX market has remained small and illiquid relative to Indonesia’s emerging market (EM) peers. Over the past decade, the growth in the value of FX transactions involving the rupiah has risen more slowly than most other major EM currencies. The weaker growth in rupiah transactions is due primarily to relatively tight restrictions on forward market activity, smaller domestic financial markets, and the high proportion of commodity exports in the balance of payments. Regarding this last factor, FX receipts tend to be used to finance capital imports or are repatriated offshore as profits, and therefore are less likely to be converted into rupiah.”*

It should be mentioned as a general remark that the bubble components estimated in stock prices (both the composite index and the two sectoral indices) and the exchange rate turn negative a year before the rate of growth in GDP. This implies that they could be a leading indicator of an economic slowdown (Figure 3). In a macroprudential regulatory framework they could be, therefore, used as a potential early warning sign that a turning point in the business cycle might be approaching.

The discussion about the degree of significance of estimated bubble components is centred on a rather ad-hoc chosen benchmark of 10% of the asset price. The same target is also specified by Glindro and Delloro (2010), notwithstanding this is a debatable issue. To put things in a more tangible perspective, we juxtapose bubble component estimates with both GDP growth rate and CPI-based inflation (Figure 4). In this way, we are better able to investigate the dynamics of bubble components versus broad fundamental indicators. Moreover, many times the rate of inflation itself disguises or hides asset bubbles, which means that bubbles can be categorically pinpointed only after accounting for and contextualizing the underlying inflation.

It can be easily detected from Figure 4 that the fundamental variables exhibit very high amplitude of movement which is not matched by the corresponding extent of dynamics in bubble estimates. GDP growth rate and inflation for the period 1985 – 2013 average 5.3% and 8.17% respectively (excluding the outlier in inflation in 1998). At the same time, even if we are generous enough to take absolute means of bubble components for the composite stock index, property stocks, financial stocks, residential properties and the exchange rate, these amount to 2.9%, 1.7%, 3.2%, 0.2%, and 0.8% respectively. Therefore, we arrive at the conclusion that bubble components, reported in Figures 3 and 4, for the most part, are not only statistically insignificant in terms of the subjective 10% mark, but also in terms of key fundamentals of the Indonesian economy. This conclusion is all the more robust, considering the upward bias of all our reported bubble estimates.

3.2. Results (contagion testing)

As mentioned earlier, we test if the Indonesian economy was susceptible to contagion from abroad in the midst of three major shocks that hit the global markets over the last six years, i.e., the Lehman bankruptcy crisis, the Greek sovereign-debt crisis, and the mid-2013 QE Tapering scare.

I. Background

Figure 5 illustrates the changes in volatility in equity markets over the three crises. The first column represents returns for Hong Kong, Indonesia and Malaysia during the Lehman crisis. The second column represents returns for Greece, Indonesia and Hong Kong during the Greek sovereign-debt crisis. The final column represents returns for India, Indonesia and Brazil during the 2013 Tapering scare. The reasons for the choice of sample periods and crisis subsamples are briefly described below.

II. Lehman Crisis: 2008-2009

There were signs as early as March 2008 when the investment bank Bear Stearns almost went bankrupt that the US subprime mortgage market was completely melting down. At the beginning of September of the same year, this fact was already clearly visible and unavoidable. First, Fannie Mae and Freddie Mac were nationalized. Eventually, Lehman Brothers filed for bankruptcy on 15 September 2008, sending the global equity markets into a prolonged tailspin, not seen for many generations. The excessive volatility and profound slump in stocks across the board carried on unabated until March 2009, when the markets finally bottomed up (Federal Reserve Bank of St. Louis, 2010).

The Lehman bankruptcy, through the interconnectedness of the contemporary banking systems and real economies, affected the entire global economy. The USA going into a prolonged recession meant that China (proxied by Hong Kong here), being its main trade partner, was going to experience a severe slowdown. However, as we mentioned earlier, Indonesia was heavily reliant on a strong Chinese growth for its export-oriented commodities revenues. Hence, it was highly likely that a trade-channel contagion from China was going to impact the Indonesian economy, as a result of the Lehman debacle.

Therefore, here we consider a potential transmission between the equity markets of Hong Kong, Indonesia and Malaysia, in order to ascertain how resilient Indonesia was to this major economic shock (in spite of being a shock, not coming direct from Indonesia's regional neighbours). Malaysia is selected for our "Asia-vu" testing, because during the "Asian flu" it was again suspected of acting as a conduit of Thai contagion spreading to Indonesia (Iriana and Sjöholm, 2002).

We use both Figure 5 and the chronological context above to choose the testable subsamples for the precrisis period and for the crisis period. The precrisis period starts on 03 January 2005 and ends on 03 September 2008, comprising 828 daily stock index observations. The crisis period starts on 03 September 2008 and ends on 03 March 2009, comprising 105 observations. In total, this makes a subsample of 933 observations.

Variances, covariances and correlations for the Lehman crisis are shown in Table 4. There is a marked increase in all variances, covariances, and correlation coefficients among the three countries from one period to the other. This is hardly surprising, since we know that correlation usually tends to increase in crisis periods. Table 5 provides a decomposition of the variances of the equity returns in the precrisis and crisis periods into various components, based on the DFGM model estimated with Generalized Method of Moments.

There is not so much diversifiable risk in all three countries in the precrisis period, with the country factors contributing less than 50% of total volatility in all three cases. In the crisis period, Indonesia experiences substantial contagion effects, with 61% of total volatility in Indonesia, sourced as contagion from Hong Kong (China). However, we also observe a weaker reverse-causality relationship, with 46% of total volatility in Hong Kong, sourced as a contagion from Indonesia.

III. Greek Crisis: 2009-2012

In November 2009, concerns about some heavily-indebted Eurozone states started to grow in the wake of the Dubai sovereign-debt crisis. In December 2009, Greece admitted that its debts had reached 300bn euros – the highest in modern history, but the PM George Papandreou insisted that his country was "not about to default on its debts". However, investors got quite scared, since Greece was burdened with debt amounting to 113% of GDP, or nearly double the Eurozone limit of 60%. Rating agencies began downgrading Greek bank and government debt, and the bond yields in the South European periphery skyrocketed. In the ensuing two years this Greek crisis evolved into a major Eurozone sovereign-debt and banking crisis.

The outcome of it was that a long-lasting stagnant growth in Europe, combined with perennial stock-market volatility, served as primary impediments to the recovery of the global economy, following the Lehman crisis (Great Recession). The constant huge tremors in all Eurozone markets persisted until at least June 2012 when the pro-austerity party New Democracy in Greece won the elections, allaying fears the country was about to leave the Eurozone (BBC Eurozone crisis timeline).

As China, Indonesia and all other emerging-market economies strongly depend on the growth in the Eurozone, which is a major consumer market for their production or export commodities, we would like to test if the Greek troubles indeed translated in any direct or indirect (via China, for instance) contagion for the Indonesian economy. In other words, we check whether this particular economic shock was not so distant from the Indonesian borders, for its ripple effects to reach the Indonesian shores. Therefore, a potential transmission between the equity markets of Greece, Indonesia and Hong Kong (China) is considered here.

Again, we use both Figure 5 and the chronological context above to choose the testable subsamples for the precrisis period and for the crisis period. The precrisis period starts on 03 March 2009 and ends on 03 December 2009, comprising 178 daily stock index observations. The crisis period starts on 03 December 2009 and ends on 31 May 2012, comprising 567 observations. In total, this makes a subsample of 745 observations. A potential inevitable problem for our testing here is that the volatility in the precrisis period may not necessarily be lower than the volatility in the crisis period, since the precrisis period is so close to the Lehman debacle. The same issue will be relevant when subsequently testing for the Tapering scare, although to a lesser extent.

As shown in Table 4, the Greek returns variance increases significantly, but the Indonesian and Hong Kong variances decrease even more significantly from one period to the other. More importantly, absolutely all covariance and correlation coefficients among the three countries counterintuitively decrease between the periods, ruling out the existence of contagion.

Table 5 only confirm these findings. In the precrisis period, volatility of returns in Greece was almost totally determined by a country factor (nearly 91%), suggesting opportunities for diversification. However, during the crisis period, there are hardly any contagion effects visible, at all, with only 0.03% of total volatility in Indonesia, sourced as a contagion from Greece. After all, we should not be so surprised by the probable absence of contagion effects from Greece to Indonesia/China during the Greek crisis. Particularly vulnerable to a potential Greek default were mainly countries, holding Greek sovereign or bank debt, such as France or Italy. Geographical proximity (absence thereof) was certainly a mitigating factor, too.

IV. Mid-2013 Tapering Scare

The unconventional monetary policy response to the Great Recession, aimed at thwarting a potential depression from occurring, was the Fed's policy of quantitative easing, or the monthly purchase of bonds worth $85 billion. This policy was conducted alongside an excessively dovish, anti-deflationary monetary stance, keeping the Fed funds rate at practically zero over a considerably extended time period. A side effect of these unorthodox expansionary levers of the US central bank was that colossal streams of money (FDI) began flowing into the still booming emerging markets. Countries, such as Indonesia, India, and Brazil attracted FDI with the relatively better yields available there.

However, in late May 2013, then Fed Chairman Ben Bernanke mentioned the term ”taper” for the first time, acknowledging that a QE exit policy (reduction in the size of the bond-buying programme) was already being considered in the near future. Unsurprisingly, this utterance had a huge sobering effect for the investors in the more fragile emerging markets, laying bare all previously neglected vulnerabilities there. India had a current account deficit and the Indian currency, the rupee, quickly melted (Irwin, 2013). The Brazilian central bank also had to step in and defend the real, amidst its rapid depreciation. Investors extrapolated the same troubles onto Indonesia. As the Fed was going to begin “tapering” soon and in a radical way, the country faced disaster, unless it credibly contained its recently widening current account deficit (at levels not seen since the “Asian flu”). Indeed, it was becoming increasingly difficult for Indonesia to fund that deficit, having relied thus far on foreign capital for the funding. The initial huge uncertainty/scare surrounding the timing and the exact size of the “tapering” subsided eventually, when in December 2013 the FED announced its first official reduction of the programme to $75 billion per month (Zumbrun, 2013).

Therefore, our task is to test if the history can repeat, and the “Asian flu” can transpire again. How likely is it that a combination of ”fledgling” macroeconomic imbalances, plus an external shock (“tapering”), leads to investor scare crisis? Furthermore, how likely is it that a crisis within one of these countries swiftly spills over (be contagious) to its other fragile neighbours with similar imbalances? Here, we consider a transmission via the investor panic channel between the equity markets of three ”Fragile Five” economies – India, Indonesia and Brazil.

Again, we use both Figure 5 and the chronological context above to choose the testable subsamples for the precrisis period and for the crisis period. The precrisis period starts on 03 January 2012 and ends on 03 June 2013, comprising 307 daily stock index observations. The crisis period starts on 03 June 2013 and ends on 30 December 2013, comprising 127 observations. In total, this makes a subsample of 434 observations.

As shown in Table 4, and exactly as in the Lehman crisis case, we observe a marked increase in all variances, covariances and correlation coefficients among the three countries from one period to the other, which is a first promising sign of existing contagion effects. Table 5 indicates that in the precrisis period India and Brazil exhibit similar variance decompositions, with the country factor contributing more than 80% in both cases. In contrast, only 32% of volatility returns in Indonesia are associated with a country-specific factor. In the crisis period, Indonesia experiences substantial contagion effects, with almost 72% of total volatility in Indonesia, sourced as contagion from India. However, we also observe a weaker reverse-causality relationship, with 40.5% of total volatility in India, sourced as a contagion from Indonesia. Therefore, the most striking result from the contagion testing during the Tapering scare seems to be the apparent reinforcement of contagion effects between Indonesia and India.

V. Results of contagion tests

Tables 6, 7, and 8 present the comparative contagion test statistics during the Lehman crisis, the Greek crisis and the Tapering scare, respectively. Some preliminary information on the data characteristics of the crisis samples is provided in Table 9. The table gives the number of observations in the precrisis and crisis periods for each test, but also gives the exceedances and co-exceedances based on the FG and BKS selection procedures, given in equations (2.15) and (2.17) in Appendix 3.

Three hypotheses are tested. Hypothesis 1 is the null of no contagion among all countries during the crisis period. Hypothesis 2 tests the null of no contagion from one country (host) to both other countries in the sample. Hypothesis 3 tests the null of no contagion between two individual countries within the group. The first two hypotheses are examined using DFGM, multivariate FR, FG, and BKS tests (the only exception is that BKS is not applied for hypothesis 1). The third hypothesis can be examined using each of these tests and the bivariate FR test.

VI. Contagion during the Lehman crisis

Table 6 provides the results of the contagion tests for the Lehman crisis (a summary of these results is presented in the first part of Table 10). Table 6 reports the results of the DFGM test, the bivariate and multivariate FR tests, the FG test, and the BKS test. The left-hand column indicates the host country, from which contagion is sourced, and the second column indicates the country potentially in receipt of contagion. Each cell gives the value of the test statistic with the *p*-value in parentheses. An asterisk (*) denotes evidence of contagion at the 10% level of significance, through a rejection of the null of no contagion.

The first result to note is that all tests strongly reject the first null hypothesis of no contagion within the group, as all the test statistics, reported in the final row of Table 6, are very large. Similarly, for the second hypothesis of no contagion from the host country to the other countries there is an absolute agreement on significant contagion, as demonstrated in the rows labelled ”Both” in the table. The results for the tests on the third hypothesis, of no contagion between pairs of countries, provide mixed evidence. The bivariate FR test supports the null of no contagion, while the multivariate FR test finds many significant linkages, but fewer than FG and BKS. The difference between the bivariate and multivariate FR tests reflects two things: one, the inclusion of additional variables; and two, the choice of the low-volatility period. The FG and BKS tests are in absolute agreement in rejecting the null of no contagion across the board. The DFGM test statistics also tilt in the direction of rejecting all null hypotheses of no contagion, with two pairwise exceptions – those of contagion from Indonesia to Malaysia, and from Malaysia to Indonesia.

Therefore, similarly to the discovered lack of contagion transmissions between these two neighbour countries during the “Asian flu”, there is again weak evidence that Malaysia serves as a conduit of contagion for Indonesia during the Lehman debacle (Iriana and Sjöholm, 2002). Table 9 provides a glimpse into the number of exceedances (individual-country extreme shocks) and co-exceedances (corresponding contemporaneous extreme shocks) between the three countries. On the whole, all test results make us more inclined to conclude that contagion effects of varying magnitude were indeed present between these countries during the Lehman crisis. Indonesia was not utterly immune to this contagion, either.

VII. Contagion during the Greek crisis

Table 7 shows there is far less agreement among the results of the contagion tests for the Greek crisis period. The final row of Table 7 again reveals that hypothesis 1, of no joint contagion, is strongly rejected in each single case. With regards to hypothesis 2, the strongest rejection of it comes when Greece serves as the host country (not rejected only by the BKS test). However, when the other two countries are hosts, the hypothesis is rejected only by the multivariate FR and FG tests, and not rejected by the DFGM and BKS tests. This is far less encouraging evidence of contagion than what we observe for the Lehman crisis.

Moreover, all the tests find only limited, or at best, contradictory evidence of contagion between pairs of countries. There are two notable exceptions to this: one, the FG test finding contagion across the board; and two, hypothesis 3 of no contagion, emanating from Greece to Indonesia, not being rejected only by the bivariate FR test. These differences in the results possibly reflect the fact that the FG test assigns a separate parameter value to each exceedance, while in the DFGM and BKS tests, for instance, the contagion is all summarized by a single parameter. All in all, the evidence in Table 7 from all the tests for contagion affecting Indonesia seems to be highly inconclusive and contradictory. Consequently, we are more inclined to refute the existence of such contagion effects during the Greek crisis, at all (a summary of the test results for the Greek crisis is presented in the central panel of Table 10).

VIII. Contagion during the Tapering scare

Table 8 reports the evidence for contagion during the Tapering scare, and is summarized in the final panel of Table 10. As with the previous two crises examined, hypothesis 1 of no contagion jointly is strongly rejected by all tests. Similarly, for the second hypothesis of no contagion from the host country to the other countries there exists an absolute agreement on significant contagion here. This resembles the Lehman crisis contagion findings. The tests of hypothesis 3, for the contagion between pairs of countries, produce mixed results again. This time around, the tilt is overwhelmingly in favour of rejection of the null, though. For instance, let us analyse the comparative statistics between all three crises, available in Table 10. From the table it is easy to conclude that in the Tapering scare across all tests the number of rejections of the three null hypotheses of no contagion (not merely hypothesis 3) either significantly exceed, or, at least, equal the rejections in both the Lehman and the Greek crises.

Most importantly, hypothesis 3 for contagion from India to Indonesia is not rejected only by the conservative bivariate FR tests, and hypothesis 3 for reverse contagion from Indonesia to India is not rejected only by the bivariate and multivariate FR tests (but is strongly rejected, with very high t-statistics values, by the other three tests). These results seem to be consistent with the variance decomposition presented in Table 5 (72% of total volatility in Indonesia, sourced as contagion from India, and 40.5% - in the opposite direction).

All four tests also present unanticipated evidence of contagion, emanating from Brazil to India. Controversially, this discovery is at odds with the variance decomposition finding (Table 5) that 0.11% of total volatility in India can be sourced as contagion from Brazil. However, it is in line with the observed significant increase in correlation (Table 4) between these countries' returns from the precrisis to the crisis period (0.165 to 0.481). Indeed, hypothesis 3 may be rejected for this pair (Brazil to India) across all tests, but its t-statistics values (for the DFGM, FG, and BKS tests) are considerably lower than the t-statistics values for the contagion effects from India to Indonesia, and from Indonesia to India. Therefore, this unexpected evidence of contagion, from Brazil to India, is more likely to be ascribed to the imperfections of the testing methodologies.

On the whole, the findings, firstly in Table 8, but mostly in Table 10, combined with the earlier variance decomposition evidence, allow us to reach a crucial conclusion. It is that the pivotal result from the contagion testing during the Tapering scare seems to be the apparent reinforcement of contagion effects between the two ”Fragile Five” member countries - Indonesia and India. The implications of these findings are really pervasive. They suggest that Indonesia, 17 years after the “Asian flu”, may still be significantly susceptible to catching contagion from severe external economic shocks (such as “tapering”), hitting its neighbours. Moreover, it could also be a source of contagion itself.

3.3. Joint conclusions and broader implications

We have at length reached a point in this paper, where we can succinctly summarize our findings about both the domestic and foreign risks, facing Indonesia. Then, we will proceed with the joint implications thereof. The unobserved components model results from the asset price decomposition have certainly made us more inclined to believe that there are not at present any ominous ready-to-burst bubbles, lurking within the salient Indonesian asset prices. Of course, we cannot be utterly conclusive when it comes to the assessment of the price dynamics within the Indonesian residential property market. There, we are confronted by small sample issues/unavailability of data, on the one hand, and by ”anecdotal evidence” for overheating in some segments of this market, reported even by the IMF, on the other (IMF, 2012).

However, what we can categorically point out as a great merit is that, since the Asian financial crisis, there is overwhelming evidence that Indonesia has carefully, prudently and consistently managed and corrected/accommodated for any abrupt short-term deviations in its main asset prices. This has naturally ushered in an era of a steady, unintermittent, above-average EM economic growth. Again, we are required to mention some of the manifestations of these praiseworthy, long-term financial stability policies, such as the increased accumulation of emergency foreign-currency reserves (ready to be deployed to stabilize the currency, for instance), or the significant reduction of the country's public debt.

Despite these overall promising signs, coming from the Indonesian asset price dynamics, and our unobserved components tests thereof, we must never underestimate the enormous risks from abroad. Seventeen years after the "Asian flu", economic contagion, especially from its EM neighbours, is still an irrefutable issue for Indonesia. This was pertinently and robustly demonstrated via four different contagion-test methodologies over three disparate recent global shocks. Especially the mid-2013 Tapering scare episode vividly reveals how seemingly small and "harmless" macroeconomic glitches, in conjunction with similar pre-existing weaknesses within neighbouring markets, can swiftly morph into a contagious financial disease. As a consequence, this disease can bring down one or more countries' economies at the same time.

The implications are that the authorities in Indonesia should always be on high level of alertness, especially for trade-channel or investor-panic-channel type of contagion risks. To counter these risks, they should always be ready with a policy mixture of buffers and pre-emptive fiscal/monetary measures. To quote the similarly-sounding insights of a September 2013 report by the Singapore-based bank DBS: "Asia-vu is five years away at least, but whether 1997 comes again will depend on policy" (DBS Report, 2013). We must acknowledge that over the last 17 years the Indonesian economic decision-makers at highest level have demonstrated amazingly consistent and successful adaptability to the constantly evolving combination of internal and external threats. However, this fact should not lull them into delusions of infallibility, because, as this paper has revealed, the risks are indeed still out there, and bigger than ever before.

This tentative implications round-up of our joint empirical evidence might depict Indonesia's economic policies track record as much more unfavourable and feckless, though, should we decide to shift our perspective from purely country-specific to more globally systemic. For instance, let us consider what undeniably constitutes a meritorious individual policy for Indonesia and other EM countries under "Bretton Woods 2", i.e., the policy of hoarding foreign currency reserves. This is done to help keep one's own exchange rate artificially weak and thus increase exports (growth). The problem is that the natural response of the developed economies is via similar beggar-thy-neighbour policies of extraordinary (un)conventional monetary stimuli to spur stagnant growth, and of borrowing to fund budget deficits. Altogether, these tit-for-tat measures cause ineluctable inflating of versatile asset-price bubbles across the globe.

Therefore, Indonesia's otherwise laudable policies of accumulating buffer foreign currency reserves provide only a second-best solution to its economic problems, and to its struggle against bubbles and contagion. These policies merely sort out the mess ex-post, but they do not tackle ex-ante its root-causes. In effect, Indonesia faces a typical fallacy-of-composition conundrum about its choice of optimal economic policies. The first-best solution seems to lie, instead, in what Keynes famously called "bilateral responsibility". This is the understanding that the severity of episodes of bubbles and financial contagion can abate significantly, only providing that both the emerging-market economies and the developed nations simultaneously quit their respective selfish, beggar-thy-neighbour policies. Nonetheless, the jury is still out, whether the world will ever be able to garner the level of cross-country consensus necessary to reach this superior (for all parties concerned) first-best solution to this classical quid-pro-quo prisoner's-dilemma.

In order to demonstrate how indispensable (for resolving this dilemma) global economic-policy coordination really is, we offer the pertinent carry trade example in the context of Indonesia. Carry trades, the forward-premium-puzzle-based strategies of borrowing in low-yielding currencies to buy higher-yielding ones, have been out of favour over the past few years. The reasons for this were weaker growth and widening current account deficits in the EM countries, heightened implied currency volatilities (caused by the Fed Tapering scare), and eagerness by EM central banks to limit currency appreciation by cutting interest rates, i.e., currency-wars retaliations.

However, since the start of 2014 the economic conditions have shifted so swiftly and dramatically that financial analysts have facetiously rebranded the "fragile five" to be the "high five", the "fabulous five", or the "solid five" (Cosgrave, 2014). For instance, so far in 2014 the Indonesian markets, underpinned by BI's higher interest rates and the country's improving growth prospects, have strongly rebounded from their taper-scare-induced 2013 troughs. The Indonesian rupiah has gained more than 7 % against the US dollar (after depreciating by more than 20% against it in 2013), the Indonesian bond yields have eased substantially, and the country's current account deficit has shrunk from 4.4 % in 2013 to less than 3% today (Strauss, 2014).

Unfortunately, at a time when this renewed Indonesian economic prosperity may seem to render the above-mentioned coordination dilemma less relevant, two seemingly favourable global factors join forces unfavourably. First, the divergence between the low yields on currencies in the developed world (products of unprecedented expansionary monetary policies) and the higher yield on the rupiah has increased. Second, the implied volatility in developed country currencies is now at its lowest level since 2007 (Strauss, 2014). Both these factors cancel any premature celebrations and herald the return of a familiar threat for Indonesia - carry trade becoming feasible again.

The problem is that low volatility (a precondition for carry trade) invariably has the seeds of its own destruction built into it. Inevitably, when investors commence flocking together in carry strategies, they build positions of untenable size, i.e., inflate unsustainable asset-price bubbles. Therefore, the optimal solution itself (lower deficit, lower currency volatility, and higher growth) may paradoxically exacerbate or reinvigorate the initial problem (proneness to boom-bust cycles). This is especially self-fulfilling, whenever the central banks' interest-rate coordination policies globally are absent or insufficient. For instance, speculative carry trade forays have historically fuelled some of the most profitable booms and the most spectacular busts in Forex markets – from the Asian crisis of 1997 to the yen-funded trades that unwound when the global financial crisis hit in 2008.

All in all, these stories of conflicting virtues make us recommend to the Indonesian economic decision-makers a more out-of-the-box, ad-hoc-solutions-based approach for resolving the country's economic conundrums. Any doctrinaire complaisance to the usually unchallenged orthodox macroeconomic toolkit must be irretrievably buried to the past (Strauss, 2014).

Last but not least, the contagion tests that we conducted make us infer that the imperviousness of Indonesia to foreign shocks must also be quite dependent on the stable prices of its commodity exports to China, India, and other commodity-intensive EM economies. After all, staggering 48 percent of Indonesia's total exports in 2013 still belong to commodities, such as coal, oil, gas, rubber and palm oil. This evidence lays bare Indonesia's huge over-reliance on China and India's permanently strong growth to maintain the prices of all these commodities constantly elevated (IMF, 2013). Unrealistic as this must be, the obvious remedy for Indonesia is broader revenues diversification, away from commodity exports over-dependence.

4. FUTURE RESEARCH AND A NEW INDEX

We realize that by investigating the domestic and foreign risks, facing one specific EM economy, inadvertently, but also rather fortuitously, we present a flexible unified analytical framework. This framework may be applied in future to any other country, in terms of examining versatile asset prices, disparate data sets, more sophisticated and consistent testing methodologies, and more adverse types of financial shocks.

However, we are also well-aware of the unavoidable limitations to our analysis, for instance, with regards to the contagion effects being measured solely via stock market returns. Thus, our hope is that future investigative forays into other markets (fixed income, Forex) can undeniably streamline and expand our current findings.

Similarly, an area for future improvement could be the incorporation of political-risks heterogeneity factor, when assessing the bubbles and contagion risks, facing the economies of the different "fragile-five" countries. The five may not be equally fragile, if we also factor in their respective prospects for post-2014-election reforms. For instance, Indonesia is currently enjoying probably the strongest political tailwinds among the "Fragile Five" (Lord, 2013). On the reverse side of the political coin for Indonesia, nevertheless, both the rise of the Indonesian trade unions and the dangerous widening of the income inequality wedge represent enormous socio-economic obstacles to sustainable growth. Hence, these threats need to be specifically accounted for in any future more holistic financial-risks report on this country.

In this paper, we do not aim at giving definitive and conclusive answers about the insurmountability of any risks at hand, because by definition any testing methodologies in finance are not impeccable and are subject to restrictive assumptions. Instead, we strive to raise awareness about the incessant existence of such risks, and motivate further and unwavering inquisitiveness into the soundness of a country's soundest fundamentals under different stress scenarios. Future research may as well employ the template of this paper into dissecting the vulnerabilities of other EM economies, confronted by similar macroeconomic imbalances. Perhaps, it could also go back and dig deeper than the analysis presented here into Indonesia's various other asset prices and external economic threats. Let us not forget that Indonesia is also a member of another illustrious EM acronym, MINT, for Mexico, Indonesia, Nigeria and Turkey. Like the “Fragile Five”, this is a similarly dynamic club of populous countries with high growth potential. Hence, MINT is a potential target for future comparative analysis within the framework of this study, too.

On a much more ambitious scale, we can even envisage a constantly updating stream of reports within this analytical modus operandi, periodically enriched by latest data sets and latest economic shocks. These reports can serve as a bellwether of Indonesian economic resilience/fragility, or a forward guidance anchor for both the Indonesian macroeconomic decision-makers and the international investing public. After all, our test results represent merely an economic snapshot at a particular point in time. Therefore, in order to get a holistic idea about dynamic trends, we must run these tests over and over again, as new shocks hit on.

Ultimately, the analytical framework, presented in the paper, could easily evolve into a conceptual framework for testing/measuring any country’s susceptibility to bubbles or contagion. Its hallmark will be a new comparative economic indicator, the so-called ”bubbagion index” (bubble + contagion = the portmanteau word ”bubbagion”) of a country, proposed for the first time here.

For instance, this comparative economic index may vary on a range between 1 and 5. A reading of 1 will manifest lethally perilous vulnerability of a specific country to both domestic and external economic shocks. On the other extreme, a reading of 5 will hypothetically signal the absolute imperviousness of that country to neither bubbles, nor contagion (i.e., the non-existing perfect economic equilibrium in all markets). To further formalise our metric, a reading of 2 can suggest a country’s significantly weakened economic conditions. A reading of 3 can indicate first grave signs of upcoming economic troubles, requiring urgent measures. Finally, a reading of 4 can be a harbinger of future economic prosperity, if there are no unwise changes in policy.

The ”bubbagion index” could be, for example, an equally weighted average sum of the quantified asset-price bubble risks, interstate contagion effects, and country’s long-term macroeconomic adaptability (or lack thereof). Thus, the systematic tracking of this indicator may provide the BI’s, or any other central bank’s toolkit, with an additional forward guidance benchmark, steering the central banks into assuming either a hawkish or a dovish monetary policy stance. In order to illustrate and exemplify in a simplistic fashion the possible quantification of the index in the context of our results for Indonesia, let us assume that:

1) Bubble evidence exceeding both the 10% threshold (in each asset class) and the growth rate of key fundamentals deserves a grade of 1. A grade of 2 is given to bubble evidence in most, but not all asset classes, again in excess of the 10% benchmark and the fundamentals growth rate. Whenever the estimated bubble components in some asset classes might or might not exceed the 10% critical level/fundamentals growth rate, the grade will be 3. Circumstantial evidence of bubbles below the two designated thresholds is given a grade of 4. Finally, the complete absence of bubble traces merits a grade of 5. Therefore, the first component (quantified asset-price bubble risks) of the "bubbagion index" for Indonesia will warrant a grade of 4. This is justified, because our study found underwhelming bubble evidence in the Indonesian stock and property prices, well below the critical levels (even with the aforementioned upward bias);

2) The grading criteria for incorporation of interstate contagion effects in the "bubbagion index" are provided in Table 11. These are based on the maximum number of tests that can reject hypotheses 1 (overall contagion), 2 (contagion from host to other countries), and 3 (pairwise contagion). The maximum score that can be achieved is 3, 4, and 5 for the three hypotheses, respectively. In obtaining the score for the third hypothesis, we take averages of the results, only including the country of interest. In quantifying contagion effects during more than one shock (as was done in this paper with three events), the average of the results for each hypothesis is calculated, and then rounded up/down to the nearest integer.

Unfortunately, we are perfectly aware of the limitations that this averaging process may have. Consequently, future improvements of the index might include various weighting schemes based on the relative importance of one hypothesis over the others, or on the relative interconnectedness (proxied by bilateral trade, for example) between countries. As a result of the averaging, the second component (quantified cross-country contagion effects) of the "bubbagion index" for Indonesia warrants a grade of 2 (Table 11). This mark of 2 tilts more towards strong contagion evidence, with grade of 1, reserved for the strongest contagion effects, and grade of 5 – for the absolute absence of such effects;

3) The macroeconomic adaptability and performance of a country must also be quantified in order to become a component of the "bubbagion index". A grade of 1 will indicate a country's lack of clear direction and/or consistency in implementing macroeconomic policies.

Insufficient efforts to achieve at least the suboptimal second-best solution to the aforementioned prisoners' dilemma will be given a grade of 2. Full attainment of this second-best (beggar-thy-neighbour) solution is awarded a grade of 3. A mark of 4 is given, whenever the stable long-term macroeconomic performance of a country suggests that there may be limited progress in pursuing the optimal first-best (global coordination) solution, beyond the narrow-focused self-survival agendas. If this first-best solution is fully and successfully pursued, then we award a grade of 5. The macroeconomic adaptability/performance of Indonesia over the last 17 years has been close to irreproachable, and it has tangibly surpassed the selfish goals of the second-best policies. Hence, we believe, that this long-term track record should be quantified with a grade of 4, to serve as a third component of the "bubbagion index".

All in all, the equally weighted sum of these three quantified components translates into a total "bubbagion index" for our study of

$$\frac{1}{3} \times 4 + \frac{1}{3} \times 2 + \frac{1}{3} \times 4 = 3.33.$$

A reading of 3.33 seems to spell both a promise and a threat for the Indonesian economy.

We are confident that this inchoate concept of a new economic-risks gauge will be able to develop, evolve and get calibrated according to the specific needs of the financial community. Ultimately, the "bubbagion index", in one form or another, may as well conquer a place among such well-established measures of market risk/sentiment, as the CBOE's Fear Index, the VIX, the IIMA-GMVI index, the ISM's PMI indicator, and the Conference Board's CCI indicator.

Finally, in order to better contextualize our innovative index idea, we are bound to mention the "fragile-five" Work/Reward Quotient, developed in the FT's Beyondbrics blog by Jonathan Wheatley (2014). This quotient aims to critically quantify that remarkable universal transition (from a state of abject pariahness to one of rekindled infatuation for investors) of all "Fragile Five" economies since the beginning of 2014. This transition was mentioned in the previous chapter, with a special emphasis on Indonesia.

Unlike the "bubbagion index", the Wheatley Measure approaches the risks from a slightly different perspective by pinpointing the real source of the 2014 "Fragile Five" rebound in currency and bond prices, and is also more short-term in focus. However, its overall features are also quite compatible and complementary to those of our own unique "bubbagion" risk metric. On a scale from 0 to 10, the Quotient strives to evaluate this most recent 2014 investor rehabilitation of the "fragile five" team. If the recovery is wholly attributable to the five countries' genuine progress in repairing economic frailties, then a mark of 10 is given. If, instead, it is entirely a fortuitous by-product of favourable global market dynamics, then the mark is 0. Such officious tailwind market factors, buoying investor EM appetite, can be Fed "tapering" procrastination, or hints at the ECB and the BoJ for (potential and additional, respectively) quantitative easing moves.

Similar to the high-grade assessment above, assigned by us, for Indonesia's long-term macroeconomic adaptability and performance, Wheatley also awards Indonesia with the relatively highest Work/Reward quotient (among the five comparable countries) of 6. This highlights the more credible monetary-policy measures, taken by the BI recently, as well as the significant current account deficit reduction. This comparative example demonstrates how our proposed "bubbagion index" can successfully co-exist with and complement other relevant economic-risks measures in extending the toolbox of financial analysts and central bankers alike (Wheatley, 2014).

5. CONCLUSION

Summarized in only one sentence, this paper is a unification of two previously unrelated financial methodologies in the common pursuit of empirically testing how vulnerable Indonesia is at present to both bubbles in domestic asset prices, and contagion from abroad.

First, Kalman filtering and unobserved components models are applied to uncover latent Indonesian asset-price bubbles. Subsequently, four distinct contagion tests (DFGM, FR, FG, and BKS) are run to assess whether or not the Indonesian economy suffered from contagion during three of the biggest recent global financial shocks. The general findings from all conducted tests make us believe that the risks for an outright repetition in future of the calamitous events of the "Asian flu" are not to be completely underestimated for this EM country. This stark admonition is given, despite Indonesia's close-to-exemplary economic achievements over the last 17 years.

Second, we recommend perennial vigilance and continuation of prudent macroeconomic and financial-stability practices on behalf of the Indonesian economic authorities. Perpetual reassessment and reevaluation of the underlying risks on behalf of the foreign investors is also encouraged. In this context, therefore, the bubble and contagion findings for Indonesia have also been analysed through the prism of the eternal conflict between beggar-thy-neighbour and global coordination strategies.

Ultimately, the paper presents the financial literature with a conceptual framework for a joint measurement of a country's internal and external threats. This unified methodology aims at making the proposed "bubbagion index" the archetype of a constantly evolving and routinely reported country-specific risk measure. After all, if indeed history has a habit of repeating itself and human learning mechanisms do fail, as financial historians assert, then regular quantitative warnings may serve as a useful alert mechanisms to both market participants and regulators.

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APPENDICES, TABLES AND FIGURES

Appendix 1[15]

1.1. The Kalman filter algorithm in scalar notation

There are two building blocks of a Kalman filter, the measurement equation and the transition equation. The measurement equation relates an unobserved variable (X_t) to an observable variable (Y_t). In general, the measurement equation has the following scalar form:

$$Y_t = m_t X_t + b_t + \varepsilon_t \quad (1)$$

To simplify the exposition, assume the constant b_t is zero and m_t $(m_t = Z_t)$ remains constant through time eliminating the need for a subscript. Further, ε_t has a mean of zero and a variance of r_t $(r_t = H_t)$. (1) becomes:

$$Y_t = mX_t + \varepsilon_t \quad (2)$$

The transition equation is based on a model that allows the unobserved variable to change through time. In general, the transition equation is of the form:

$$X_{t+1} = a_t X_t + g_t + \theta_t \quad (3)$$

Again, for simplicity sake, we assume the constant g_t is zero and a_t $(a_t = T_t)$ remains constant through time eliminating the need for a subscript. Further, θ_t $(\theta_t = \eta_t)$ has a mean of zero and a variance of q_t $(q_t = V_t)$. (3) becomes:

$$X_{t+1} = aX_t + \theta_t \quad (4)$$

To begin deriving the Kalman filter algorithm, we insert an initial value X_0 into (4) for X_t, X_0 has a mean of ν_0 and a standard deviation of σ_0. It should be noted that ε_t, θ_t and X_0 are uncorrelated (Note: these variables are also uncorrelated relative to lagged variables). (4) becomes:

$$X_{1P} = aX_0 + \theta_0 \quad (5)$$

where X_{1P} is the predicted value for X_1.

[15] The appendix has its theoretical justification in the paper by Arnold, Bertus, and Godbey (2008).

X_{1P} is inserted into (2) or the measurement equation to get a predicted value for Y_1, call it Y_{1P}:

$$Y_{1P} = mX_{1P} + \varepsilon_1 = m[aX_0 + \theta_0] + \varepsilon_1 \tag{6}$$

When Y_1 actually occurs, the error, Y_{1E}, is computed by subtracting Y_{1P} from Y_1:

$$Y_{1E} = Y_1 - Y_{1P} \tag{7}$$

The error can now be incorporated into the prediction for X_1. To distinguish the adjusted predicted value of X_1 from the predicted value of X_1 in (5), the adjusted predicted value is called X_{1P-ADJ}:

$$X_{1P-ADJ} = X_{1P} + k_1 Y_{1E}$$

$$= X_{1P} + k_1[Y_1 - Y_{1P}]$$

$$= X_{1P} + k_1[Y_1 - mX_{1P} - \varepsilon_1]$$

$$= X_{1P}[1 - mk_1] + k_1 Y_1 - k_1 \varepsilon_1 \tag{8}$$

where k_1 is the Kalman gain, which will be determined shortly.

The Kalman gain variable is determined by taking the partial derivative of the variance of X_{1P-ADJ} relative to k_1 in order to minimize the variance based on k_1 (i.e., the partial derivative is set to zero and then one finds a solution for k_1). For ease of exposition, let p_1 be the variance of X_{1P} (technically, p_1 equals: $(a\sigma_0)^2 + q_0$). The solution for the Kalman gain is as follows:

$$Var\left(X_{1P-ADJ}\right) = p_1[1 - mk_1]^2 + k_1^2 r_1 \tag{9}$$

$$\frac{\delta Var(X_{1P-ADJ})}{\delta k_1} = -2m[1\text{-m}k_1]\, p_1 + 2k_1 r_1 = 0 \tag{10}$$

$$k_1 = \frac{p_1 m}{(p_1 m^2 + r_1)} = \frac{Cov(X_{1P}, Y_{1P})}{Var(Y_{1P})} \tag{11}$$

Notice, the Kalman gain is equivalent to a β-coefficient from a linear regression with X_{1P} as the dependent variable and Y_{1P} as the independent variable. Not that one would have a sufficient set of data to perform such a regression, but the idea that a β-coefficient is set to reduce error in a regression is equivalent to the idea of the Kalman gain being set to reduce variance in the adjusted predicted value for X_1.

The next step is to use X_{1P-ADJ} in the transition equation (4) for X_t and start the process over again to find equivalent values when t = 2 (the so-called “recursive” feature of the Kalman filter, entailing consecutive prediction and update cycles). However, before concluding, it is important to note the advantages of X_{1P-ADJ} over X_{1P}. Recall the variance of X_{1P} is p_1. Substituting (11) into (9), the variance of X_{1P-ADJ} is

$$Var(X_{1P-ADJ}) = p_1 \left[1 - \frac{1}{\left(1+\frac{r_1}{p_1 m^2}\right)}\right]^2 + k_1^2 r_1 \tag{12}$$

The portion of the equation that pertains to the variance of X_{1P}, i.e., p_1, has a bracketed term that is less than one (and is further reduced because the “less than one quantity” is squared). This means that the portion of the variance attributed to estimating X_1 has been reduced by using X_{1P-ADJ} instead of X_{1P}, or that the Kalman filter minimizes the *a posteriori* error variance.

Finally, let us present the mean and variance of X_{1P-ADJ} and of Y_{1P} for $(t = 1\ to\ T)$.

$$E[X_{tP-ADJ}] = E[X_{tP} + k_t Y_{tE}] = E[X_{tP}] + k_t(Y_t - E[Y_{tP}]) \tag{13}$$

$$Var(X_{tP-ADJ}) = p_t \left[1 - \frac{1}{\left(1+\frac{r_t}{p_t m^2}\right)}\right]^2 + k_t^2 r_t \tag{14}$$

$$E[Y_{tP}] = E\left[m(X_{tP-ADJ}) + \varepsilon_t\right] = mE[X_{tP-ADJ}] \tag{15}$$

$$Var[Y_{tP}] = Var[X_{tP-ADJ}]m^2 + r_t \tag{16}$$

Note: ε_t technically appears within Eq. (13) within the Y_{tE} term and within Eq. (15); however, these error terms are independent of each other. In other words, Eqs. (15) and (16) refer to an “updated” or “adjusted” version of the Y_{tP} term in Eqs. (13) and (14). Consequently, the error terms corresponding to Y_{tP} within the two sets of equations are uncorrelated.

1.2. Maximum likelihood estimation and the Kalman filter

The Kalman filter provides output throughout the time series in the form of estimated values for an unobservable variable: X_{tP-ADJ} with a mean and a variance defined in (13) and (14). Further, the observable variable has a time series of values and a distribution based on its predicted value, Y_{tP}, which has a mean and a variance defined by (15) and (16). What the Kalman filter cannot determine are unknown model parameters in the measurement equation, ε_t, in Eq. (2) (note: m is a constant and assumed known) and unknown parameters in the transition equation, a and θ_t, in Eq. (4). Consequently, it is necessary to have a means of estimating these parameters and, when estimated, allow the Kalman filter to generate the time series of the unobservable variable that is desired.

If we assume that the distribution for each Y_{tP} is serially independent and normally distributed with a mean and a variance as defined by Eqs. (15) and (16), a joint likelihood function emerges (note: the mean and variance both incorporate the mean and variance of the unobservable variable X_{tP-ADJ}):

$$\prod_{t=1}^{t=T}\left\{\left[\frac{1}{\sqrt{2\pi\, Var[Y_{tP}]}}\right]^{T} e^{-\frac{\sum_{t=1}^{T}(Y_t-E[Y_{tP}])^2}{2Var[Y_{tP}]}}\right\} \tag{17}$$

The idea behind the likelihood function is that the observable data emerge from this jointly normal distribution. Consequently, the parameters to be estimated within the distribution are chosen in a manner that maximizes the value of the likelihood function (i.e., provides the highest probability that the observed data actually occur). To simplify calculation using the likelihood function, it is common to use the natural logarithm of the likelihood function (i.e., the log-likelihood function):

$$-\frac{T\ln(2\pi)}{2}-\frac{1}{2}\sum_{t=1}^{T}\ln[Var[\,Y_{tP}]]-\frac{1}{2}\sum_{t=1}^{T}\frac{(Y_t-E[Y_{tP}])^2}{Var[Y_{tP}]} \tag{18}$$

As previously mentioned, the parameters of interest are $\varepsilon_t, a,$ and θ_t, which may be constants or defined by a distribution (the parameters of the distribution that generates the variable then become the parameters of interest instead of the variable). Further simplifying assumptions may be employed; for example, the variance of ε_t and θ_t will be constant through time (i.e., $q_t = q$ and $r_t = r$). The partial derivative of the log-likelihood function with respect to each parameter is calculated and set to zero in order to maximize the log-likelihood function.

After a set of parameters is estimated (these are called maximum likelihood estimates, or MLEs), the Kalman filter algorithm is applied again, which will produce new time series of Y_{tP} and X_{tP-ADJ} with associated distributions. The likelihood estimation is then performed again, producing ne MLEs, which will again enter into the Kalman filter. This iterative process will continue until the value of Eq. (18) does not improve by a significant amount (say 0.0001). In this context, Eq. (18) is often referred to as "the score". The use of maximum likelihood estimation in conjunction with the Kalman filter in an iterative fashion is referred to as the expectation maximization (EM) algorithm (Arnold, Bertus, and Godbey, 2008).

Appendix 2

2.1. Two pivotal models within the class of unobserved components time series models are (Glindro and Delloro, 2010):

1) Univariate local level or random walk plus noise model:

Letting $X_t = \mu_t,\ \eta_t$ - unchanged, $Z_t = T_t = D_t = 1$, $H_t = \sigma_\varepsilon^2$, $V_t = \sigma_\eta^2$,

(all of order 1×1) for t = 1,…,T, the model of equations (1.1) - (1.2) reduce to the local level model:

$y_t = \mu_t + \varepsilon_t,\ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$ $\qquad\qquad$ t = 1,2, ……, T

$\mu_t = \mu_{t-1} + \eta_t,\ \ \eta_t \sim NID\ (0, \sigma_\eta^2)$

The level component μ_t can be conceived of as the equivalent of the intercept in the classical linear regression model $y_t = \mu + \varepsilon_t$ which is obtained by setting all the level disturbances η_t equal to zero and with $\mu = \mu_1$. The key difference is that the intercept μ in a regression model is fixed whereas the level component μ_t in the above equations is allowed to change from time point to time point. Since the second equation defines a random walk, the local level model is also referred to as the random walk plus noise model (where the noise refers to the irregular componentε_t) (Commandeur, Koopman, and Ooms, 2011).

2) Local linear trend model (stochastic trend component):

By defining $X_t = \binom{\mu_t}{\beta_t},\ \eta_t = \binom{\xi_t}{\zeta_t}, T_t = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}, Z_t = (1\ 0)$,

$H_t = \sigma_\varepsilon^2$, $V_t = \begin{bmatrix} \sigma_\xi^2 & 0 \\ 0 & \sigma_\zeta^2 \end{bmatrix}$, and $D_t = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$,

the scalar notation of eqs. (1.1) and (1.2) leads to the local linear trend model:

$y_t = \mu_t + \varepsilon_t,\ \ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2)$

$\mu_t = \mu_{t-1} + \beta_{t-1} + \xi_t, \xi_t \sim NID\ (0, \sigma_\xi^2)$, state equation.

$\beta_t = \beta_{t-1} + \zeta_t, \zeta_t \sim NID\ (0, \sigma_\zeta^2)$, state equation.

This model requires a 2×1 state vector X_t: one element for the level component μ_t and one element for the slope component β_t. A stochastic μ_t contains ξ_t. Otherwise, if μ_t is fixed, the state equation for μ_t does not have ξ_t, hence $\sigma_\xi^2 = 0$. The choice of a fixed level results in a smooth trend and is also often combined with a cycle or autoregressive component.

The slope of the trend is given by β_t. It can be conceived of as the equivalent of the regression coefficient in the classical regression model where the observed time series y_t is regressed on the independent variable time *t*: $y_t = \mu + \beta t + \varepsilon_t$ with $\mu = \mu_1$ and $\beta = \beta_1$. Again, the important difference is that the regression coefficient or weight β is fixed in classical linear regression, whereas the slope β_t in the local linear trend model is allowed to change over time. The irregular disturbance ε_t, the level disturbance ξ_t, and the slope disturbance ζ_t are mutually independent and uncorrelated (Commandeur, Koopman, and Ooms, 2011).

The estimation of these models is implemented with the STAMP software package of Koopman et al. (2000). In a nutshell, STAMP carries out maximum likelihood estimation of the variances, σ_ε^2, σ_ξ^2 and σ_ζ^2 (Appendix 1, Eqs. (17) and (18)). After estimation, STAMP runs the Kalman filter through the observations to estimate the state μ_t. The process of finding the “best estimate” from noisy data leads to “filtering out” the noise. Essentially, the Kalman filter involves the following two iterative steps – prediction and measurement update/correction. In the first step, we use the initial conditions and previous information observations to produce an estimate of the current state. This predicted state estimate is referred to as the *a priori* state estimate because, although it is an estimate of the state at time *t*, it only includes observation information up to time *t-1* (Appendix 1, Eq. (5)). In the second step, we update our estimate of the state by combining or blending it with the current observation information at time *t*. This refined estimate is referred to as the *a posteriori* state estimate (Appendix 1, Eq. (8)). The combination of prediction and residual yields an optimal estimate with a smaller variance (Appendix 1, Eq. (12)) (Glindro and Delloro, 2010). Check Appendix 1 for a detailed discussion on how the Kalman filter operates.

2.2. An extension to the unobserved components time series models is the inclusion of one or more cycles to them. By defining

$$X_t = \begin{pmatrix} \mu_t \\ \psi_t \\ \psi_t^* \end{pmatrix},\ \eta_t = \begin{pmatrix} \xi_t \\ \kappa_t \\ \kappa_t^* \end{pmatrix}, T_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \rho\cos(\lambda_\psi) & \rho\sin(\lambda_\psi) \\ 0 & -\rho\sin(\lambda_\psi) & \rho\cos(\lambda_\psi) \end{bmatrix},$$

$$Z_t = (1 \quad 1 \quad 0),\ H_t = \sigma_\varepsilon^2,\ V_t = \begin{bmatrix} \sigma_\xi^2 & 0 & 0 \\ 0 & \sigma_\psi^2(1-\rho^2) & 0 \\ 0 & 0 & \sigma_\psi^2(1-\rho^2) \end{bmatrix}, \text{ and}$$

$$D_t = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

in (1.1) and (1.2), we obtain the following local level plus cycle model as given by

$$y_t = \mu_t + \psi_t + \varepsilon_t,\ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2),$$

$$\mu_{t+1} = \mu_t + \xi_t,\ \xi_t \sim NID\ (0, \sigma_\xi^2),$$

$$\psi_{t+1} = \rho\left[\cos(\lambda_\psi)\,\psi_t + \sin(\lambda_\psi)\,\psi_t^*\right] + \kappa_t,\ \kappa_t \sim NID\left(0, \sigma_\psi^2(1-\rho^2)\right),$$

$$\psi_{t+1}^* = \rho\left[-\sin(\lambda_\psi)\,\psi_t + \cos(\lambda_\psi)\,\psi_t^*\right] + \kappa_t^*,\ \kappa_t^* \sim NID\left(0, \sigma_\psi^2(1-\rho^2)\right),$$

For $t = 1,\ldots,T$, where $0 < \rho \leq 1$ is the *damping factor* and λ_ψ is the frequency of the cycle measured in radians so that $2\pi/\lambda_\psi$ is the *period* of the cycle. In case $\rho = 1$, the cycle reduces to a fixed sine-cosine wave but the component is still stochastic since the initial values ψ_1 and ψ_1^* are stochastic variables with mean zero and variance σ_ψ^2. A typical application of this model is for the signal extraction of business cycles from asset price time series. STAMP allows modelling cycles of 5, 10 and 20 years (Commandeur, Koopman, and Ooms, 2011).

2.3. A seasonal component in the time series data can be detected either via visual inspection and/or via dummy variables testing. The time-varying seasonal effects can be incorporated in an unobserved components time series model in a variety of ways – as a fixed dummy seasonal, time-varying dummy seasonal, fixed trigonometric seasonal, time-varying trigonometric seasonal, and as the random walk seasonal component (Koopman and Ooms, 2010). We choose to illustrate the time-varying (stochastic) dummy seasonal component (denoted by γ_t), being incorporated in the univariate local level model for a quarterly time series. By defining

$$X_t = \begin{pmatrix} \mu_t \\ \gamma_{1,t} \\ \gamma_{2,t} \\ \gamma_{3,t} \end{pmatrix}, \eta_t = \begin{pmatrix} \xi_t \\ \omega_t \end{pmatrix}, T_t = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -1 & -1 & -1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}, Z_t = \begin{pmatrix} 1 & 1 & 0 & 0 \end{pmatrix},$$

$$H_t = \sigma_\varepsilon^2, V_t = \begin{bmatrix} \sigma_\xi^2 & 0 & 0 & 0 \\ 0 & \sigma_\omega^2 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, D_t = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \\ 0 & 0 \end{bmatrix},$$

and expanding (1.1) and (1.2) in scalar notation, we obtain

$$y_t = \mu_t + \gamma_{1,t} + \varepsilon_t,\ \varepsilon_t \sim NID\ (0, \sigma_\varepsilon^2),$$

$$\mu_{t+1} = \mu_t + \xi_t,\ \xi_t \sim NID\ (0, \sigma_\xi^2),$$

$$\gamma_{1,t+1} = -\gamma_{1,t} - \gamma_{2,t} - \gamma_{3,t} + \omega_t, \omega_t \sim NID\ (0, \sigma_\omega^2),$$

$$\gamma_{2,t+1} = \gamma_{1,t},$$

$$\gamma_{3,t+1} = \gamma_{2,t},$$

For $t = 1,\ldots,T$, which is a local level and dummy seasonal model for a quarterly time series where the seasonal component is allowed to change over time. STAMP offers the option to model these different forms of seasonality if necessary. Proietti (2002) offers a comprehensive review of the abovementioned various seasonal specifications and their properties (Commandeur, Koopman, and Ooms, 2011).

Appendix 3[16]

I. The DFGM test

The Dungey, Fry, Gonzalez-Hermosillo, and Martin (2002, 2005) contagion test (DFGM) is based on modelling contagion as the transmission of idiosyncratic shocks across asset markets. This involves extending the noncrisis period asset returns equation in (2.1) to

$$y_{i,t} = \lambda_i w_t + \delta_i u_{i,t} + \sum_{j=1,j\neq i}^{N} \gamma_{i,j}\, u_{j,t}, \quad i=1, 2... N, \tag{2.2}$$

where the $x_{i,t}$ is replaced by $y_{i,t}$ as the model is defined for the crisis period. The term $\gamma_{i,j}u_{j,t}$ represents the effect of a shock in asset j at time t transmitted to the returns of asset i. To test the null hypothesis of no contagion in all asset markets amounts to a joint test of $\gamma_{i,j}= 0$ for all $i, j, i\neq j$.

In performing the DFGM test, the world shocks are treated as a latent factor. The simplest representation is given by specifying w_t to be independently and identically distributed with zero mean and unit variance:

$$w_t \sim \text{i.i.d. } (0,1). \tag{2.3}$$

To complete the specification of the model, the idiosyncratic shocks are also assumed to be

$$u_{i,t} \sim \text{i.i.d. } (0,1). \tag{2.4}$$

The assumptions on the factors mean that the difference in the volatility of the i-th asset return between crisis and noncrisis periods is solely due to contagion, where

$$E\left[y_{i,t}^2\right] - E\left[x_{i,t}^2\right] = \sum_{j=1,j\neq i}^{N} \gamma_{i,j}^2, \tag{2.5}$$

A more general specification is to let the common factor exhibit autocorrelation and a GARCH volatility structure; see Dungey and Martin (2004). This property is particularly important when using high-frequency asset returns data as the conditional volatility structures of asset returns tend to exhibit common features that can be parsimoniously modelled within a latent factor structure (Dungey et al., 2002).

The DFGM test is implemented by equating the theoretical moments as derived from equations (2.1) to (2.4) with the empirical moments from the sample data. The estimation is

[16] The appendix is largely based on the paper of Dungey and Tambakis (2005).

based on Generalized Method of Moments (GMM). For example, when the number of assets N = 3, the number of unknown loading parameters in equations (2.1) and (2.2) is 12. These parameters can be uniquely identified from the variance-covariance matrix of the asset returns in the precrisis and crisis periods, as both matrices contain six unique moments, yielding a total of twelve empirical moments. For this model a test of contagion amounts to testing the overidentifying restrictions arising from setting the relevant $\gamma_{i,j}$ parameters in equation (2.2) to zero.

Due to its assumptions, a weakness of the DFGM model is that it presupposes that the increase in volatility during the crisis period is solely generated by contagion, that is, $\gamma_{i,j} \neq 0 \forall i, j$. However, another scenario is that there is a general increase in volatility without any contagion; denoted as increased interdependence by Forbes and Rigobon (2002). This would arise if either the world loadings λ_i change, or idiosyncratic loadings δ_i change, or a combination of the two. The former would be representative of a general increase in volatility across all asset markets brought about, for example, by an increase in the risk aversion of international investors. The latter would arise from increases in the shocks of (some) individual asset markets which are entirely specific to those markets and thus independent of other asset markets. This weakness of the DFGM model can be corrected via an allowance for both contagion and structural breaks. However, this may, in turn, result in identification problems if the number of structural breaks entertained is unrestricted (Dungey et al., 2002).

II. The FR test

The Forbes and Rigobon (2002) test is based on testing the (unconditional) correlations between pairs of asset returns in the crisis and noncrisis periods. The common shocks w_t in equation (2.2) are modelled using a vector autoregression (VAR), augmented by additional control variables, with the residuals representing the idiosyncratic factors. In computing the unconditional correlation in the crisis period, an adjustment factor is introduced to allow for any increases in asset return volatility (heteroskedasticity bias) arising from increases in the volatility of the factors in equation (2.1).

To test for contagion from one asset market, the host market, to another asset market using the FR test, the FR test statistic is

$$FR = \frac{\frac{1}{2}ln\left(\frac{1+v_y}{1-v_y}\right) - \frac{1}{2}ln\left(\frac{1+\rho_x}{1-\rho_x}\right)}{\sqrt{\frac{1}{T_y-3}+\frac{1}{T_x-3}}}, \tag{2.6}$$

where $\rho_x$is the correlation coefficient between the two asset returns in the noncrisis period. Forbes and Rigobon (2002) define the noncrisis period as the total sample. The unconditional correlation coefficient in the crisis period, ν_y, is adjusted to account for the higher volatility in that period using

$$\nu_y = \frac{\rho_y}{\sqrt{1+\left(\frac{\sigma_{y,i}^2\sigma_{x,i}^2}{\sigma_{x,i}^2}\right)(1-\rho_y^2)}}, \tag{2.7}$$

where ρ_y is the correlation between two asset returns in the crisis period, and $\sigma_{x,i}^2$ and $\sigma_{y,i}^2$ are, respectively, the variances of the asset returns in the noncrisis and crisis periods of the *i*-th (host) asset returns.

An alternative way to represent the FR test is to express it as a Chow test (Dungey et al., 2005). This has the advantage that it provides a natural framework in which to generalize the FR test to allow for multivariate versions of the test as well as correcting for endogeneity bias. A further advantage is that this representation is computationally easier to implement than the multivariate extension based on the DCC test proposed by Rigobon (2002). For the bivariate problem, the approach is based on the following regression equation:

$$\left(\frac{z_{2,t}}{\sigma_{x,2}}\right) = \gamma_0 + \gamma_1 d_t + \gamma_2\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) + \gamma_3\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) d_t + \eta_t, \tag{2.8}$$

where

$$z_i = (x_{i,1},\ x_{i,2}, \ldots x_{i,T_x} y_{i,1},\ y_{i,2}, \ldots y_{i,T_y})',\ \ i = 1, 2 \tag{2.9}$$

represents the $(T_x + T_y) \times 2$ scaled pooled data set by stacking the precrisis and crisis scaled data with T_x and T_y observations, respectively. The dummy variable,d_t, is defined as

$$d_t = \begin{cases} 1: & t > T_x \\ 0: & otherwise \end{cases} \tag{2.10}$$

and $\sigma_{x,i}$ is the standard deviation of the *i*-th asset returns during the noncrisis period and η_t is an error term. The test of contagion is based on testing γ_3 = 0 in equation (2.8). Rewriting the FR test as in equation (2.8) shows that contagion is modelled by the additional contemporaneous effects of $y_{1,t}$ on $y_{2,t}$ in the crisis period.

This improved correlation-coefficients FR model of contagion focuses on adjusting for one problem with the cross-market correlation coefficients: heteroskedasticity. After all, when testing for contagion by means of correlation, it is crucially important to distinguish a true rise in correlation from one, rather induced by rise in variance. Indeed, the proposed adjustment for heteroskedasticity by Forbes and Rigobon, first put forward by Ronn (1998) in the bivariate setting, is clearly an improvement over previous contagion correlation-coefficients models, such as the King and Wadhwani (1990) one.

However, FR still does not resolve all issues. An inevitable inherent weakness of the FR's model is that the correction can be used meaningfully only if there are no simultaneous equations (i.e., lack of endogeneity) and no omitted variable issues. These are quite restrictive assumptions, though.

Furthermore, another feature (but also weakness) of the FR contagion test is its use of the Fisher transformation (Fisher, 1921) to improve the finite sample properties of the test statistic. However, this transformation is inappropriate where there is sampling dependence between the correlation coefficients in the two sample periods (Williams, 1969). This dependence arises in one of two ways. First, through the use of overlapping data, and second, through the heteroskedasticity correction. Since the FR may not correct for dependences in the sample correlations, its results bias the standard errors upwards and the test statistics downwards (Martin and Tang, 2006).

III. FG Test

The Favero and Giavazzi (2002) outlier test of contagion is based on modelling increases in volatility during the crisis period in one asset market by the extreme movements in the asset returns of other markets. Interestingly, Favero and Giavazzi (2002) use the term "nonlinearities" to refer to the phenomenon of contagion. In this way they circumvent the implicit meaning of contagion as a significant reinforcement in cross-market links in times of market turmoil. In fact, significant reduction in these links should also be interpreted as contagion (Wälti, 2003). To highlight their approach, consider a bivariate version (N = 2) of the crisis period model in equation (2.2):

$$y_{i,t} = \lambda_i w_t + \delta_i u_{i,t}, \tag{2.11}$$

$$y_{j,t} = \lambda_j w_t + \delta_j u_{j,t} + \gamma u_{i,t}, \tag{2.12}$$

where a test of contagion is given by the impact of $u_{i,t}$ on $y_{j,t}$, a test of $\gamma = 0$. The FG approach is to replace the $u_{i,t}$ in equation (2.12) by a set of exogenous dummy variables representing points in time when an asset market experiences an extreme movement, as follows:

$$y_{i,t} = \lambda_i w_t + \delta_i u_{i,t}, \tag{2.13}$$

$$y_{j,t} = \lambda_j w_t + \delta_j u_{j,t} + \sum_{k=1}^{K} \gamma_{i,k}\, d_{i,k,t}\ , \tag{2.14}$$

where $d_{i,k,t}$ represent the K extreme observations associated with $y_{i,t}$, defined as

$$d_{i,k,t} = \begin{cases} 1: & |e_{i,t}| > THRESH_i \\ 0: & otherwise \end{cases}, \tag{2.15}$$

where $e_{i,t}$ is taken as the residuals from a VAR containing the asset returns of all variables in the system. $THRESH_i$, a pre-assigned threshold value, is set equal to $3\sigma_i$, where σ_i is the pertinent residual standard deviation of equation i of the VAR. The dummy variables $d_{i,k,t}$ are also commonly referred to as *exceedances*. A dummy variable is constructed each time an observation is judged extreme/outlier, $|e_{i,t}| > THRESH_i$, with 1 placed in the cell corresponding to the point in time when the extreme observation occurs, and 0 otherwise (Dungey et al., 2005).

The FG test contrasts with the DFGM and FR tests where the latter tests use all information during the crisis period, not just the extreme values, to test for contagion. The test of contagion is a test of the parameter $\gamma_{i,k}$. FG, in defining w_t, includes the exceedances of all other countries. Further, the FG test requires specifying the common factor as consisting of own lagged returns and contemporaneous returns on the other assets. This choice is partly governed by identification issues. For a bivariate system the model is just identified with estimation based on an instrumental variables (IV) procedure. However, as asset returns exhibit very little autocorrelation, identification of the model may be problematic. This may manifest itself into a weak instrument problem resulting in the moments of the sampling distribution being undefined and in inflated standard errors. It may even work out that the bias caused by ignoring simultaneity, may be of a much smaller magnitude than the bias caused by working with weak instruments (Dungey et al., 2005).

These identification issues do not arise for the DFGM test, as the common factor is modelled explicitly as a latent factor that is identified by information on the returns in all asset markets. In contrast, endogeneity issues are not taken into account in the FR test in equation (2.6), which suggests that this test statistic is likely to be affected by endogeneity bias.

The FG approach is very similar to the multivariate Forbes and Rigobon (2002) correlation test as both tests are based on testing the significance of dummy variables in an augmented model. There exist, however, two main differences between these two models. Firstly, while FR identifies a crisis period as a period of higher volatility using a single dummy which has a non-zero value during the entire crisis period, FG identifies potentially many (short-lived) crisis periods associated with extreme returns. Secondly, the FG test assigns a different parameter to each dummy variable, whereas the FR test is based on a single parameter to represent contagion between two countries (Dungey et al., 2002).

IV. The BKS Test

In their contagion test Bae, Karolyi, and Stulz (2003) focus on the tails of the distribution of asset returns by identifying the exceedances of individual returns and co-exceedances across asset returns. The exceedance $d_{i,t}$in asset market *i* at time *t*in their approach is defined as a dummy variable:

$$d_{i,t} = \begin{cases} 1: & |y_{i,t}| > THRESH_i \\ 0: & otherwise \end{cases}, \qquad (2.16)$$

where $THRESH_i$, a pre-assigned threshold value, is set to capture the 5 percent tail of large positive and negative values. Baur and Schulze (2002) extend this to consider a number of different thresholds endogenously. Unlike the FG test, there is only a single exceedance variable for each asset market. Once the exceedances have been identified, the co-exceedances between shocks originating from asset *i* and asset *j* are constructed when

$$d_{i,t} d_{j,t} = 1. \qquad (2.17)$$

For *N* asset markets, categorizing asset returns into coexceedances yields a polychotomous variable that gives the number of coexceedances occurring at each point in time. A multinomial logit framework is then used to model the coexceedances as

$$P_{j,t} = \frac{exp(\beta_j x_{j,t})}{\sum_{k=0}^{N} exp(\beta_k x_{k,t})}, \ j = 0, 1, 2, ...N, \qquad (2.18)$$

where $P_{j,t}$ is the probability that there are *j* co-exceedances occurring at time *t*, and $x_{j,t}$ represents a set of explanatory variables used to explain asset returns and hence the co-exceedances. The model is normalized by setting $\beta_0 \equiv 0$, which corresponds to the case of no exceedances (i.e., no outliers).

The BKS contagion test consists of specifying the exceedances/co-exceedances of other sets of countries in the set of explanatory variables, given by $x_{j,t}$ in equation (2.18), and testing the joint significance of the corresponding parameters. To test for contagion within a region of three countries, for example, the co-exceedance variable is initially constructed for a pair of countries (the *j*-th and *k*-th) with the polychotomous variable consisting of the values 0, 1, 2. The exceedance of the remaining country (the *i*-th) is then constructed and included in the set of explanatory variables. The BKS contagion test is then a test of the significance of the *i*-th exceedance variable in explaining the *j*-th and *k*-th co-exceedances.

A special case of the BKS contagion test is the approach of the Eichengreen, Rose, and Wyplosz (1995,1996), who test for significant correlations between extreme movements in asset returns by creating a binary variable for the presence or otherwise of domestic and international crises as left- and right-hand-side variables, respectively. As noted above, the BKS and FG tests are similar in that both tests amount to testing the significance of the effects of extreme observations in one market, or set of markets, on another asset market. One obvious difference between the two approaches is that the BKS test uses information on co-exceedances in measuring contagion, whereas the FG test uses co-exceedances as conditioning information. Part of the reason for this is the way in which Favero and Giavazzi (2002) construct their exceedance variables - namely, assigning a separate dummy variable to each extreme observation.

Both the FG and BKS tests use a filter to identify large shocks, in contrasts with the FR and DGFM tests, which use all of the information in the sample to test for contagion. This may be problematic for the former pair of tests in that the filtering represents a loss of information, which may be expected to result in a loss of power. The extent of this loss in power can be identified using a range of Monte Carlo experiments (Dungey et al., 2004).

Appendix 4[17]

All four contagion tests are implemented with proprietary GAUSS software codes. The codes are available from Prof. Mardi Dungey’s website. They are adapted to the specifics of the three analysed shocks (the Lehman crisis, the Greek crisis and the Tapering scare), as well as to the specifics of our own data sets.

[17] The appendix uses the estimation template of Dungey and Tambakis (2005).

DFGM

Step 1: Estimate the following unconstrained system of equations by Generalized Method of Moments:

$x_{i,t} = \lambda_i w_t + \delta_i u_{i,t}$, i = 1, 2, 3,

$y_{i,t} = \lambda_i w_t + \delta_i u_{i,t} + \sum_{j=1,j\neq i}^{3} \gamma_{i,j} u_{j,t}$, i = 1, 2, 3.

The system is just identified as there are twelve empirical moments based on the variances and covariances for the noncrisis and crisis periods, and twelve unknown parameters ($\lambda_1, \lambda_2, \lambda_3, \delta_1, \delta_2, \delta_3, \gamma_{1,2}, \gamma_{1,3}, \gamma_{2,1}, \gamma_{2,3}, \gamma_{3,1}, \gamma_{3,2}$).

Step 2: Contagion tests are performed by using a Wald test on the contagion parameters ($\gamma_{i,j}$).

FR/Bivariate FR

Step 1: Compute the unconditional correlation between two returns over the precrisis period (ρ_x).

Step 2: Compute the unconditional correlation (ν_y) between two returns over the total period based on equation (2.7).

Step 3: Compute the FR test statistic given in equation (2.6).

Step 4: Perform a one-sided test of the null hypothesis $\nu_y = \rho_x$ against the null of $\nu_y > \rho_x$, indicating contagion.

FR/Multivariate FR

Step 1: Construct the dummy (d_t) in equation (2.10).

Step 2: Estimate the following system of equations:

$$\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) = \gamma_{1,0} + \gamma_{1,1} d_t + \gamma_{1,2}\left(\frac{z_{2,t}}{\sigma_{x,2}}\right) + \gamma_{1,3}\left(\frac{z_{3,t}}{\sigma_{x,3}}\right) + \gamma_{1,4}\left(\frac{z_{2,t}}{\sigma_{x,2}}\right) d_t + \gamma_{1,5}\left(\frac{z_{3,t}}{\sigma_{x,3}}\right) d_t + \eta_{1,t}$$

$$\left(\frac{z_{2,t}}{\sigma_{x,2}}\right) = \gamma_{2,0} + \gamma_{2,1} d_t + \gamma_{2,2}\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) + \gamma_{2,3}\left(\frac{z_{3,t}}{\sigma_{x,3}}\right) + \gamma_{2,4}\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) d_t + \gamma_{2,5}\left(\frac{z_{3,t}}{\sigma_{x,3}}\right) d_t + \eta_{2,t}$$

$$\left(\frac{z_{3,t}}{\sigma_{x,3}}\right) = \gamma_{3,0} + \gamma_{3,1} d_t + \gamma_{3,2}\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) + \gamma_{3,3}\left(\frac{z_{2,t}}{\sigma_{x,2}}\right) + \gamma_{3,4}\left(\frac{z_{1,t}}{\sigma_{x,1}}\right) d_t + \gamma_{3,5}\left(\frac{z_{2,t}}{\sigma_{x,2}}\right) d_t + \eta_{3,t}$$

Step 3: Perform Wald tests for contagion on the parameters $\gamma_{i,4}$ and $\gamma_{i,5}$.

FG

Step 1: Estimate a VAR on returns over the total period and identify dummy variables corresponding to outliers in the residuals based on equation (2.15).

Step 2: Classify local shocks for each asset return ($d_{1,j,t}$, $d_{2,j,t}$, $d_{3,j,t}$; i.e., where there is an outlier that is unique to that asset return at a point in time). Let the number of local shocks for each asset return be*M*, *N*, and *P*, respectively.

Step 3: Classify dummy variables into *K* global shocks, $d_{c,k,t}$, where the *c* subscript denotes common shocks (i.e., where there is an outlier in at least two asset returns at time *t*).

Step 4: Estimate the following structural model by instrumental variables:

$$y_{1,t} = \alpha_{1,t} + \beta_1 y_{1,t-1} + \delta_{1,1} y_{2,t} + \delta_{1,2} y_{3,t} + \sum_{k=1}^{K} \gamma_{1,k}\, d_{c,k,t} + \sum_{j=1}^{M} \gamma_{1,1}\, d_{1,j,t} + \sum_{j=1}^{N} \gamma_{1,2}\, d_{2,j,t} + \sum_{j=1}^{P} \gamma_{1,3}\, d_{3,j,t} + e_{1,t},$$

$$y_{2,t} = \alpha_{2,t} + \beta_2 y_{2,t-1} + \delta_{2,1} y_{1,t} + \delta_{2,2} y_{3,t} + \sum_{k=1}^{K} \gamma_{2,k}\, d_{c,k,t} + \sum_{j=1}^{M} \gamma_{2,1}\, d_{1,j,t} + \sum_{j=1}^{N} \gamma_{2,2}\, d_{2,j,t} + \sum_{j=1}^{P} \gamma_{2,3}\, d_{3,j,t} + e_{2,t},$$

$$y_{3,t} = \alpha_{3,t} + \beta_3 y_{3,t-1} + \delta_{3,1} y_{1,t} + \delta_{3,2} y_{2,t} + \sum_{k=1}^{K} \gamma_{3,k}\, d_{c,k,t} + \sum_{j=1}^{M} \gamma_{3,1}\, d_{1,j,t} + \sum_{j=1}^{N} \gamma_{3,2}\, d_{2,j,t} + \sum_{j=1}^{P} \gamma_{3,3}\, d_{3,j,t} + e_{3,t},$$

where the instruments are the three lag returns. The system of equations is just identified.

Step 5: Perform likelihood ratio tests for contagion on the parameters $\gamma_{1,2,j}$ and $\gamma_{1,3,j}$ in the first equation in the system, $\gamma_{2,1,j}$ and $\gamma_{2,3,j}$ in the second equation in the system, and $\gamma_{3,1,j}$ and $\gamma_{3,2,j}$ in the third equation in the system.

BKS

Step 1: Construct exceedances based on equation (2.17) for all asset returns.

Step 2: For asset returns *i* and *j*, classify the number of co-exceedances, ranging from 0,1,2.

Step 3: Construct an indicator variable that is I = 0 for no co-exceedances in asset returns *i* and *j*, I = 1 for exceedances in asset *i* but not asset *j*, I = 2 for exceedances in asset *j* but not asset i, and I = 3, for co-exceedances in assets i and k, where the indicator variable enters the likelihood function of equation (2.18).

Step 4: Estimate the multinomial logit model in equation (2.18), with the explanatory variables consisting of an intercept and the exceedances of asset k.

Step 5: Perform Wald tests on the parameter associated with the exceedances of asset return k.

Step 6: Repeat the tests for the other two combinations of asset returns.

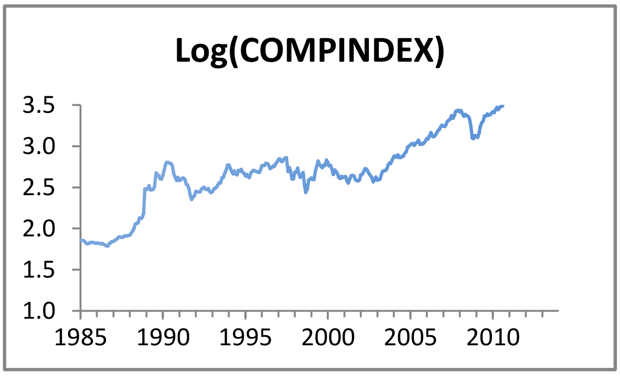
Table 1: Descriptive statistics of five log time series, used in asset price decomposition.

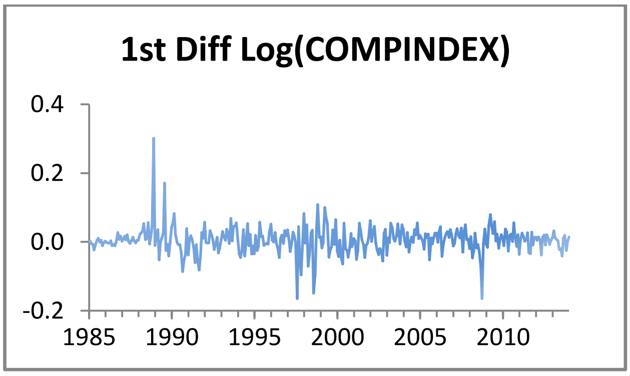
	COMPINDEX	FinStockIndex	PropStockIndex	ResPropIndex	USDIDR
No. of observations	349	217	217	47	244
Minimum	1.79	1.48	1.30	2.00	3.32
Mean	2.79	2.14	1.95	2.10	3.84
Maximum	3.70	2.83	2.75	2.23	4.17
Standard Deviation	0.50	0.39	0.38	0.06	0.25
Kurtosis	-0.44	-1.21	-1.16	-0.42	0.12
Skewness	-0.08	0.10	0.01	0.16	-1.37

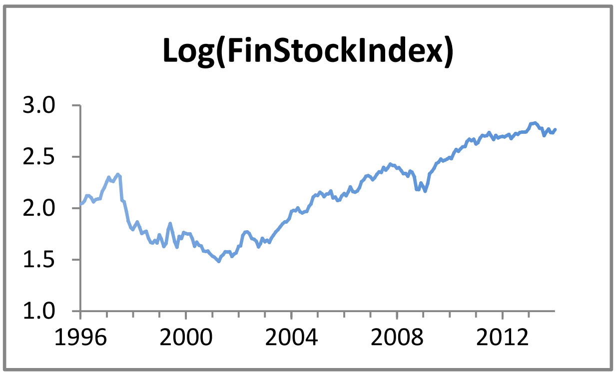
Table 2: Correlation matrix of the five time series (in logs), used in asset price decomposition.

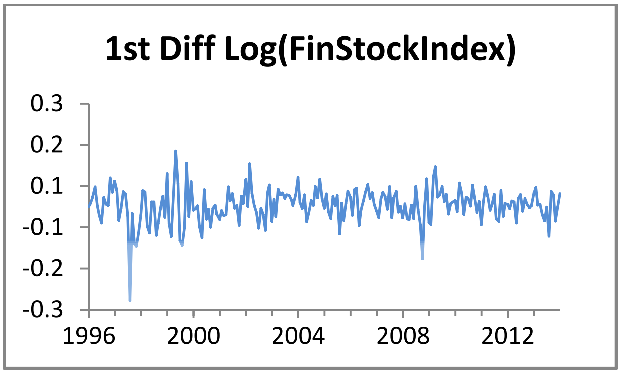
	COMPINDEX	FinStockIndex	PropStockIindex	ResPropIndex	USDIDR
COMPINDEX	1.00				
FinStockIndex	0.34	1.00			
PROPSTOCKINDEX	0.23	0.95	1.00		
ResPropIndex	0.82	-0.74	-0.73	1.00	
USDIDR	0.92	0.33	0.18	0.93	1.00

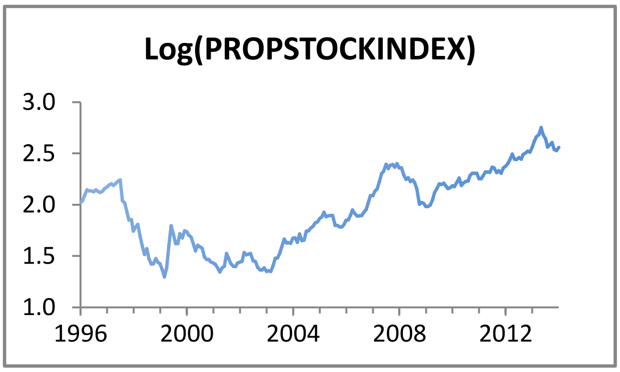
Figure 1: **Composite Stock Price Index, Financial Stock Price Index, Residential Stock Price Index, Residential Property Index and USD/IDR Nominal Exchange rate time series in logarithms (left column), and first differences of logarithms (right column).**

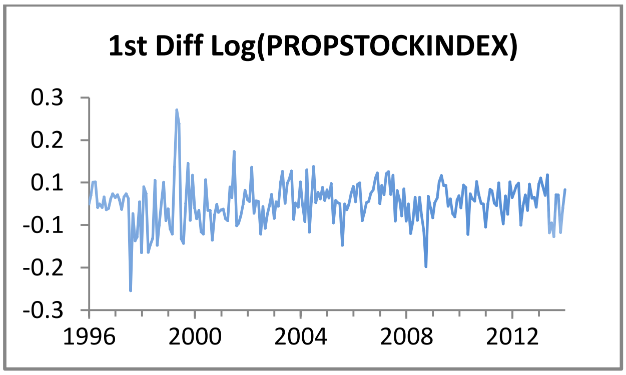


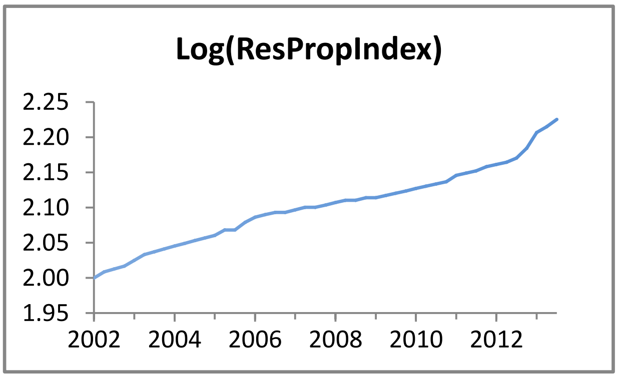


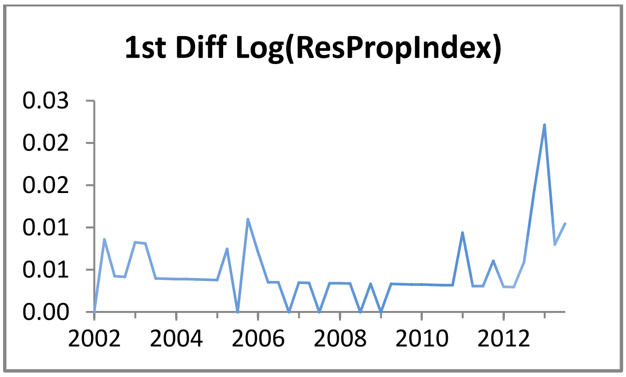

Log(FinStockIndex)
3.0
2.5
2.0
1.5
1.0
1996
2000
2004
2008
2012

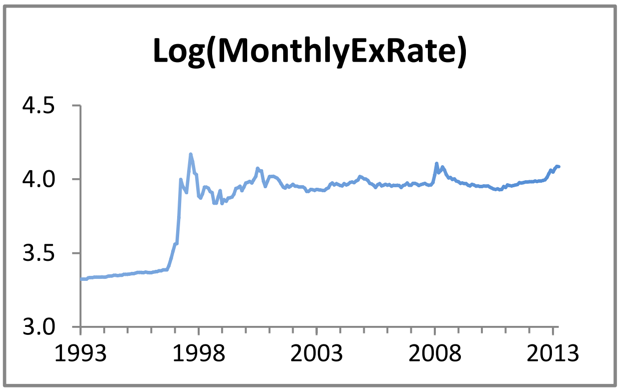

1st Diff Log(FinStockIndex)
0.3
0.2
0.1
-0.1
-0.2
-0.3
1996
2000
2004
2008
2012


Log(PROPSTOCKINDEX)
3.0
2.5
2.0
1.5
1.0
1996
2000
2004
2008
2012


1st Diff Log(PROPSTOCKINDEX)
0.3
0.2
0.1
-0.1
-0.2
-0.3
1996
2000
2004
2008
2012


Log(ResPropIndex)
2.25
2.20
2.15
2.10
2.05
2.00
1.95
2002
2004
2006
2008
2010
2012


1st Diff Log(ResPropIndex)
0.03
0.02
0.02
0.01
0.01
0.00
2002
2004
2006
2008
2010
2012


Log(MonthlyExRate)
4.5
4.0
3.5
3.0
1993
1998
2003
2008
2013

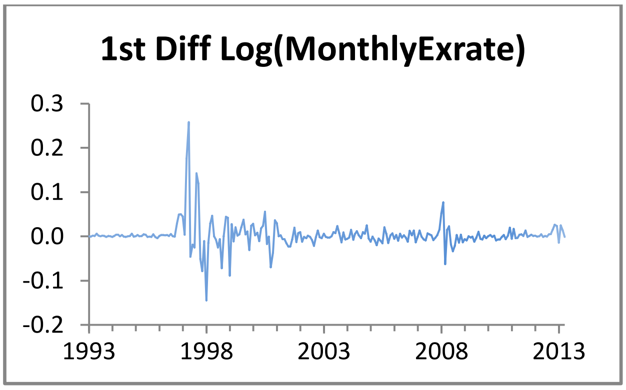
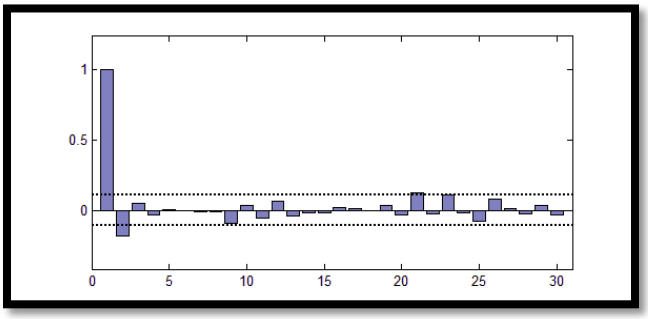

1st Diff Log(MonthlyExrate)
0.3
0.2
0.1
0.0
-0.1
-0.2
1993
1998
2003
2008
2013

Table 3: **t-statistics for the regression coefficients, obtained from regressing monthly/quarterly dummy variables on the five time series (in logs), used in asset price decomposition.**

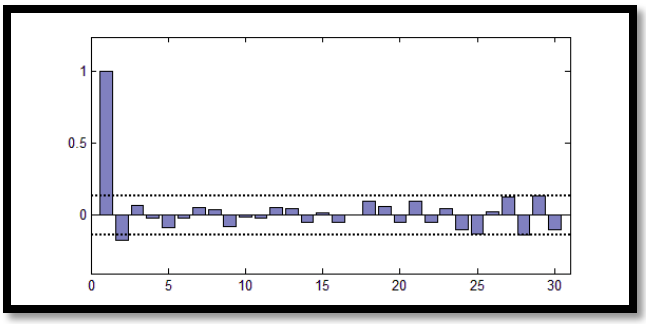
Asset price\Monthly Dummy	1	2	3	4	5	6	7	8	9	10	11	12
COMPINDEX	0.03	-0.25	-0.16	-0.06	0.04	0.09	0.14	0.03	-0.05	-0.06	-0.02	0.27
FinStockIndex	0.11	-0.25	-0.11	0.05	0.07	0.16	0.23	-0.09	-0.06	-0.12	-0.08	0.07
PropStockIndex	0.00	-0.31	-0.16	0.00	0.13	0.24	0.45	0.03	-0.03	-0.14	-0.18	-0.02
USDIDR	0.20	-0.03	-0.04	-0.08	0.06	0.13	0.06	0.09	0.24	-0.34	-0.21	-0.07
ResPropIndex (quarterly)		-0.29			0.06			0.31			-0.09	

Figure 2: Partial autocorrelation functions (PACFs) of the five time series (in logs), used in asset price decomposition.

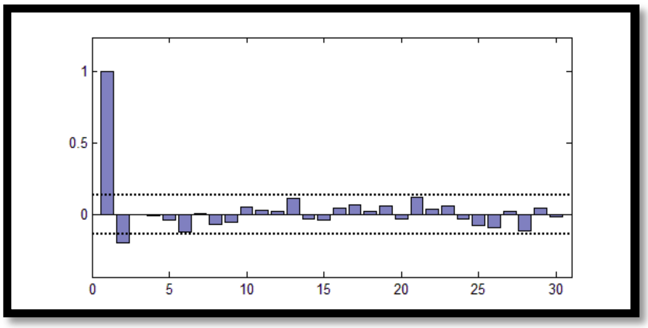
COMPINDEX



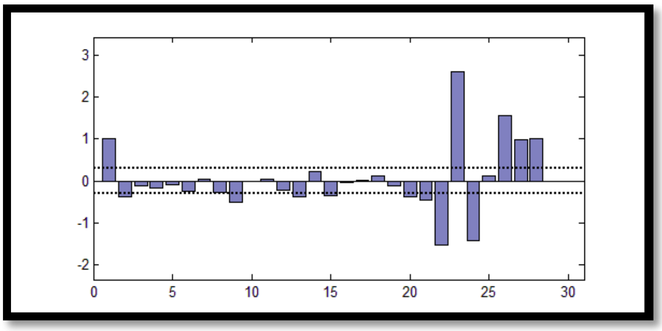
FinStockIndex



PropStockIndex



ResPropIndex



USDIDR

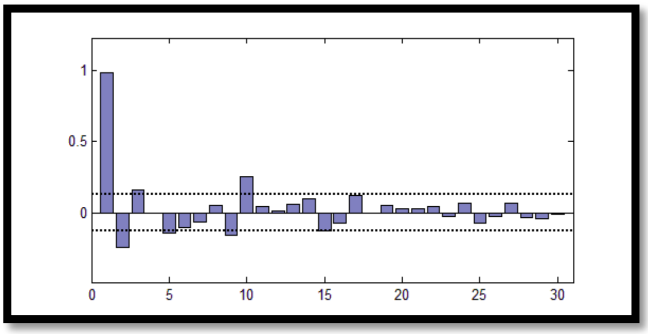
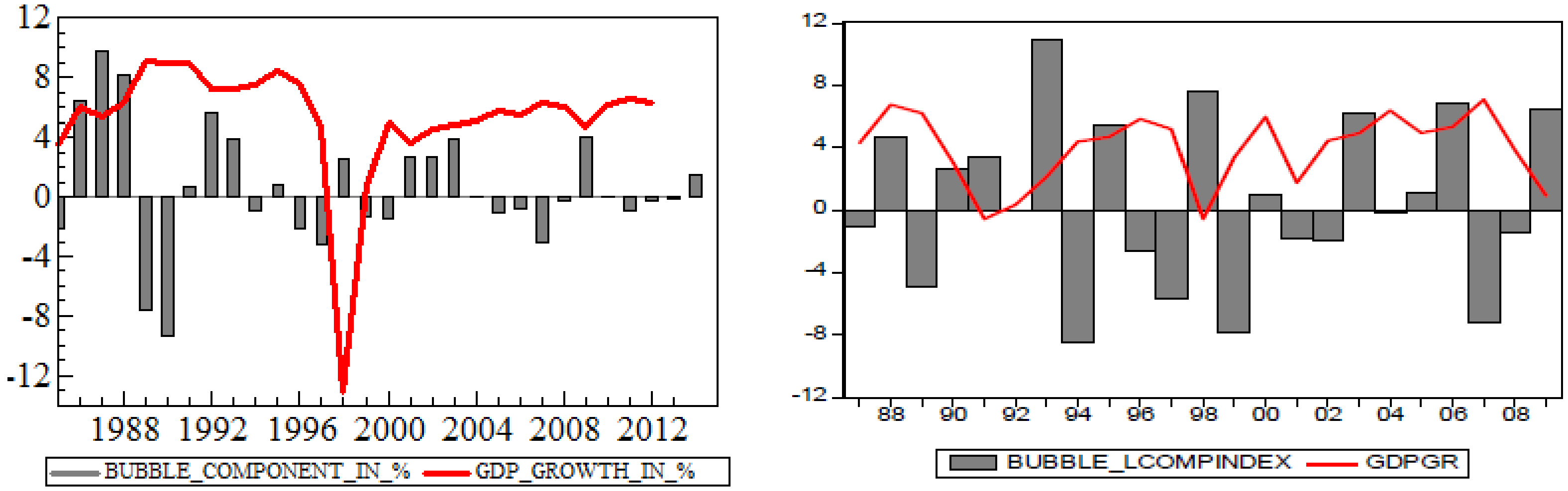
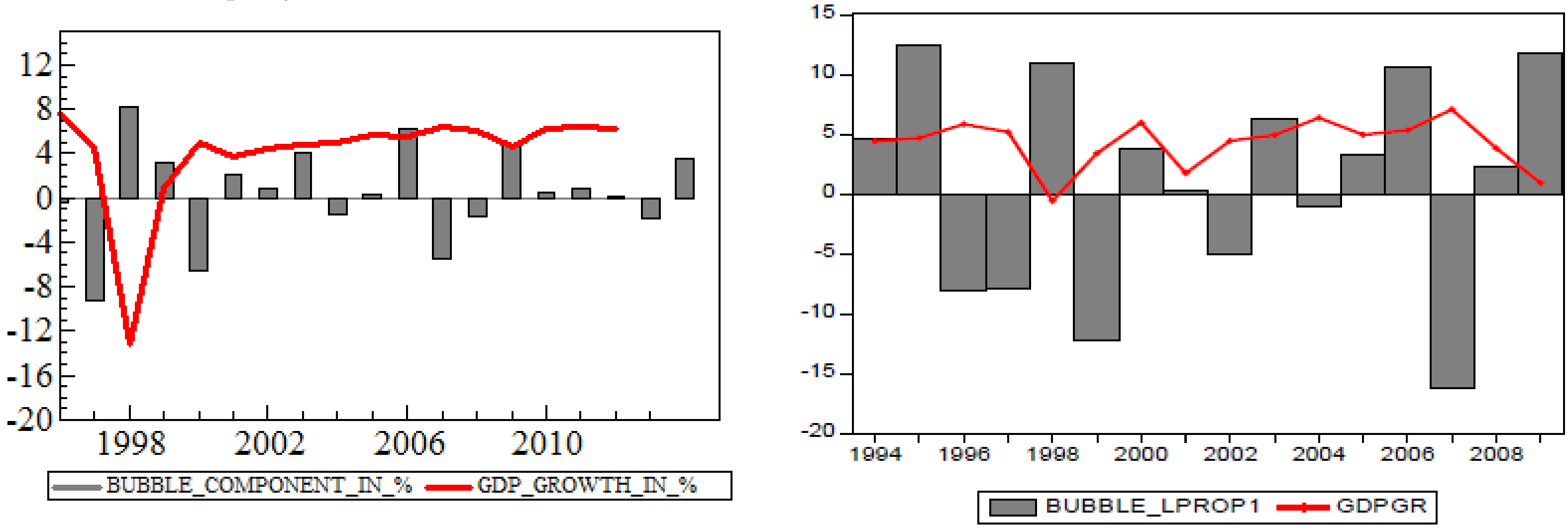


Figure 3: **Bubble components in asset prices in percentage, obtained by applying the procedure of Glindro and Delloro (2010). Results for Indonesia (left column) and the Philippines (from Glindro and Delloro (2010), right column) for comparison purposes.**

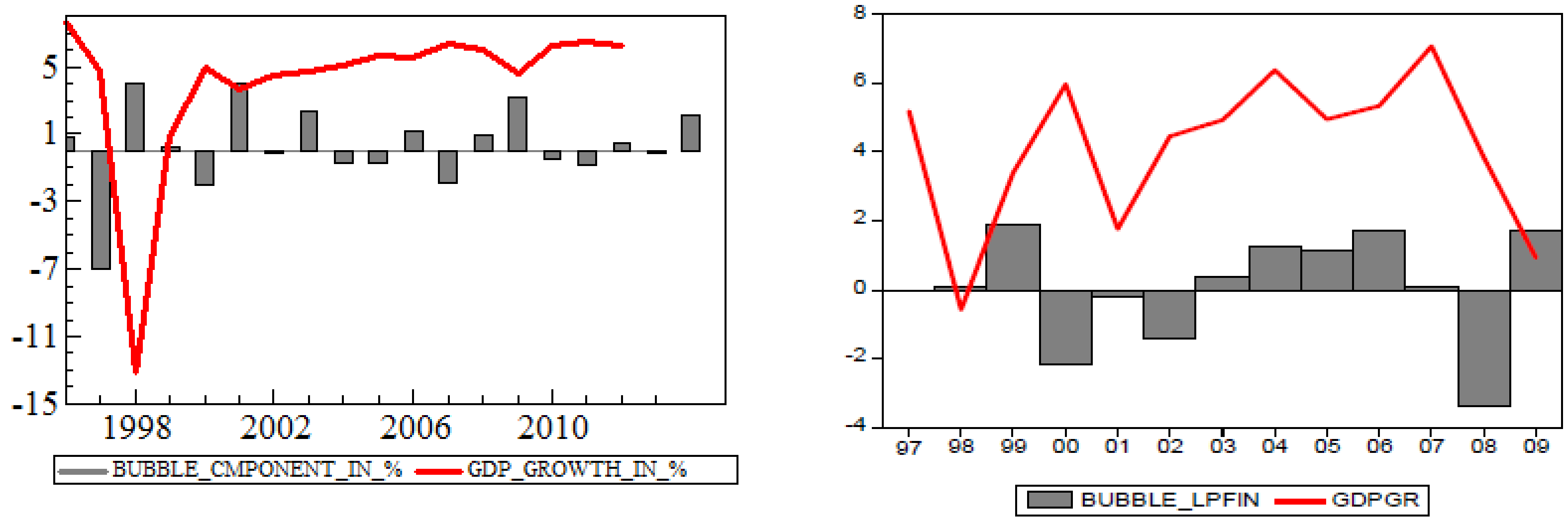
Composite Stock Price Index



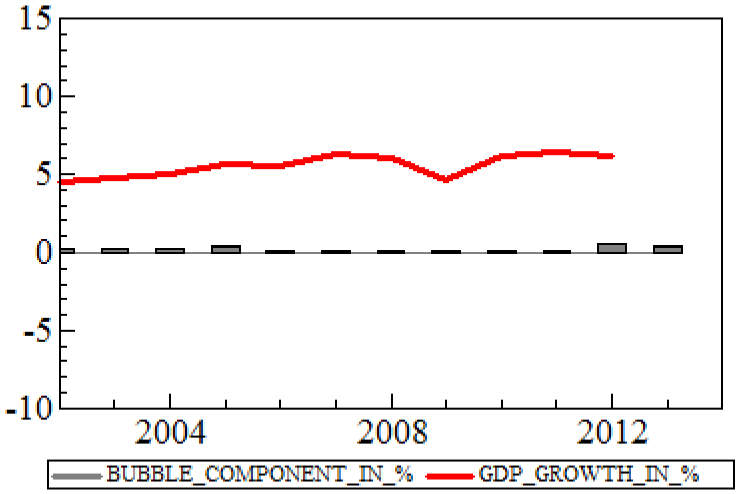
Property Stock Price Index

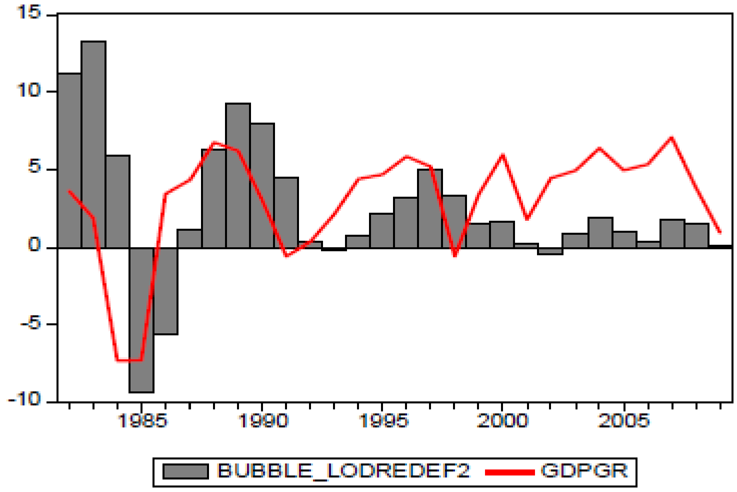


Financial Stock Price Index

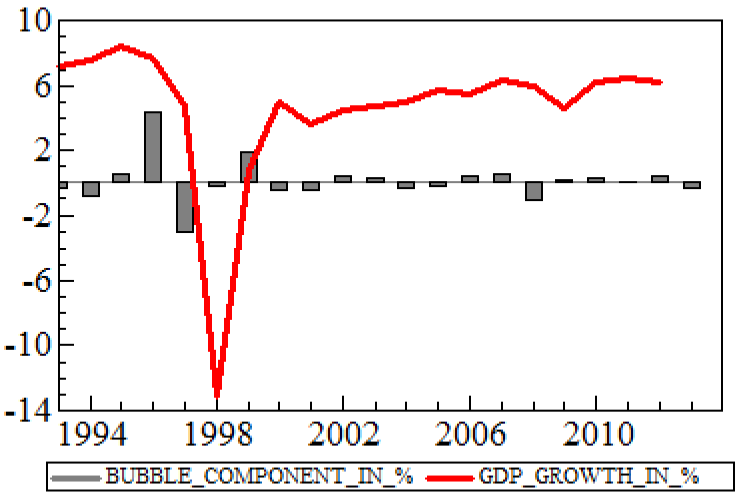


Residential Property Price Index





Nominal exchange rate between the Indonesian Rupiah and the US dollar



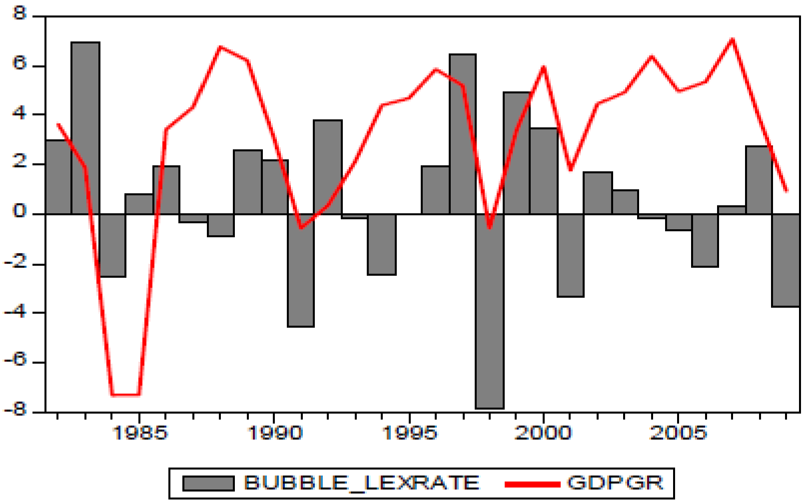
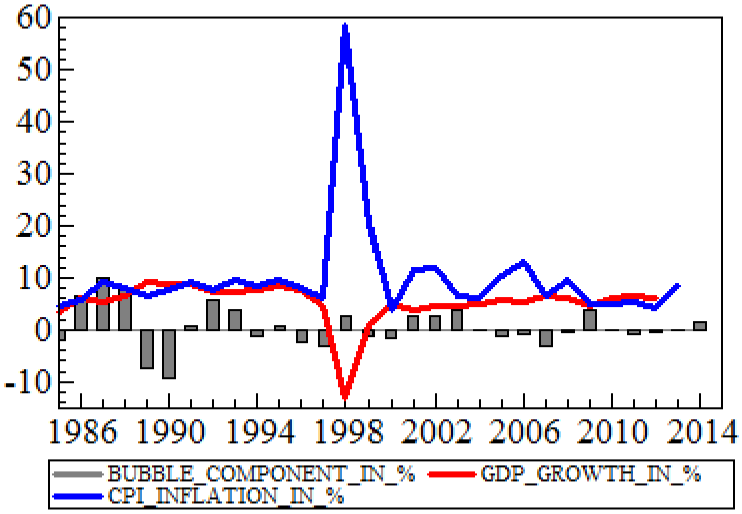
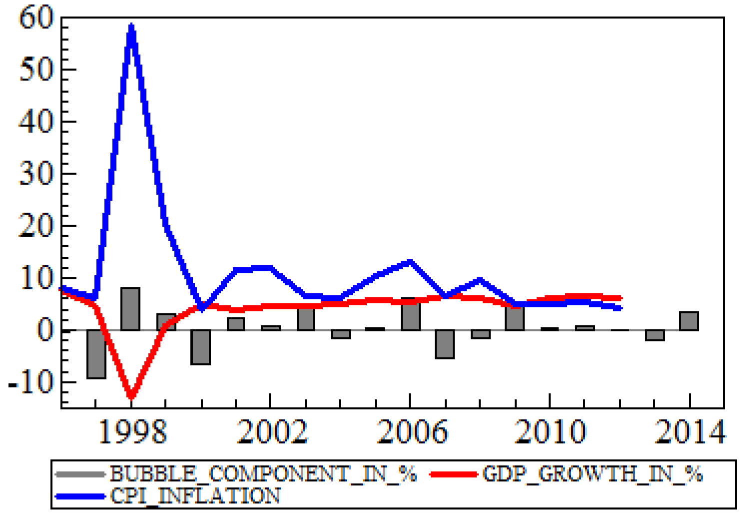


Figure 4: Bubble components in Indonesian asset prices, obtained by applying the procedure of Glindro and Delloro (2010), juxtaposed with rate of Indonesian GDP growth and Indonesian CPI inflation (all time series are in percentages).

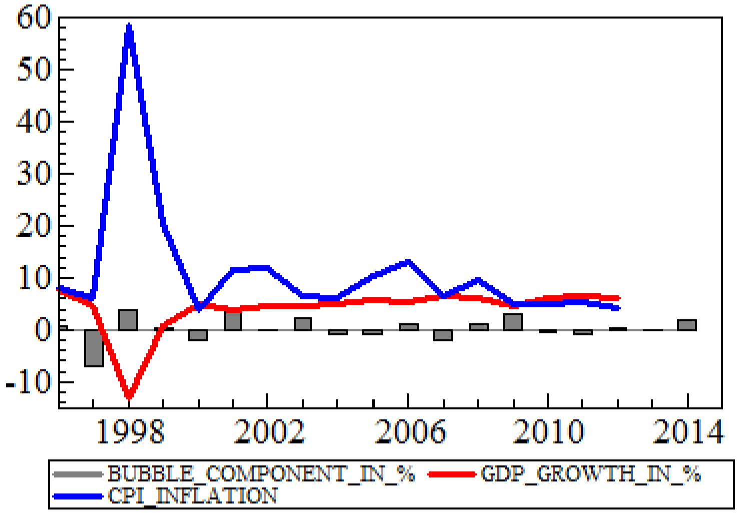
Composite Stock Price Index



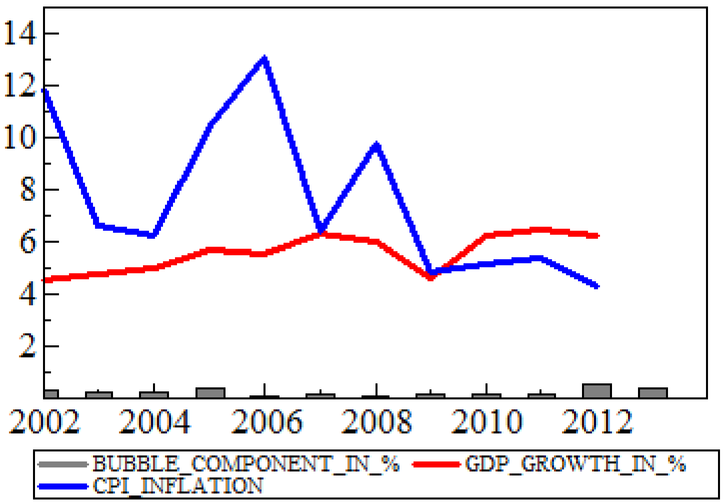
Property Stock Price Index



Financial Stock Price Index



Residential Property Price Index



Nominal exchange rate USD/IDR

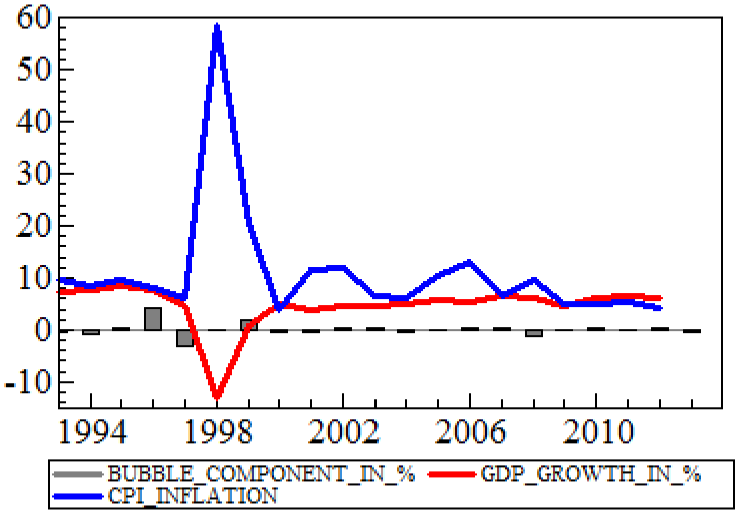


Figure 5: Equity returns in percentage points for various crises: Lehman Brothers (first column), Greek sovereign-debt crisis (second column), Tapering scare (third column). The precrisis period in each figure is to the left of the vertical dashed line, crisis period is to the right.

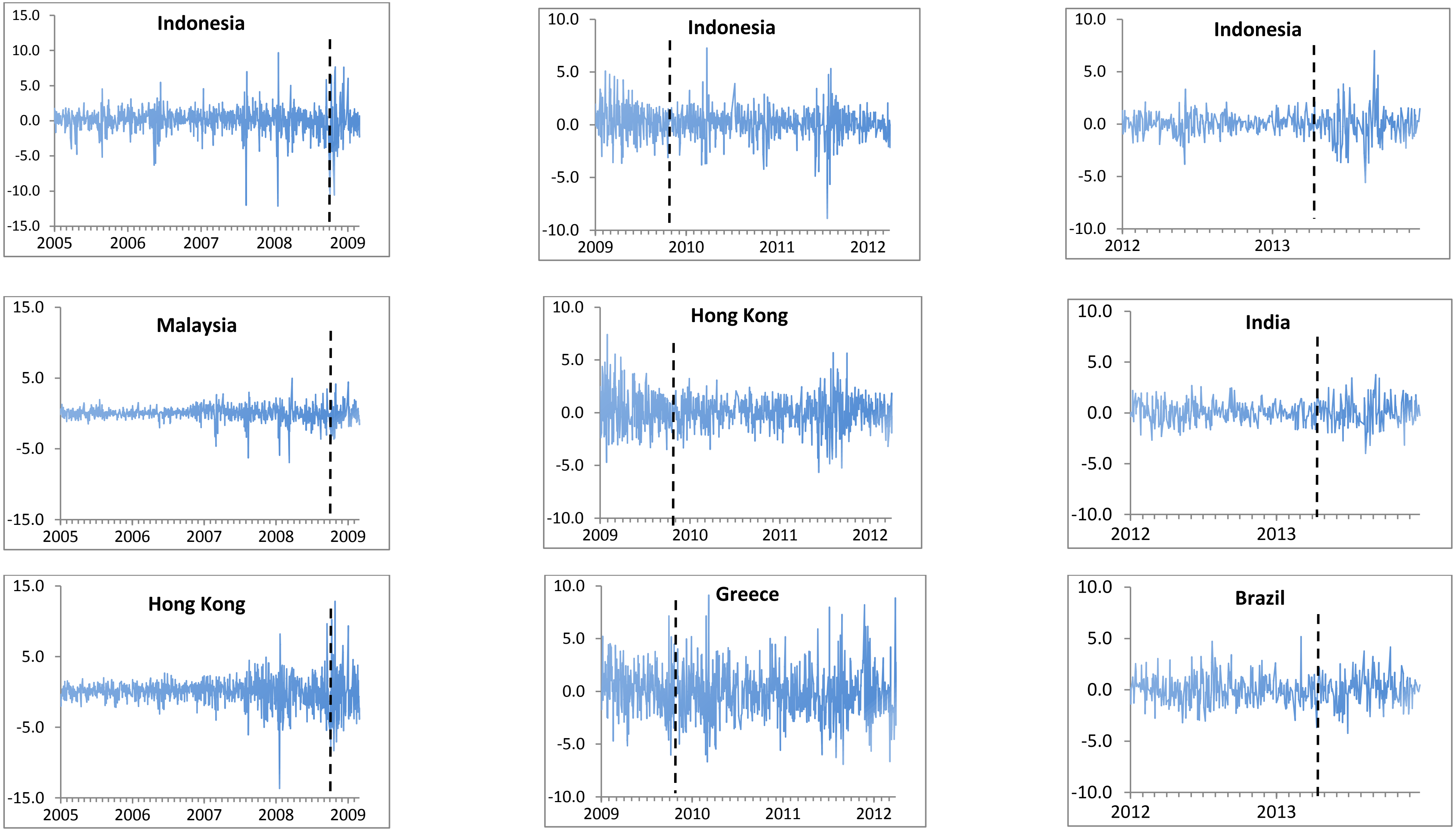


Table 4: Variances and Covariances (Correlations above Diagonal) of Daily Percentage Equity Returns for Selected Sample Periods.

	Precrisis Period			Crisis Period		
	1	2	3	4	5	6
Lehman crisis						
	Hong Kong	Indonesia	Malaysia	Hong Kong	Indonesia	Malaysia
Hong Kong	2.313	0.613	0.541	14.256	0.674	0.713
Indonesia	1.479	2.516	0.558	8.105	10.148	0.688
Malaysia	0.759	0.817	0.851	3.888	3.164	2.086
Greek crisis						
	Greece	Indonesia	Hong Kong	Greece	Indonesia	Hong Kong
Greece	4.013	0.406	0.378	5.526	0.265	0.297
Indonesia	1.305	2.575	0.678	0.834	1.794	0.660
Hong Kong	1.538	2.207	4.116	0.966	1.224	1.916
Tapering Scare						
	India	Indonesia	Brazil	India	Indonesia	Brazil
India	0.920	0.354	0.165	1.712	0.580	0.481
Indonesia	0.302	0.789	0.263	1.322	3.034	0.335
Brazil	0.212	0.314	1.801	0.912	0.845	2.101

Table 5: Variances Decomposition for the Lehman, Greek, and Tapering Crises Based on the DFGM Estimation (%).

	Precrisis Period			Crisis Period		
Components	1	2	3	4	5	6
Lehman crisis						
	Hong Kong	Indonesia	Malaysia	Hong Kong	Indonesia	Malaysia
World factor	60.358	66.230	50.913	23.580	23.823	32.164
Country factor	39.642	33.770	49.087	15.487	12.147	31.011
Origin of contagion						
Hong Kong	-	-	-	-	61.041	31.851
Indonesia	-	-	-	46.385	-	4.974
Malaysia	-	-	-	14.547	2.990	-
Total	100.000	100.000	100.000	100.000	100.000	100.000
Variance	2.313	2.516	0.851	14.256	10.148	2.086
Greek crisis						
	Greece	Indonesia	Hong Kong	Greece	Indonesia	Hong Kong
World factor	9.124	99.788	35.772	5.866	98.648	35.772
Country factor	90.876	0.212	64.228	58.429	0.209	64.228
Origin of contagion						
Greece	-	-	-	-	0.029	9.0E-07
Indonesia	-	-	-	31.975	-	0.0003
Hong Kong	-	-	-	3.730	1.113	-
Total	100.000	100.000	100.000	100.000	100.000	100.000
Variance	4.013	2.575	4.116	5.526	1.794	1.916
Tapering Scare						
	India	Indonesia	Brazil	India	Indonesia	Brazil
World factor	19.517	67.580	10.227	11.590	18.816	8.886
Country factor	80.483	32.420	89.773	47.796	9.026	77.998
Origin of contagion						
India	-	-	-	-	71.965	6.656
Indonesia	-	-	-	40.501	-	6.460
Brazil	-	-	-	0.112	0.193	-
Total	100.000	100.000	100.000	100.000	100.000	100.000
Variance	0.920	0.789	1.801	1.712	3.034	2.101

Table 6: Alternative Contagion Test Statistics during the Lehman Crisis, p-Values in Parentheses.

Host Country	Recipient Country	DFGM	FRB	FRM	FG, EndogeneityCorrrection	BKS
Hong Kong	Indonesia	51.042*	-2.871	4.387*	438.965*	23.978*
		[0.000]	[0.998]	[0.036]	[0.000]	[0.000]
	Malaysia	4.334*	-1.355	0.002	251.469*	18.173*
		[0.037]	[0.912]	[0.969]	[0.000]	[0.000]
	Both	82.839*	-	5.578*	2944.859*	65.234*
		[0.000]		[0.061]	[0.000]	[0.000]
Indonesia	Hong Kong	34.700*	-2.285	0.551	996.198*	23.526*
		[0.000]	[0.989]	[0.458]	[0.000]	[0.000]
	Malaysia	0.989	-1.661	5.711*	47.532*	39.557*
		[0.320]	[0.952]	[0.017]	[0.000]	[0.000]
	Both	37.601*	-	10.862*	1262.486*	69.781*
		[0.000]		[0.004]	[0.000]	[0.000]
Malaysia	Hong Kong	6.303*	0.503	59.050*	898.345*	18.995*
		[0.012]	[0.307]	[0.000]	[0.000]	[0.000]
	Indonesia	1.583	-0.642	3.952*	1737.063*	38.176*
		[0.208]	[0.739]	[0.047]	[0.000]	[0.000]
	Both	7.318*	-	100.474*	449.993*	75.270*
		[0.026]		[0.000]	[0.000]	[0.000]
Joint		121.426*	-	130.446*	3034.074*	-
		[0.000]		[0.000]	[0.000]	

*** Indicates the presence of statistically significant contagion at the 10 percent level.**

Table 7: Alternative Contagion Test Statistics during the Greek Crisis, *p*-Values in Parentheses.

Host Country	Recipient Country	DFGM	FRB	FRM	FG, EndogeneityCorrrection	BKS
Greece	Indonesia	43.481*	-0.866	5.411*	1115.352*	3.767*
		[0.000]	[0.807]	[0.020]	[0.000]	[0.052]
	Hong Kong	1.396	-0.508	0.570	763.024*	12.831*
		[0.237]	[0.694]	[0.450]	[0.000]	[0.000]
	Both	66.492*	-	13.496*	184.400*	0.019
		[0.000]		[0.001]	[0.000]	[0.890]
Indonesia	Greece	0.000	-0.528	1.073	911.318*	4.115*
		[0.995]	[0.701]	[0.300]	[0.000]	[0.043]
	Hong Kong	2.686	0.443	6.412*	979.146*	46.258*
		[0.101]	[0.329]	[0.011]	[0.000]	[0.000]
	Both	2.686	-	9.428*	876.030*	0.006
		[0.261]		[0.009]	[0.000]	[0.939]
Hong Kong	Greece	0.000	0.315	1.198	37.195*	12.266*
		[1.000]	[0.376]	[0.274]	[0.000]	[0.000]
	Indonesia	0.000	1.390*	2.631	411.309*	45.357*
		[0.999]	[0.082]	[0.105]	[0.000]	[0.000]
	Both	0.000	-	16.976*	404.544*	0.026
		[1.000]		[0.000]	[0.000]	[0.871]
Joint		69.555*	-	31.898*	1788.362*	-
		[0.000]		[0.000]	[0.000]	

*** Indicates the presence of statistically significant contagion at the 10 percent level.**

Table 8: Alternative Contagion Test Statistics during the Tapering Scare, *p*-Values in Parentheses.

Host Country	Recipient Country	DFGM	FRB	FRM	FG, EndogeneityCorrrection	BKS
India	Indonesia	81.410*	0.415	20.256*	60.689*	34.004*
		[0.000]	[0.339]	[0.000]	[0.000]	[0.000]
	Brazil	1.074	1.229	7.634*	240.811*	3.974*
		[0.300]	[0.109]	[0.006]	[0.000]	[0.046]
	Both	83.922*	-	33.835*	389.461*	10.155*
		[0.000]		[0.000]	[0.000]	[0.001]
Indonesia	India	124.085*	-0.360	0.052	138.011*	33.996*
		[0.000]	[0.641]	[0.820]	[0.000]	[0.000]
	Brazil	0.137	-0.466	4.706*	428.279*	15.007*
		[0.711]	[0.679]	[0.030]	[0.000]	[0.000]
	Both	148.875*	-	5.261*	87.209*	12.062*
		[0.000]		[0.072]	[0.000]	[0.001]
Brazil	India	3.532*	1.649*	16.067*	30.642*	4.190*
		[0.060]	[0.050]	[0.000]	[0.000]	[0.041]
	Indonesia	0.989	0.183	3.283*	49.604*	15.458*
		[0.320]	[0.427]	[0.070]	[0.000]	[0.000]
	Both	16.093*	-	9.619*	67.779*	6.581*
		[0.000]		[0.008]	[0.000]	[0.010]
Joint		190.188*	-	50.024*	363.917*	-
		[0.000]		[0.000]	[0.000]	

*** Indicates the presence of statistically significant contagion at the 10 percent level.**

Table 9: The Number of Observations involved in Testing the Significance of Contagion, by Crisis and Test.

	Tests				
	DFGM	FRB	FRM	FG	BKS
Lehman Crisis					
Total observations	933	933	933	933	933
Pre-crisis observations	828	828	828	828	828
Crisis observations	105	105	105	105	105
Exceedances					
Hong Kong				4	47
Indonesia				6	47
Malaysia				7	47
Co-exceedances				11	
Hong Kong and Indonesia					20
Hong Kong and Malaysia					19
Indonesia and Malaysia					22
Greek Crisis					
Total observations	745	745	745	745	745
Pre-crisis observations	178	178	178	178	178
Crisis observations	567	567	567	567	567
Exceedances					
Greece				8	37
Indonesia				8	37
Hong Kong				6	37
Co-exceedances				3	
Greece and Indonesia					3
Greece and Hong Kong					5
Indonesia and Hong Kong					11
Tapering Scare					
Total observations	434	434	434	434	434
Pre-crisis observations	307	307	307	307	307
Crisis observations	127	127	127	127	127
Exceedances					
India				3	22
Indonesia				5	22
Brazil				5	22
Co-exceedances				2	
India and Indonesia					9
India and Brazil					4
Indonesia and Brazil					6

Table 10: **Corroboration of Evidence across Tests: The Number of Tests That Reject the Null Hypothesis of No Contagion in Each Case.**

Crisis	Host Country	Bivariate Links			Host to Others	Overall
		Hong Kong	Indonesia	Malaysia		
	Hong Kong	-	4	3	4	
Lehman Crisis	Indonesia	3	-	3	4	3
	Malaysia	4	3	-	4	
		Greece	Indonesia	Hong Kong		
	Greece	-	4	2	3	
Greek Crisis	Indonesia	2	-	3	2	3
	Hong Kong	2	3	-	2	
		India	Indonesia	Brazil		
	India	-	4	3	4	
Tapering Scare	Indonesia	3	-	3	4	3
	Brazil	5	3	-	4	
Possible high score		5	5	5	4	3

Table 11: Grading criteria for incorporation of quantified cross-country contagion effects component in the Bubbagion Index. A grade of 1 is given for the strongest contagion evidence, whereas a grade of 5 indicates weakest evidence of contagion for a given country.

Grade	Number of tests that reject the null hypothesis of no contagion		
	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**
1	3	4	5
2*	3	4	<5
3	2	3	3-4
4	2	2	2-3
5	0-1	0-1	0-1

* - This grade applies for the case of Indonesia presented in this paper.