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Time and Frequency Domain Analysis of Volatility Spillovers across Financial Asset Classes in Malaysia

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Abstract

This paper investigates the connectness and spillovers among classes of financial asset in Malaysia in the post-decade of global financial crisis. First, the Diebold & Yilmaz (2012)'s time-domain analysis is applied with the spillover index reported at 10.7%. This implies a low level of connectedness but possible diversification among different asset classes across time. Furthermore, most of the assets except foreign exchanges, are net reciever of volatility. Second, the Barunik & Krehlik (2018)'s frequency-domain analysis reveals that, at higher frequencies, the degree of connectedness increases and, the net transmitter of volatility spillovers across financial markets is contingent on the frequency under consideration. By frequency domain, the role of Gold in long run from transmitter to receiver has emerged, and there is also increase in magnitude of spillover from oil prices. The findings are insightful for risk assessment and portfolio diversification.

Keywords: Malaysian Financial Assets, Volatiltiy spillover, Connectedness, Time and frequency Domain

1. Introduction

In the aftermath of the global financial crisis, 2008 interlinkages among asset classes emerge as an important area of focus. Because in integrated markets shock transmission occurs from one market to another quite easily which have an adverse impact upon overall financial system. In financial crisis 2008-2009 spillover effect is prominent where one market went down after another. The crisis originated in mortgage market of US but spill over to other developed and emerging economies and their financial systems (Cheung, Fung, & Tsai, 2010). So, being an emerging export-oriented economy Malaysia is not spared from drastic impacts of this crisis event. The financial crisis in 2008 effected aggregate demand for Malaysian products abroad. Therefore during that time export fell by more than 16% (Department of statistics Malaysia, 2016).

Similarly financial system of Malaysia also experienced such rampant condition. For example Malaysian stock market went down by 1000 percentage points on other hand Malaysian ringgit exchange rate tumble to 92% in start of 2009. Investors consider bonds as an investment substitute for stocks. Ibrahim (2010) explains that in later part of 2008 the Malaysian bond market rates went down in response to flight to quality. During crisis time when financial assets are downgraded investors switch to alternative assets such as real estate. There is permanent and strong relationship between stock market and real estate market of Malaysia (Pillaiyan, 2015).During times of global financial crisis there was a negative growth as well in property index value of most states (National Property Information centre, 2008).

So investors looking for assets which are shock absorbent and act as safe heaven against adverse market conditions. In this connection, crude oil and gold are an effective hedge and safe haven in case of stock market crisis for Malaysia (Robiyanto, 2017). Because in time of stock price decline gold and oil prices go up (Dorsman, Koch, Jager, & Thibeault, 2013; Ibrahim, 2012).Further these commodities provide effective hedge against inflation while simultaneously due to low correlation with other assets provide diversification benefit in terms of risk reduction (Mensi, Hammoudeh, & Kang, 2015). Therefore investors include these two commodities as an investment in their portfolios. Malaysia is ranked 26th globally and 2nd largest in ASEAN oil-producing countries (Central Intellegence Agency, 2017). This market contributes 20-30 percent to GDP of Malaysia. At the same time Malaysian investment demand for gold coin and bar increased by 3% in 2018 in comparison to 2017 (World Gold Council, 2019). Similarly another alternative asset which occupied prominent position in investment scene and finance literature is Bitcoin. Given its importance Bank Negara Malaysia allowed the registration while Finance ministry announced regulations for crypto currency exchanges and bring it under formal channel. As per survey of Bitcoin start-up Luno there is high level of awareness and ownership of Bitcoin in Malaysia. In the end of 2017 Bitcoin surpassed Malaysian GDP with market capitalization of US$322.5 billion (RM1.3 trillion). Bitcoin alone was more than 12 times Malaysian Banking market cap. Table 1 shows the production and trading volumes of crude oil and Bitcoin in Malaysia.

Table 1: Oil production and Bitcoin volume

Year	Crude Oil Production(Thousand Barrel)	Bitcoin Volume Ringgit
2014	220045	34118
2015	241491	273931
2016	243395	2571311
2017	240918	6619149
2018	238238	1250185

Source: Malaysia Energy information Hub (2020) and Coin.dance (2020)

Theoretical foundation which explains spillover is based upon theories such as asset substitution, hedging demand shift, and financial contagion. Asset substitution establishes a competing relationship among various asset classes that investors consider for investment. For example, any positive information which makes one asset class attractive can blow the attractiveness of other asset classes.

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Therefore investors sell one asset to buy other assets which seem to provide more return. Hedging demand shift explains that investors are concerned about hedge ratio. Therefore if there is change in price of one asset investor change position in other asset class to maintain same hedge ratio. It implies that positive innovation in one asset class leads to negative innovation in other asset class. Contagion hypothesis is based on mechanism where investors in bad times overlook fundamentals and overreact to negative innovations. It implies that when negative innovation occurs in one market it spill over to other markets not following fundamentals. Portfolios with a mix of traditional and alternative assets provide better risk-return profile (Dewandaru, Masih, Bacha, & Masih, 2017). Studies suggest adding number of assets not only increase the return but also reduce the risk. But simultaneously there is addition of externalities and systematic risk with each asset class added (Ibragimov, Jaffee, & Walden, 2011). Therefore a deeper understanding of connectedness is necessary to know whether interlink age adds into risk of financial system and what is relative contribution of each asset class.Therefore the objective of this paper is to find spillover in major asset classes of Malaysia namely Stock, bonds, real estate, commodities (crude oil and gold), and Bitcoin. This paper is using time and frequency domain framework to estimates volatility among mentioned asset classes for period from August 2011 to December 2018. There is twofold contribution of current study first by measuring directional and total connectedness using Diebold and Yilmaz (2012) method. This method determines the contribution of each asset class to overall volatility and simultaneously to find which are net transmitter and net receiver of volatility. Second, Baruník and Křehlík (2018) spillover index to determine contribution of each asset class to system at different frequencies. To the best of our knowledge this is first study to measure volatility spillover across major asset classes of Malaysia.

In the next section, literature review will be presented. Then, research methodology will be discussed highlighting the Diebold-Yilmaz (2012)'s time domain and Barunik and Krehlik (2018)'s frequency domain in spillover measurement. Following that will be a detailed discussion on the results and findings on the research. And lastly, in the final section, we conclude.

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2. Previous literature

The event of global financial crisis 2008 spurred the discussion of information transmission across markets. We focus only on Malaysian asset classes due to the wide scope of literature on such topic. A large number of studies are already available which investigate spillover across different countries and asset classes. Recently Yoon, Al Mamun, Uddin, and Kang (2018) examined market connectedness and spillover across borders as well asset classes. They measured connectedness among seven stock markets namely US, China, Japan, Australia, Hong Kong, Korea, and Singapore. Moreover, bond market, forex market, and commodity market are also examined for spillover. Yang and Zhou (2016) examined the network of volatility spillover and spillover intensity using implied volatility indices. Results suggest that US stock market is the center of volatility spill over to other major stock markets. Also quantitative easing in US has intensifying impact on volatility spillover across stock and commodity markets.

Xu, Ma, Chen, and Zhang (2019) examine dynamic volatility spillover among stock markets and crude oil by applying spillover index and asymmetric generalized dynamic conditional correlation (AG-DCC) method. Authors found that spillover due to negative shocks are more prominent in comparison to spillover due to positive shocks hence there is asymmetric spillover effect. (Bouri, de Boyrie, & Pavlova, 2017) focused on emerging and frontier markets to examine the spillover effect from commodity to credit default swap. They found that although there is significant spillover from commodity to credit default swap but varies from country to country as well over time. It implies in case of countries where such strong impacts of commodity on CDS lacks is probably due to political turmoil, economic downturn and quantitative easing or tightening measures. Conrad, Custovic, and Ghysels (2018) applied GARCH-MIDAS model to examine permanent and transitory volatility component of Bitcoin. The found that equity market volatility has significant and negative impact on permanent volatility component of Bitcoin.

Mensi, Hammoudeh, Al-Jarrah, Sensoy, and Kang (2017) analyzed the risk spillover among oil, gold, conventional and Islamic aggregate as well as disaggregate sector indexes. This study used Diebold and Yilmaz (2012) to examine directional shock and multivariate DECO-FIAPARCH model to analyze time variation in spillover. They found that commodities, energy, financial, technology, and telecommunication are receivers of spillover and rest are responsible for spillover transmission.

Tiwari, Cunado, Gupta, and Wohar (2018) examined volatility spillover across major financial asset classes of the US such as stocks, sovereign bonds, credit default swap and currency using time and frequency domain approach. Results based on Diebold and Yilmaz (2012) method suggest that there is low connectedness among asset classes further it tells that stocks and credit default swaps are net transmitters while bond and currency are net receivers. Baruník and Křehlík (2018) results suggest that connectedness and transmission are dependent on frequency it implies that in case of high frequency there's higher connectedness. Kang, McIver, and Yoon (2017) examined spillover effect among major commodity futures namely gold, silver, crude oil, corn, wheat, and rice in US using DECO-GARCH model and the spillover index.Findings suggest there is increase in spillover during Global financial crisis and European sovereign debt crisis. Furthermore gold and silver are transmitters while other commodity futures are receivers.

The above studies focus on the spillover effect in the developed and developing market other than Malaysia. However, there are studies which focus on Malaysian asset classes. You-How, Lai-Kwan, Yoke-Chin, and Chooi-Yi (2018) applied Granger Causality Analysis and Forecast Error Variance Decomposition to analyze the spillover effect between oil and stock market. They found that there is significant shock transmission from oil market to stock market of Malaysia. Wong (2019) examined volatility spillover between exchange rate and stock market of Malaysia using component GARCH model. They found that permanent component of volatility spillover between two markets is stronger in comparison to the short-run component. Raza, Shahzad, Tiwari, and Shahbaz (2016) examined impact of gold and oil volatilities on stock markets of emerging countries using nonlinear ARDL approach. They found that gold and oil price volatilities have a negative impact on Malaysian stock market in short run as well as long run. Although volatility spillover is well documented in literature but still one the area that which market are transmitter and which are receivers is untapped. Moreover these studies examine spillover among traditional asset classes. To the best of our knowledge there are not many studies to focus on Malaysia across broad asset classes. Most studies of spillover are focused on developed countries however those which are in Malaysian context focus on traditional asset classes. Moreover despite the body of literature there is little understanding of spillover among traditional and alternative financial asset classes in Malaysia.

3. Empirical methodology and Data

Following Diebold and Yilmaz (2012), we assume a covariance stationary VAR(p) as:

$$y_t = \sum_{i=1}^{p} \Phi_i \, y_{t-1} + \varepsilon_t \tag{1}$$

where y_t is an n × 1 vector of endogenous variables, Φ_i are n × n autoregressive coefficient matrices, and ε_t is a vector of error terms assumed to be serially uncorrelated. Using the GVAR framework, the H-step-ahead generalized forecast-error variance decomposition is expressed as:

$$Q_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\, e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (\, e_i' A_h \sum A_h' \, e_i)} \tag{2}$$

where Σ denotes the variance matrix of the vector of errors ε, and σij denotes the standard deviation of the error term of the jth equation. Finally, ei is an n × 1 vector with one on the ith element and zero otherwise. The connectedness index is composed of an n × n matrix θ(H) = [θij(H)] i, j = 1,2 , and each entry of the variance decomposition matrix is normalized by its row sum, as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{n} \theta_{ij}(H)} \tag{3}$$

with $\sum_{j=1}^{n} \theta_{ij}(H) = 1$ and $\sum_{j=1}^{n} \theta_{ij}(H) = n$ by construction. $\tilde{\theta}_{ij}(H)$ provides a natural and immediate measure of pairwise directional connectedness from j to i at horizon H.We can compute the net pairwise directional connectedness as:

$$C_{ij} = C_{i\leftarrow j}(H) - C_{j\leftarrow i}(H) \tag{4}$$

There are two versions: "from" and "to." The total directional connectedness from all markets to market i is denoted as Ci←•(H) and is computed as:

$$C_{i\leftarrow .}(H) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta_{ij}}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}}(H)} * 100 = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta_{ij}}(H)}{N} * 100 \tag{5}$$

Similarly, we compute through partial aggregation how a particular market i contributes to the shocks of all other markets. The total directional connectedness from market i to all markets is denoted as C•←i(H) and can be computed as:

$$C_{.\leftarrow i}(H) = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta_{ji}}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}}(H)} * 100 = \frac{\sum_{j=1, j\neq i}^{N} \widetilde{\theta_{ji}}(H)}{N} * 100 \tag{6}$$

Together with two pairwise directional indices, net total directional connectedness is defined as:

$$C_i(H) = C_{.\leftarrow i}(H) - C_{i\leftarrow .}(H) \tag{7}$$

The total aggregation of the variance decomposition across all markets measures the total connectedness index. The total connectedness in all markets can be computed as:

$$C(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\theta_{ij}}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}}(H)} * 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\theta_{ij}}(H)}{N} * 100 \tag{8}$$

After this, we discuss connectedness in frequency domain. Barunik and Krehlik (2018) proposed an accumulative connectedness table over an arbitrary frequency band d(a;,b) expressed as:

$$(\widetilde{\theta}_d)_{i,j} = \int_a^b (\widetilde{\theta}(h))_{i,j} dh. \tag{9}$$

The overall connectedness within a frequency band *d* can be expressed as:

$$C^d = \frac{\sum_{i,j=1, i\neq j}^{N} \widetilde{\theta_{ij}}(d)}{\sum_{i,j=1}^{N} \widetilde{\theta_{ij}}(d)} = 1 - \frac{\sum_{i,j=1}^{N} \widetilde{\theta_{i,i}}(d)}{\sum_{i,j} \widetilde{\theta_{i,j}}(d)} \tag{10}$$

A value of C^d close to unity indicates strong connections within the spectral band d= (a;,b). The *within from* connectedness measures the contribution of one market (i≠j) to another market *i*on the spectral band *d*, which can be expressed as:

$$C_{i\leftarrow}^d = \sum_{i,j,i\neq j} \widetilde{\theta_{i,j}}(d) \tag{11}$$

The *within to* connectedness measures the contribution to one market (i≠j) from another market *i*on the spectral band *d*, which can be expressed as:

$$C_{i\to}^{d} = \sum_{i,j,i\neq j} \widetilde{\theta_{j,\iota}}(d) \tag{12}$$

We examine daily volatilities of returns on Malaysia stock, bond, foreign exchange, REIT, commodities, and Bitcoin. In particular, we examine the KLCI index, the 10-year Treasury bonds yield, commodities (oil and gold) closing prices, Bitcoin closing price, and REIT Malaysia Index. The closing oil prices are taken from the US Energy Information Administration (EIA) website (www.eia.gov), while gold prices which are in MYR are taken from World Gold Council website (https://www.gold.org/). Bitcoin price data is taken from coindesk website (https://www.coindesk.com/price/bitcoin) while data for exchange rate, KLCI index, REITs are taken from Thomson Reuters Datastream. We have selected period from August 2011 to December 2018 because it contains two prominent events of Global economic crisis namely European debt crisis, and crude oil price crash 2014.

4. Results and discussion

We start our analysis with the descriptive statistics of seven Malaysian financial assests presented in the Table 2. For each series, 1922 observations have been analyzed. All data are in natural logarithm and the data distribution are generally not normal with negative skewness, except REIT and BOND prices.

Table 2: Descriptive Statistics

	KLCI	FX	OIL_PRICE	GOLD	REIT	BOND	BITCOIN
Mean	6.11E-05	0.000170	-0.000315	-5.54E-07	0.000172	6.06E-05	0.003031
Median	0.000000	0.000000	0.000000	0.000176	0.000000	0.000000	0.002613
Maximum	0.033222	0.020260	0.137421	0.763384	0.094438	0.065847	0.484776
Minimum	-0.032368	-0.035957	-0.124625	-0.763206	-0.095410	-0.041304	-0.663948
Std. Dev.	0.005628	0.004415	0.016084	0.026393	0.008229	0.006810	0.060038
Skewness	-0.365906	-0.546139	-0.069595	-0.023754	0.477629	1.117602	-0.988061
Kurtosis	6.395565	8.590622	21.74098	729.0078	25.55440	17.59508	22.72598
Jarque-Bera	966.2382	2598.554	28128.76	42210911	40811.55	17441.00	31474.30
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
N	1922	1922	1922	1922	1922	1920	1922

The overall static spillover results are provided in Table 3. A seven variable- VAR based on DY(2012) method is estimated along with 200 period horizon to get connectedness table. The total connectedness figure is 10.7% which is low in financial asset classes. This connectedness figure shows how much spillover exists in the system. Results of DY (2012) are given in Table 3 which indicates a weak connectedness among asset classes and there exist diversification opportunities. Furthermore, the time-domain spillover results reveal that stock market, forex market, and bond market contribute most spillovers in the financial system, while real estate, oil, and Bitcoin contribute 1.58%, 0.65%, and 0.3% respectively. Lowest contribution to financial system comes from gold which is only 0.17%. Results suggest that regulatory steps are necessary for stock market as it contributes most to the system volatility.

We follow the BK(2018) approach which shows short and long-run frequency interconnectedness in asset classes. Table 3 with two frequency bands is the static measure of interconnectedness among asset classes within and absolute frequency domain. Results suggest that lower frequency (corresponds to 1 to 4 days) contribute 6.52% while whereas contribution from frequency (corresponds to more than 10 days) (freq3) contribute to 4.18% of the total connectedness. Moreover across frequencies stock market contribute most to connectedness followed by foreign exchange market. The contribution of bond market is high at frequency 2 in comparison to frequency 1. While contribution of all other markets to connectedness has declined in long run. According to these results contribution of all markets except bond and oil is higher in short run than in long run which suggest that diversification opportunities are high in long run.

The next step is to build net connectedness of Malaysian financial asset classes. Table 4 shows the net connectedness in the overall system. Results of DY (2012) shows that all asset classes except the forex market have net negative spillover. Further, oil market has highest net negative spillover followed by gold while forex market is only asset with net positive spillover.It means that forex contributes to the risk transmission to the other assets while other assets are recievers of volaitlty. Next we move to results of BK (2018) method which shows that at frequency 1 all asset except Forex has net negative spillover. Results at frequency 2 differ in magnitude of spillover plus forex and gold have net positive spillover. The findings of BK(2018) are important because with only DY(2012) method it is not possible to obtain horizon based results. Frequency-based results highlight the importance of difference which arises as results of different frequencies considered. For example policies to reduce system-wide risk should be directed to forex market according to results obtained from frequency 1, and to forex, and Gold when long run is considered. If only time-domain had been considered then policies would have focused on forex market always without taking into account investment period. The policy formulation while ignoring difference in spillover due to time variation lead to incorrect policies.

To further investigate spillover among financial asset classes we build pairwise connectedness and report results in Table 5. The results of DY(2012) show that net connectedness in stock to forex, stock to bond, real estate to oil, oil to gold and oil to bond is positive whereas it is negative for most of the pairs. However, when we analyze connectedness at different frequencies we find that in asset pairs such as stock to forex, real estate to oil, oil to gold and oil to bond the connectedness sign is same as DY(2012) approach for all frequencies. However, for other asset pairs signs vary according to frequency such that oil to Bitcoin and Gold to Bitcoin are positive at frequency 1. While at frequency 2 stock to Bond, stock to Bitcoin, Real estate to gold and Real estate to Bond are also positive which were negative with DY (2012) method. These differences highlight importance of using frequency-based approach.

Table 3: DY (2012) and BK (2018) spillover results

DY spillover result

	KLCI	FX	REIT	Oil	Gold	Bond	Bitcoin	From
KLCI	78.1	11.3	7	0.5	0.1	2.7	0.3	3.13
FX	10.4	80.3	1.4	0.7	0.1	6.9	0.3	2.81
REIT	7.9	1.7	89	0.2	0.1	0.9	0.1	1.58
Oil	1.6	2.1	0.2	95.4	0.1	0.4	0.2	0.65
Gold	0.3	0.5	0.1	0.1	98.8	0	0.1	0.17
Bond	3.4	9.4	1.2	0.1	0.2	85.5	0.2	2.06
Bitcoin	0.4	0.4	0.4	0.1	0.2	0.4	98	0.3
To	3.43	3.64	1.47	0.25	0.12	1.63	0.17	10.7

BK spillover results

Freq 1: The spillover table for band: 3.14 to 0.79 roughly corresponds to 1 days to 4 days.

	KLCI	FX	REIT	Oil	Gold	Bond	Bitcoin	FROM ABS	FROM WTH
KLCI	56.0	6.3	5.26	0.35	0.1	1.48	0.22	1.96	2.6
FX	7.28	57.5	0.8	0.67	0.06	4.57	0.21	1.94	2.58
REIT	5.62	1.06	73.86	0.22	0.1	0.47	0.09	1.08	1.44
Oil	0.58	1.01	0.14	72.61	0.1	0.32	0.14	0.33	0.44
Gold	0.22	0.39	0.12	0.05	93.8	0.03	0.09	0.13	0.17
Bond	1.45	3.68	0.44	0.03	0.13	52.48	0.18	0.85	1.12
Bitcoin	0.4	0.4	0.35	0.06	0.2	0.21	75.13	0.23	0.31
TO ABS	2.22	1.84	1.02	0.2	0.1	1.01	0.14	6.52	
TO WTH	2.95	2.22	1.35	0.26	0.13	1.35	0.18		8.66

Freq 2: The spillover table for band: 0.31 to 0.00 roughly corresponds to more than 10 days.

	KLCI	FX	REIT	Oil	Gold	Bond	Bitcoin	FROM ABS	FROM WTH
KLCI	22.02	5.04	1.76	0.11	0.04	1.18	0.07	1.17	4.75
FX	3.12	22.78	0.58	0.22	0.03	2.29	0.07	0.87	3.53
REIT	2.26	0.7	15.1	0.02	0.02	0.46	0.01	0.49	2
Oil	1.03	1.07	0.04	22.82	0.01	0.12	0.01	0.32	1.31
Gold	0.06	0.14	0	0	5.03	0.02	0.04	0.04	0.15
Bond	1.94	5.64	0.71	0.1	0.04	33.12	0.04	1.21	4.9
Bitcoin	0.03	0.03	0.04	0.09	0.05	0.24	22.78	0.07	0.27
TO ABS	1.2	1.8	0.45	0.05	0.03	0.61	0.03	4.18	
TO WTH	4.88	7.3	1.81	0.2	0.1	2.49	0.14		16.91

Table 4: Net spillover

	Total DY (2012)	Total BK (2018) Freq 1	Total BK (2018) Freq 2
KLCI	-0.07404	-0.05175	-0.02229
FX	0.564693	0.307332	0.257361
REIT	-0.04377	-0.03248	-0.0113
Oil	-0.17366	-0.01931	-0.15435
Gold	-0.11503	-0.11703	0.001998
Bond	-0.05846	-0.03282	-0.02565
Bitcoin	-0.09973	-0.05395	-0.04578

Then to capture time-varying effect in overall and pairwise connectedness between seven variables we applied rolling window approach. Rolling window like recursive procedures do not depends on when the sample begins for detection of anomalies in the system (Chong & Hurn, 2017). Another approach to measure time variying effect is Kalman filter which is superior in terms of estimation but is not used widely in literature due to complexity of its understanding (Van Vuuren & Yacumakis, 2015). In order to implement rolling window the forecast horizon is 100 along with window size of 300 days to allow enough sample (about one-tenth of total observations) to show time variation in connectedness. The results of DY and BK methods are shown in fig. 1 where data points depict total connectedness. The first windows start on January 6, 2012, and end on October 10, 2012(200 observations). The connectedness for this window is about 28% which remain stable throughout the year. The peak is observed in May 2013 with spillover of around 85%. This figure also depicts rolling window connectedness in the frequency domain which highlights that DY results are driven by short run. Rolling window results are reported are similar for all graphs. These results are in similar to that of previous paper on time-varying spillover effect. Now consider pairwise connectedness with rolling window in time and frequency domain. Results are presented in fig 2 in which it is clear that directional connectedness among asset classes is volatile with positive and large negative movements especially for Bond-Bitcoin markets in 2013 and Gold-Bitcoin, in 2016.

Table 5: Pairwise spillover

	DY	BK1	BK2
KLCI-FX	0.207227	0.127981	0.079246
KLCI-REIT	-0.03591	-0.02335	-0.01256
KLCI-oil.price	-0.07177	-0.00194	-0.06983
KLCI-Gold	-0.03851	-0.03767	-0.00084
KLCI-Bond	0.020161	-0.00476	0.024918
KLCI-Bitcoin	-0.00715	-0.0085	0.001356
FX-REIT	-0.04328	-0.03948	-0.0038
FX-oil.price	-0.08722	-0.00317	-0.08404
FX-Gold	-0.08103	-0.06631	-0.01473
FX-Bond	-0.10809	-0.03328	-0.07481
FX-Bitcoin	-0.03784	-0.03711	-0.00073
REIT-oil.price	0.016008	0.014709	0.001298
REIT-Gold	-0.01291	-0.01527	0.002362
REIT-Bond	-0.01207	-0.01308	0.001007
REIT-Bitcoin	-0.02645	-0.01672	-0.00973
oil.price-Gold	0.0051	0.004127	0.000973
oil.price-Bond	0.025853	0.020574	0.005279
oil.price-Bitcoin	-0.00028	0.004203	-0.00448
Gold-Bond	-0.01068	-0.00385	-0.00683
Gold-Bitcoin	-0.00164	0.00576	-0.0074
Bond-Bitcoin	-0.02636	-0.00157	-0.02479

Fig 1: DY (2012) Total Spillover and BK 1

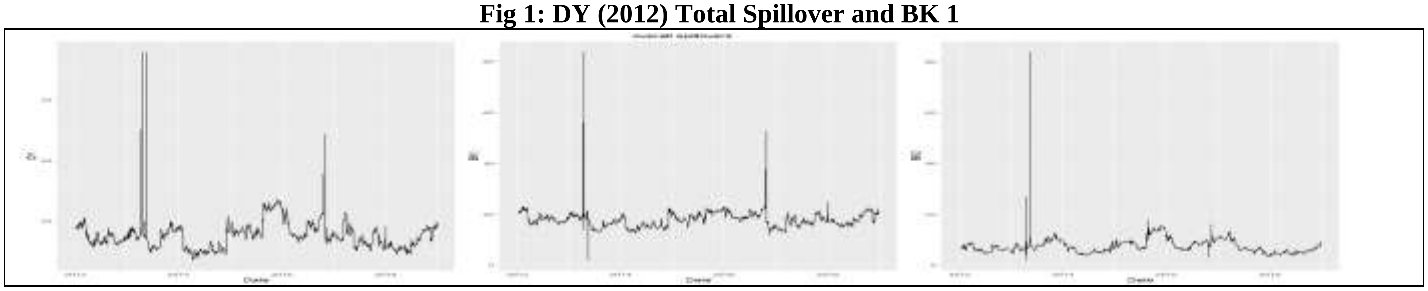
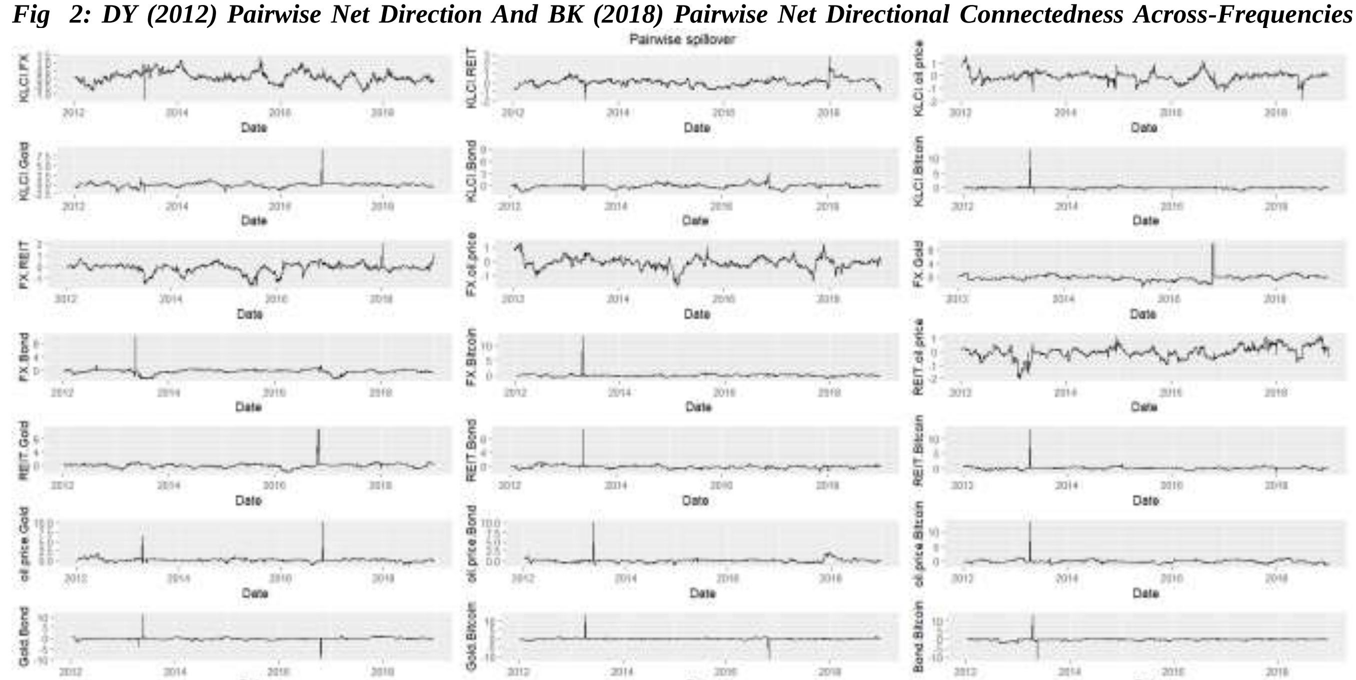
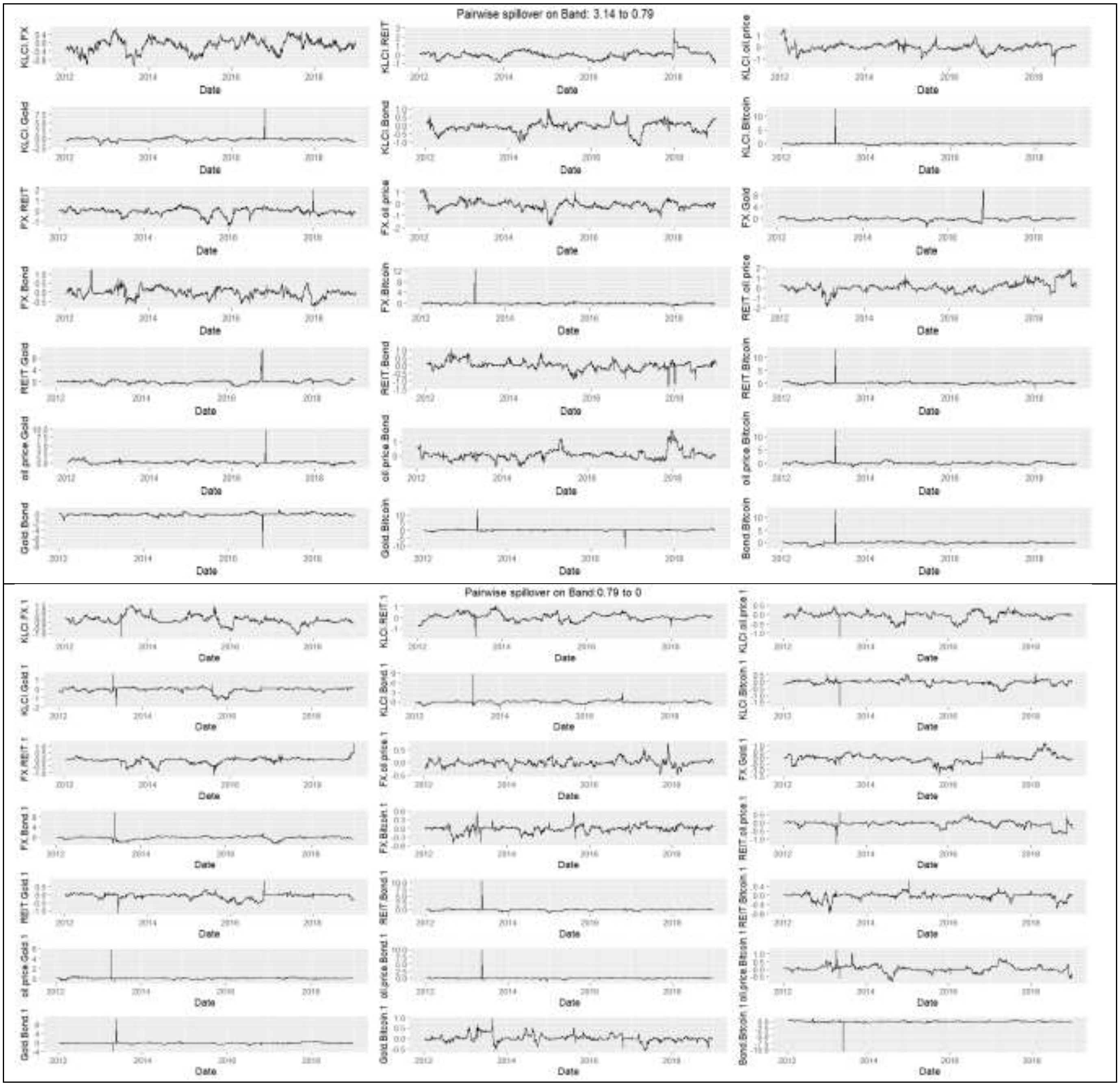


Fig 2: DY (2012) Pairwise Net Direction And BK (2018) Pairwise Net Directional Connectedness Across-Frequencies





Then we discuss pairwise net directional connectedness in the frequency domain. Results suggest that connectedness between pairs such as Stock-REIT, Stock-Gold, Forex-Gold, REIT-Gold, REIT-Bitcoin, oil-Gold and Gold-Bitcoin is mostly positive on other hand in Stock-Bond, and Forex-Oil spillover is mostly negative. There are pairs with mixed spillovers results where it is predominantly positive with large negative swings such as Stock-forex, stock-Bitcoin, Forex-Bond, Forex-Bitcoin, REIT-Oil, REIT-Bond, and Gold-Bond. On contrary there are pairs with mostly negative and large positive spillover swings such as Forex-Bond, oil-Bond and Bond-Bitcoin. Overall results suggest that spillover among asset classes are volatile with large positive and negative swings.

5. Conclusions

This paper analyzes connectedness and spillovers among financial assests (Stock, Forex, Real estate, oil, gold, bond, and Bitcoin) in Malaysia using data from August 2011 to December 2018, based on both the time-domain and frequency-domain analysis. When Diebold and Yilmaz (2012) method is applied, the spillover index of 10.7% is reported, which is low enough to suggest that diversification opportunities still exist. Furthermore, during the study period, forex has been the main contributor to system volatility which justifies the financial regulatory actions for this market. Moreover, the time-domain results reveal that all financial assets except forex are net reciever of spillovers. Such finding is supporting the conventional wisdom that investors concern about different time horizons before making investment decision. In the same vein, we adopt the Barunik and Krehlik (2018) analysis to discover that the second net transmitter of volatility and spillovers depend upon frequency domain. We observe that all asset except forex are net transmitter of volatility at higher frequency while at low frequency gold also become net receiver of volatility. The magnitude of volatility transmission reduced substantially at lower frequency. This suggests that at higher frequency there is much spillover and low diversification. At the same time, the role of Gold in long run from transmitter to receiver has emerged. Whereas in the long run there is increase in magnitude of spillover from oil prices. Our study provides insightful indication for risk assessment and portfolio investment. The outcome of analysis is useful for pontential construction of an early warning system in Malaysia.

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