UNDERSTANDING EMERGING AND FRONTIER MARKETS DYNAMICS THROUGH NETWORK THEORY

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Abstract. *This paper investigates the volatility spill-over effects between emerging and frontier markets in an effort to understand if the discrimination between the two is categorical or subject to investor interpretation. Analyzing data from a period of nine years, from 2008 to 2017, we prove that some frontier markets are more connected to the emerging sector than to the frontier sector and that regional correlation is predominant over asset class correlation. The methodology used combines univariate and multivariate filtering of daily returns for auto-regressive, mean reversion and volatility clustering effects. This study is taking advantage of the most recent data analysis methods in a complex but robust manner, in order to best answer the market segregation question.*

Keywords*: emerging markets; frontier markets; volatility spill-over; Granger causality; Diebold-Yilmaz.*

Introduction and literature review

The free movement of capital and the continuous suppression of trade barriers have transformed financial markets into a more compact structure where information is available in real time and investment opportunities in all types of assets become viable options for those institutions and private investors who seek higher returns and risk diversification. In this paper, we argue that the boundary between emerging and frontier markets is not limited to the MSCI separation criteria because performance and risk characteristics are perceived differently by international traders.

Portfolio theory has always been centered on the objective of finding a constant upward trend with the lowest risk attached to it. If classical investment practice would consider that large developed markets would offer sufficient diversification so as to mitigate idiosyncratic risk, current developments prove that there still exist global systematic risk sources that can erase portfolio gains if not previously anticipated, or at least properly hedged (De Bandt & Hartmann, 2000).

In nominal terms, if we follow the evolution of the MSCI emerging market and world indices, we would notice that the total capitalization of emerging market listed equities has grown from 35 billion USD in 1988 to over 4 trillion USD in 2016, which stands for an increase from 1% in global shares to 10% (Morgan Stanley Capital International, 2016).

The drawback of this new high risk endeavors has manifested itself through high volatility, the dependence of some national economies to price swing in raw materials and the flight to safety of capital during crises. Regarding the latter enumerated weakness, history shows that portfolio is prone to brutal rebalancing due to herding behavior when investment institutions see that future growth in emerging markets is hampered by bad national balance-sheets, fixed rate currencies and current accounts in deficit (Dornbusch, 2001). Of the crises that have significantly impacted emerging market returns, we mention the 1994 Mexican peso crisis, the 1998 Russian rubble crisis, the 2001 Dot-com Bubble, the 2007 Sub-Prime crisis and the 2008 Economic crisis.

Today, investors are seeking new opportunities similar to those in emerging markets pushing the edge of stock selection into less developed economies officially categorized as frontier markets. Due to regulatory restrictions, some funds cannot allocate a significant part of their capital to regions that are under-scored by the credit rating agencies or cannot invest altogether. That is why some listed companies in frontier markets might be undervalued due to a lack of demand. This effect is not generally proven by data as the MSCI frontier market index has equaled or underperformed world stock in the last ten years (Morgan Stanley Capital International, 2017). Despite this, previous research has proven that frontier markets are an option for portfolio diversification due to their diminished integration with the rest of the world exhibited by low correlation in daily returns (Berger, Pukthuanthong & Yang, 2011). The authors of the previously cited research also show that this kind of diversification cannot be replicated by choosing proxy stocks from non-frontier markets.

It is for these reasons that this research tries to enrich the scarce literature on frontier markets and their links to the emerging sector. Three main question regards the actual barrier that delimits these two groups and its characteristics: is the segregation done by the leading financial institutions a definitive one? Do some markets transit this barrier when looking at their correlation with the rest of the world? Are the investors' risk assessments taking into account the market type delimitation?

In this research, we have tried to find an answer to the above inquiries by studying the volatility spill-overs between markets with an emphasis on data that has been extensively filtered for biasing effects, well known in the literature. The stylize facts concern momentum and mean reversion tendencies in the trend and volatility of daily asset returns like univariate auto-regressive effects (AR), univariate moving average effects (MA), volatility clustering and volatility mean reversion (GARCH), multivariate autoregressive effects (VAR). After eliminating all understandable variation sources, what we are left with could represent a refined form of market noise that usually incorporates unexpected news, macroeconomic reports, panic and general herding behavior.

The volatility spillover effects are identified following the Diebold-Yilmaz methodology of decomposing the variance-covariance matrix the VAR forecast errors. This novel approach allows us to trace the transfers of volatility between asset returns, either orthogonal or bi-directional, asses their intensity and draw a conclusion on which assets or indices are more prone to systemic risk or which contribute more to it. The paper continues with a description of the data selected for the investigation, followed by a three-part methodology section and ending with the research results and conclusion.

Data

When talking about emerging or frontier markets, a stable definition has to be employed for identification purposes. Some supranational institution like the World Bank or the IMF categorizes national economies based on their GNI per capita, export diversification, and integration into the international financial system[1]. These criteria generally apply to entire national economies but when speaking about capital markets the criteria is established by large private institutions the most prominent in this field being MSCI (Morgan Stanley Capital International). These institutions are acting as rating agencies for the capital markets. Their compilation of market indices represents the leading indicator for investors worldwide, the MSCI emerging market index being the first of its kind in 1988. The classification criteria take into account the following three characteristics of a market: “economic development, size, and liquidity as well as market accessibility”[2]. Economic development criteria for emerging and frontier markets are not mandatory. Below we present these criteria in the synthetic format found in the MSCI methodology.

Table 1. MSCI market classification criteria (www.msci.com)

Criteria			Frontier	Emerging
B. Size and Liquidity Requirements				
	B.1	Number of companies meeting the following Standard Index criteria	2	3
		Company size (full market cap)	USD 630 mm	USD 1260 mm
		Security size (float market cap)	USD 49 mm	USD 630 mm
		Security liquidity	2.5% ATVR	15% ATVR
C.	Market Accessibility Criteria			
	C.1	Openness to foreign ownership	At least some	Significant

[1] https://www.imf.org/external/pubs/ft/weo/faq.htm#q4b
[2] MSCI Market Classification Framework www.msci.com

	C.2	Ease of capital inflows/ outflows	At least partial	Significant
	C.3	Efficiency of the operational framework	Modest	Good and tested
	C.4	Stability of the institutional framework	Modest	Modest

According to these criteria, we've selected daily Bloomberg prices for the main stock market indices of each country, 22 emerging and 13 frontier. Logarithmic returns were computed for each trading day from May 2008 to May 2017, a total of 2295 observations. The chosen markets are:

Table 2. Data set segmentation according to the MSCI market classification

Emerging Markets			**Frontier Markets**		
Americas	Europe, Middle East, and Africa	Asia	Americas	Europe, Middle East, and Africa	Asia
Brazil	Czech Republic	China	Argentina	Serbia	Pakistan
Chile	Greece	India		Croatia	Vietnam
Colombia	Budapest	Indonesia		Estonia	
Mexico	Russia	South Korea		Lithuania	
Peru	Poland	Malaysia		Romania	
	Qatar	Philippines		Bulgaria	
	South Africa	Taiwan		Slovenia	
	Egypt	Thailand		Morocco	
	Turkey			Nigeria	
				Oman	
				Kuwait	

These countries were arranged into groups for spill-over analysis as such: emerging + frontier, emerging, frontier, South-American Countries, Central and East European countries.

Methodology

Whether the investment strategy has an integrated or dedicated place for frontier and emerging markets, trying to diversify in these untapped areas can lead to diffusion in portfolio correlation and premiums from holding under-owned stocks. An ample understanding of the inherent topology of market links is essential for a well-informed investment strategy creation. To this scope we have made use of three different methodologies aimed:

- ARMA-GARCH filtering of daily stock index returns for the elimination of all trend, cyclical and volatility clustering effects that would produce biased correlation coefficients.

- A multivariate VAR has been fitted to each indices group in order to identify the dependencies of each index return on all of the other returns. This is an un-orthodox route taken as the number of parameters to be estimated for the VAR exponentially increases in the number of variables considered. It is known that in practice, VARs with more than 6 variables yields biased estimators. To overcome this problem an intelligent algorithm of variable selection has been employed for the VAR reducing the number of parameters to estimate almost five-fold.
- Diebold-Yilmaz index used to capture the volatility spillover effects between markets. This relatively new approach has the advantage of decomposing the system variance into distinct bi-directional or orthogonal links that give the viewer insight into the flows of volatility that propagate from market to market revealing which ones are net givers or receivers.

ARMA-GARCH filtering

Stylized facts in the econometrical realm have for a long time shown that daily returns follow patterns that can be easily identified an extracted from the random path that the stock price follows. The best documented ones are:
- Momentum: the tendency of the return to follow an upward or downward path depending on the preceding returns, one or multiple lags behind. This dependency can be summarized as an auto-regressive effect (AR).
- Mean-reversion: the cyclicality of prices, or the tendency of the price to revert to a historical average, or to symmetrically fluctuate around a positive or negative trend. This pattern has been formalized as moving average behavior (MA).
- Volatility clustering: if markets are efficient, then all future and available information should be embedded in today's price so tomorrow's return is completely random, independent of that from today. Nonetheless, researchers have for a long time observed that the amplitude of returns does depend on past return absolute sizes. Markets are not defined by stable evolution, as periods of calm are followed by large sustained swings and vice versa. These are called ARCH effects (Bollerslev, Engle, & Wooldridge, 1988) and can be filtered out, leading to a homoscedastic (constant variance) return.

All of these three stylized facts can be embedded into a single equation as the following:

$$R_t = \mu + \sum_{i=1}^{l} \Phi_i R_{t-i} + \sum_{i=1}^{l} \theta_i \varepsilon_{t-i} + \sqrt{h_t} z_t \quad (1)$$
$$z_t \sim NID(0,1) \quad (2)$$
$$h_t = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=i}^{p} \beta_i h_{t-i} \quad (3)$$

Extracting the ARMA effects and standardizing the residuals for the GARCH effects through division by the square of the estimate volatility h_t produces the presumably normally distributed residual error term z_t.

To see if this procedure was helpful one year rolling window correlations were computed for the entire data set. The mean of the resulting correlation matrices was computed and plotted in the chart below. As it stands out, correlations for the standardized residuals drop each period, signaling that the previously perceived connections were not entirely deterministic, part of them being explained either by cyclicality or volatility.

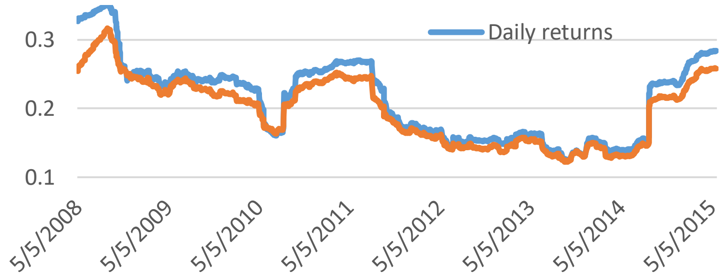

***Figure 1**. Evolution of daily vs ARMA-GARCH filtered returns for a one year rolling window*

The standardizing character of the filtration can also be observed through a visual inspection of the returns together with their histogram plotted against the normal distribution. The returns are obviously transformed:

a. The return path is no longer clustering at different moments in time exhibiting homosckedacity, meaning constant variation along a stable channel.

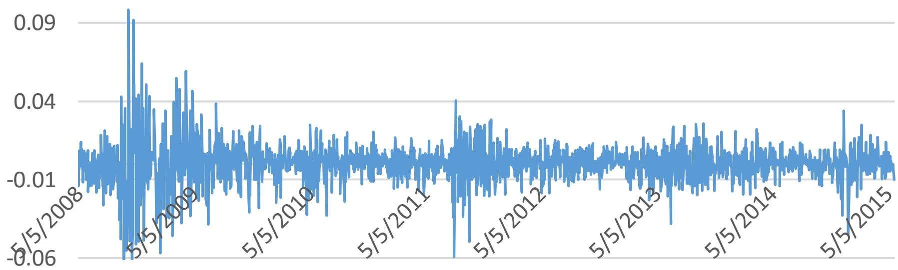

***Figure 2**. Heteroskedastic shape of un-filtered returns*

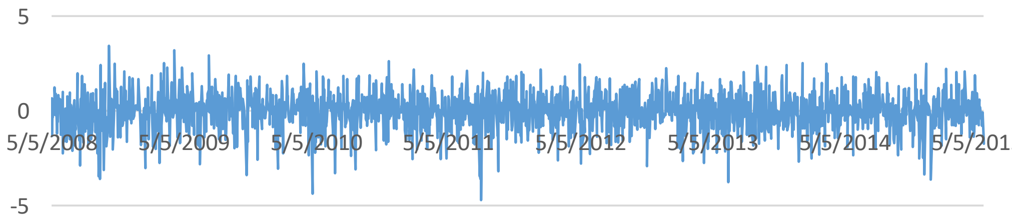

***Figure 3**. Constant variance shape of ARMA-GARCH filtered returns*

b. The histogram of the returns is less peaked (less kurtosis), the tails of the distribution are smaller, generally, the empirical distribution approaching the normal distribution.

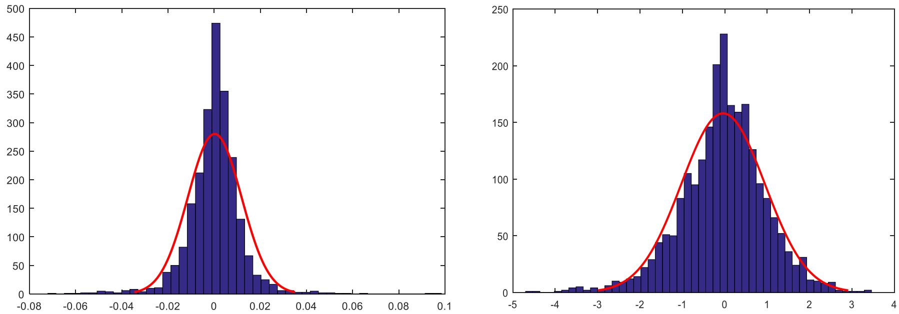

Figure 4. Transition toward a more normally distributed histogram of filtered returns

VAR fitting and filtering

So far we have treated each time series individually. But the evolution of markets cannot be explained solely by univariate dependencies. Macroeconomics, news and other markets belong to an intertwined network of influences that act simultaneously. The VAR framework has been extensively used in macroeconomics (Sims, 1980) with ramifications to neuroscience and genetics. Here we chose the vector auto-regression framework to identify and extract cross-market dependencies, presuming that those dependencies are linear in nature. Even if some econometric methods can be infinitely generalized, in practice the VAR estimations become spurious for systems larger than 6 variables, when the explanatory power is distributed between all variables equally with no economic sense (Lütkepohl, 2005). Worse, if the number of observations is smaller than the number of variables times the lags considered the system becomes undetermined and cannot be solved.

For this reason, we have applied an intelligent variable search method based on the "partial Granger causality" employed by (Guo, 2008) to process large data sets of time series without the VAR breakdown. The search concept is simple: starting from the belief that Granger causality can mathematically be proven only when the entire set of deterministic factors is brought into the analysis, an iterative search through all combinations of possible factors is performed until all possibilities have been theoretically exhausted. This might seem adaunting task given the number of all possible combinations, but the search does not pass through all of them. Instead, it builds a hierarchical tree of "ancestors", meaning those time series that Granger causes the one under study and then trims down this tree by testing the resilience of each initial ancestors on increasing combinations of all others. The procedure consists of much more detailed and structured steps but this not in the scope of the current paper.

What is of interest is the performance of the method employed in producing simplified and efficient VAR's for the scope of filtering out the linear multivariate autoregressive effects. In this sense the method of Granger causality search was tested in montecarlo simulations against other three VAR procedures:
- Unrestricted full VAR estimation

- VAR variable selection through iterative elimination of null coefficients and re-estimation until no improvements are visible
- Lasso VAR estimation – equation by equation estimation of the VAR through lasso regression

To better understand the disadvantage of large VARs, we've plotted the number of parameters to be estimated for all of the four methods, depending on the number of variables that make up the system.

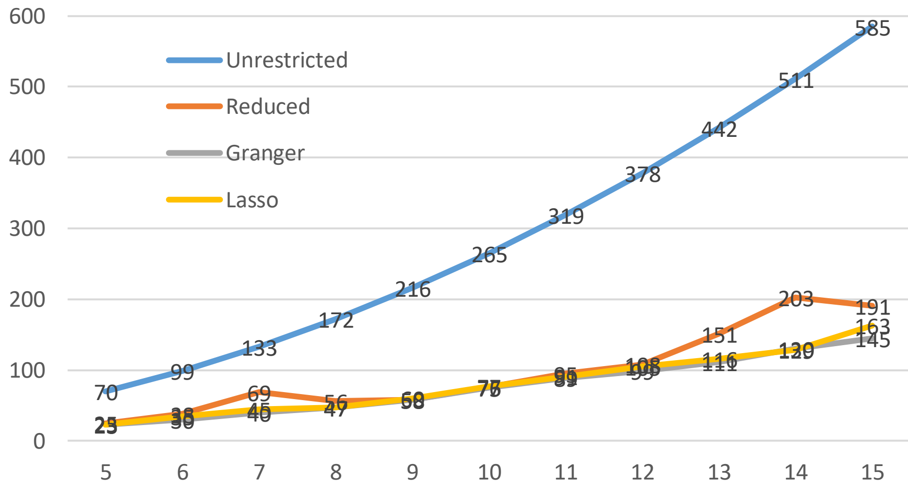

***Figure 5**. Increase in number of VAR parameters dependent on the method of choice*

As we can see from the chart above, for 15 variable systems the unrestricted VAR estimates a total of 585 parameters a number exponentially increasing. On the other hand, alternative three methods have significantly lower estimation charges and present a linearly increasing trend. The results of the montecarlo simulations have looked at multiple performance criteria like Akaike and Bayesian information criterions, mean forecast errors, the number of parameters to estimate and model likelihood.

***Table 3**. Performance indicators VAR variable selection methods in montecarlo simulations*

	Akaike information criterion	Bayesian information criterion	Forecast error	Model parameter number	Model likelihood
Unrestricted	100.3%	103.4%	100.1%	216.8%	99.1%
Reduced	99.7%	98.9%	100.0%	71.9%	100.0%
Granger	99.8%	98.7%	100.0%	59.5%	100.2%
Lasso	100.2%	98.9%	99.9%	51.8%	100.7%

The simulations demonstrate that the Granger variable selection methodology performs similarly to all other algorithms for likelihood and forecast power but the number of parameters estimated is half as large. Of the four, Granger and Lasso produce more parsimonious models but the Granger causality search departs from a robust deterministic principle which makes it out the method of choice. After the VAR estimation, we filter out the multivariate effects and pass the residuals on for variance decomposition through the Diebold-Yilmaz methodology.

The Diebold-Yilmaz framework

Diebold and Yilmaz (2012) have recently proposed a novel way to analyze large system interdependencies using VARs. Instead of focusing on the estimated AR parameter matrices, they look into the variance matrix of the forecast errors, post estimation. By decomposing this matrix into unidirectional (orthogonal) or bidirectional (generalized) volatility spillover one can foresee the effect of a shock applied to one variable on all the other variables.

We continue with a short description of the mathematical equations that underlie the Diebold-Yilmaz methodology. The vector autoregression is described in structural form by

$$x_t = \sum_{i=1}^{p} \phi_i x_{t-i} + \epsilon_t \tag{4}$$

Where Φ is the coefficient matrix and ε_t a vector of identical and independently distributed errors.

Expanding the previous equation to infinity we get:

$$x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i} \tag{5}$$

Where

$$A_i = \Phi_i A_{i-1} + \phi_2 A_{i-2} \ldots \tag{6}$$

The Cholesky decomposition is applied to the errors variance matrix under the form $\Sigma = PP$ and transforming the VAR into

$$x_t = \sum_{i=0}^{\infty} (A_i P)(P^{-1} \varepsilon_{t-i}) = \sum_{i=0}^{\infty} (A_i P)(\overline{\varepsilon_{t-\iota}}) = \sum_{i=0}^{\infty} \overline{A_\iota} \overline{\varepsilon_{t-\iota}} \tag{7}$$

This way the error become orthogonal and the effects of shocks to the system propagate to each variable as

$$\theta_{ij}(H) = \frac{\sum_{h=0}^{H-1} \left(e_i' A_h P e_j\right)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \tag{8}$$

Where e_i is a zero column vector except for the element i, which is equal to 1.After obtaining the orthogonal shocks we can aggregate to get the entire system volatility transfer to a single variable as

$$S(H) = \frac{\sum_{i,j=1, i \neq j}^{N} \theta_{ij}(H)}{N} * 100 \tag{9}$$

Final filtering results

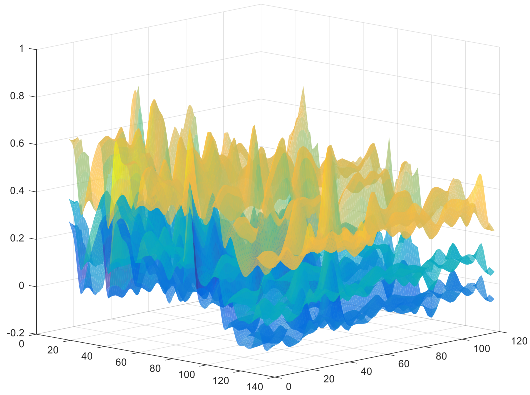

Figure 6. Correlation triangular matrix for different levels of filtration
(Upper chart – normal returns (unfiltered). Middle chart- standardized returns, filtered for AR (auto regressive effects), MA (mean reversion effects), and GARCH (volatility clustering effects. Lower Chart – standardized returns filtered for VAR –vector autoregression effects (other variables effects))

By eliminating all of the stylized facts, the resulting residuals isolate the contagion effects or the pure spillover effects. The mean absolute correlation was computed for the entire dataset, at each level of filtration

- Normal returns mean correlation (0.25)
- Standardized returns mean correlation (0.19)
- VAR filetered standardized returns mean correlation (0.17)

The filtering takes out 30% of the correlation bias, from 0.25 to 0.17.

Research results and spill-over effects representation

Emerging and Frontier markets

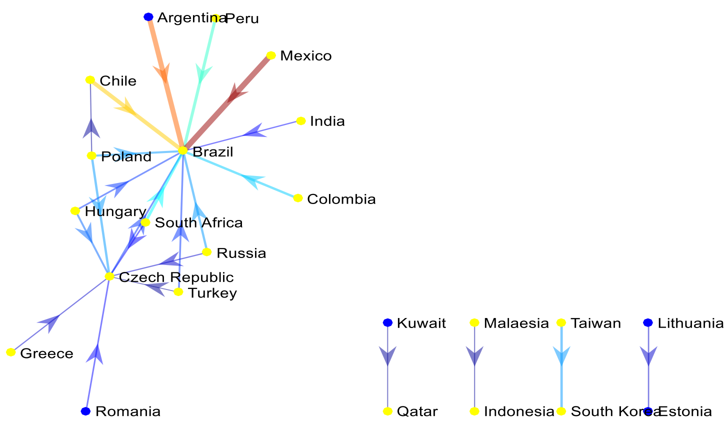

Figure 7. Emerging and frontier markets orthogonal spill-overs

Analyzing the orthogonal forecast errors variance decomposition for the entire dataset one can observe that the most important volatility spillovers happen between emerging markets with the Czech Republic and Brazil forming centers of attraction for their specific region. Only two frontier markets are present in the large exchange groups, these are Romania and Argentina. Even if the MSCI criteria places these two markets in the frontier category, investors perceive them as equally risky as emerging markets and moreover as generators of volatility. It should also be noted that Romania and Argentina have good chances to be upgraded from frontier to emerging market status (Pinzaru, Anghel & Mihalcea, 2015). This might also influence the investor's decisions regarding the emerging market universe.

Taking into account the color code of the volatility arrows which signal important transfers of risk for red and lower intensity flows for blue, it seems that the South American region is characterized by strong dependencies amongst all of its markets. Brazil as a regional net receiver of volatility demonstrates a high sensitivity to events on other markets, approaching itself mostly to Mexico, Argentina, and Chile, in this order. On the other side of the Atlantic, the Czech Republic seems to attract volatility transfer from its regional counterparts like Poland, Hungary, Romania, Greece, and Russia.

The establishment of the Czech Republic as a regional volatility hub seems quite peculiar given its limited size, importance in the region and also its low weight in the MSCI indices. Most probably the Czech markets stand as a proxy for other European developed markets like the German or Austrian ones. This hypothesis is highly likely given the high correlation of the Czech market with its closest neighbors and probably an analysis that would encompass those markets would bring another volatility hub in the center of the network. Beside the regional connections which are to be expected, there are some international players that spread their influence trans-continentally like Poland, Turkey, Russia, South Africa, and Hungary. This comes to show that investors have designated these dynamic, large and globally integrated economies as benchmarks for the emerging stock universe with lasting impact in all directions.

Zooming out from the network area of the chart, volatility spill-overs also manifest themselves as binomial relationships, with an exclusive regional character, the most preeminent pairs being: Kuwait-Qatar, Malesia-Indonesia, Taiwan-South Korea, Lithuania-Estonia.

Table 4. Emerging and frontier markets aggregated spill-overs

No	Labels	From	To	Net
1	Brazil	0.01	2.66	-2.65
2	Czech Republic	0.21	1.08	-0.87
3	Chile	0.28	0.76	-0.48
4	Egypt	0.04	0.21	-0.18
5	Qatar	0.09	0.24	-0.15
6	Romania	0.31	0.05	0.26
7	South Africa	0.44	0.12	0.33

8	Poland	0.48	0.15	0.33
9	Russia	0.38	0.04	0.34
10	Argentina	0.40	0.02	0.38
11	Taiwan	0.42	0.03	0.39

The spill-over aggregation table of orthogonal variance decompositions comes into agreement with the chart. Brazil and the Czech Republic are the principal net receivers whereas Argentina and Taiwan are net givers, although not of the same magnitude as the receivers.

Emerging Markets

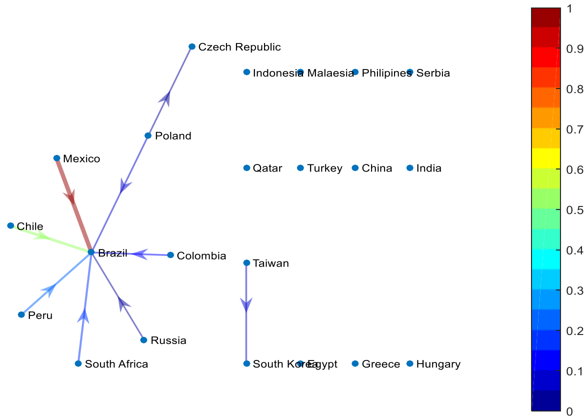

Figure 8. Emerging markets orthogonal spill-overs

Applying the entire procedure but only to the emerging markets sector, the map topology remains constant, with Brazil in its center. This is to be expected as Brazil houses the largest stock market in the region (Korez-Vide, 2014). An interesting observation could arise around the Chinese market which is missing from both charts. The Integration of Chinese stocks in the MSCI index with a high weight attributed to it (almost 28%), does not seem to come into agreement with the investors view on risk. Despite its size, China follows a decoupled path from the rest of the emerging market. Continuing to analyze this reduced dataset, one can understand the drawback of changing the sample analyzed, as Turkey and India no longer produce significant volatility spillovers in the emerging market sector.

Table 5. Emerging markets aggregated spill-overs

No	Labels	From	To	Net
1	Brazil	0.00	2.19	-2.19
2	Czech Republic	0.20	0.83	-0.63
3	Chile	0.28	0.64	-0.36
4	China	0.08	0.19	-0.10
5	Egypt	0.03	0.10	-0.07
6	Thailand	0.30	0.01	0.29
7	South Africa	0.44	0.10	0.34

8	Poland	0.47	0.13	0.35
9	Russia	0.38	0.03	0.35
10	Taiwan	0.42	0.02	0.40

The aggregated spill-over table again places Brazil and the Czech Republic on top of the net spill-over receivers with Taiwan, Russia, and Poland as net givers.

Frontier Markets

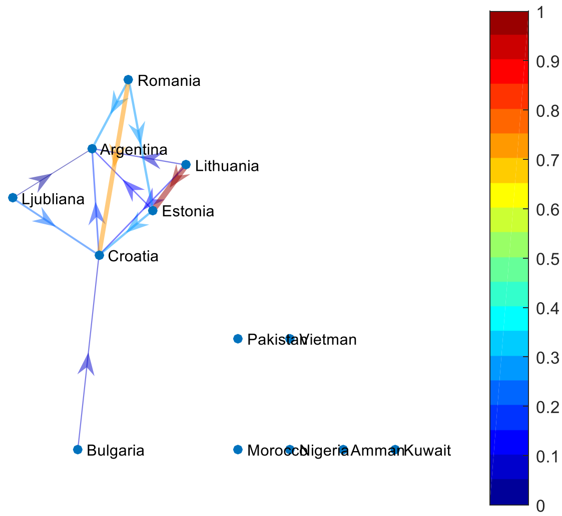

Figure 9. Frontier markets orthogonal spill-overs

In the frontier markets universe, the only relational structure that emerges is one form of the Central and Eastern Europe states which also attract Argentina, a country with an important weight in the MSCI index. There is no Asian counterpart to the European block, demonstrating that with frontier markets integration can be so low that spill-over do not happen regionally. One conclusion from this could be that frontier markets could be much more connected to the global economy then to their own region, with regional trade and capital flow systems still to emerge in the future. As a transition structure between the highly centralized emerging market one and the non-existent Asian frontier regional system, the CEE plus Argentina frontier network lacks a leader.

Table 6. Frontier markets aggregated spill-overs

No	Labels	From	To	Net
1	Croatia	0.04	0.28	-0.24
2	Argentina	0.01	0.17	-0.17
3	Estonia	0.08	0.22	-0.14
4	Amman	0.03	0.03	-0.01
5	Morocco	0.02	0.02	0.00
6	Vietnam	0.06	0.01	0.05

7	Kuwait	0.07	0.01	0.06
8	Slovenia	0.11	0.03	0.07
9	Romania	0.20	0.07	0.14
10	Lithuania	0.18	0.03	0.15

The variance decomposition aggregator table also emphases the uniformity and miss-direction of volatility spillovers in the frontier group. The net givers are at par with the net receivers and spill-overs in nominal flows are small meaning that financial distress propagates through other channels but not inside the frontier market sector.

South America: Emerging+Frontier

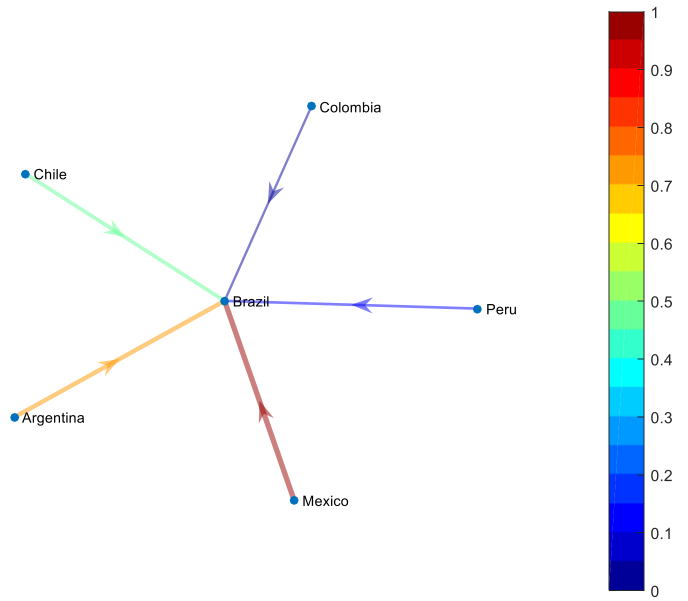

Figure 10. South American markets orthogonal spill-overs

Isolating the South American continent and embedding all markets irrelevant of their emerging or frontier status, Brazil maintains its role as leader. By leader here we refer to the capacity of reacting to regional financial distress, and in this specific dataset, being sensitive to unexplained fluctuations elsewhere. For Brazil, it is Mexico, Argentina, and Chile who bring the most variance dependency, with Colombia and Peru playing a minor role.

***Table 7**. South American aggregated spill-overs*

No	Labels	From	To	Net
1	Brazil	0.00	1.29	-1.28
2	Chile	0.26	0.16	0.10
3	Colombia	0.21	0.05	0.16
4	Mexico	0.45	0.03	0.41
5	Peru	0.24	0.01	0.23
6	Argentina	0.38	0.00	0.38

CEE: Emerging and Frontier

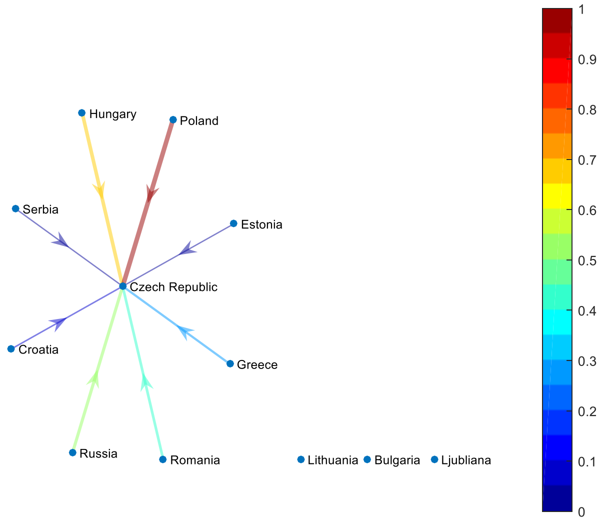

Figure 11. CEE markets orthogonal spill-overs

The last analysis looks into the volatility dynamics of all CEE economies available in the dataset. The peculiarity of the Czech market as a center for volatility spill-over determined us to investigate the scarce literature for a similar observation and check if this market is actual a proxy for another European market, most probably a developed trading partner. Indeed, other specialized researchers have found that the Czech market is deeply integrated with the German and Polish counterparts (Deev & Kajurová, 2012). Departing from Granger causality and fitting a Vector Error Correction model to a dataset formed of the Czech Republic's most important trading partners, the researchers found that most of the deterministic influence in times of crisis comes from Germany and Poland, Poland being a second lag intermediary for Germany. Therefore, the representation of volatility spill-overs in network format has shown its versatility in identifying the existence of outside links without explicit testing for that.

***Table 8**. CEE markets aggregated spill-overs*

No	Labels	From	To	Net
1	Czech Republic	0.01	1.64	-1.63
2	Greece	0.17	0.14	0.03
3	Hungary	0.29	0.18	0.11
4	Poland	0.44	0.12	0.32
5	Russia	0.34	0.03	0.30
6	Estonia	0.15	0.13	0.01
7	Lithuania	0.22	0.01	0.21
8	Romania	0.32	0.02	0.30
9	Bulgaria	0.06	0.01	0.05
10	Slovenia	0.12	0.00	0.12

Conclusion

Today's international investors are seeking new opportunities to improve their long term return and simultaneously reduce idiosyncratic risk through diversification. This study shows that up to the current moment only the diversification goal can successfully be attained. Volatility spill-overs as a measure of market inefficiencies are mostly regional in nature with some markets like Poland, Turkey or Russia demonstrating global impact. This paper proves that the barrier between frontier and emerging markets in terms of risk and investor perceptions hold for most of the indices analyzed with few notable exceptions like Romania and Argentina who would qualify as candidates already integrated into the risk profile of the emerging sector. Through extensive filtering of deterministic effects like momentum, mean reversion and volatility clustering, this study has been able to dive in the unexplained domain of market variation. The volatility-spillover network representation has shown us that on each continent, with the except of Asia, regional leaders form that aggregate all of the net volatility transfers, like Brazil in South America and Germany (proxied by the Czech Republic) in Europe. Our research results suggest that forecast error decomposition is an efficient way of understanding market linkages and as a continuation, larger systems of variables should be analyzed, encompassing not only frontier and emerging markets, but also developed ones.

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