SENIOR RESEARCH

Measuring Systemic Risk in the Global Equity Markets

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Abstract

The disastrous impacts of the 2008 global financial crisis on the real economy underline the urgent need for financial industry and policymakers to develop better measures that effectively capture and signal the presence of systemic risk in the financial system. In the first part of this paper, I apply so-called 'absorption ratio' that is a measure based on principal components technique to assess systemic risk in the global equity markets. Then I assign the absorption ratio in a probit model to form an early warning signal that can identify the macroeconomic determinants of systemic events. The analysis shows that the absorption ratio is able to capture major financial distress in the global economy. The result from the model estimation reveals six macroeconomic determinants of systemic events, it also signifies a complementary relationship between credit-to-GDP gap and Debt Service Ratio. This research therefore affirms the efficiency of the absorption ratio and recommends the use of the measure as an early warning signal of systemic events in the global economy.

1. Introduction

It has been almost a decade since the dawn of the global financial crisis of 2007 – 2009 yet the event remains ever-present at the center of discussion in the financial world. The crisis exhibited that the failure of financial system can have disastrous effects on the real economy and that there are much more to the complexity of our global financial system than most had ever anticipated. One particular concern following the aftermath of the crisis evolves around the issue of financial stability – how we define it and how do we manage it. According to the World Bank, the common definition of financial stability is "the absence of system-wide episodes in which the financial system fails to function" and capability of financial system to be resilient to stress (Financial Stability, n.d.). Even though by definition, financial stability appears to be straightforward, but in truth the definition of financial system itself is comprised of numerous dimensions; we could be focusing on financial and non-financial institutions, or on financial markets which include equity markets, bond markets, commodity markets, etc., or on financial sectors such as companies, governments or households, or on the interconnectedness among these agents. Thus, it is no simple task to identify, let alone measure or control financial stability by using one smooth toolset.

The term "VUCA" has recently been embraced into the financial world, the acronym was originally developed by the US military to describe a multipolar world that comprised of Volatility, Uncertainty, Certainty, and Ambiguity (McNulty, 2015). In financial context, volatility echoes speed and turbulence of change or deviation such as prices fluctuation after a natural disaster. Uncertainty conveys that market behaviors have become less predictable, while complexity considers interconnectedness of the global economies. Lastly, ambiguity indicates that the causal relationships between actions and outcomes are perfectly unclear – in other words, sometimes we face a situation of "unknown unknowns" (Bennett and Lemoine, 2014). Acknowledging the many dimensions of financial stability is perhaps a very first step of understanding financial markets, though apprehending the definition alone are not nearly sufficient, we need to be able to manage or at least have some basic ideas of what is going on in the markets and possess enough information to assess what are the outcomes given the current conditions of the markets. Nonetheless, given the slow and painful recovery the global economy has experienced from the recent global financial crisis, many studies have been attempting to draw a more extensive understanding on financial stability, among these works are the studies of systemic risk.

Similar to financial stability, the term "Systemic Risk" is multidimensional. The Systemic Risk Centre defines systemic risk as "a risk of a breakdown of entire system rather than simply the failure of individual part… (or, in financial context), the risk of a cascading failure in the financial sector resulting in a severe economic downturn." (Systemic Risk, n.d.). While Bisias et al (2012) and Oosterloo and de Haan (2003) suggest that definitions of systemic risk depend on the different aspects of the phenomenon; for examples, imbalances, correlated exposures, spillovers to the real economy, asset bubble, negative externalities, feedback behaviors, contagion and information disruptions.

The most discernible systemic events were the infamous fall of Lehman Brothers and Bear Stern in 2008 as well as the European sovereign debt crisis of 2011-2012. These events demonstrated that because of the presence of systemic risk in the financial system, failure of an individual institution in a specific sector from a specific economy can have detrimental impacts to the rest of the global economy. Hence, policymakers and regulators have since urgently called for a more concrete measurement of systemic risk specifically ones that able to notify the policymakers when to sound the alarm or when to take actions (Blancher et al, 2013). There are currently plentiful amount of systemic measures and conceptual frameworks that have been developed over the past years, however, the fact that there are various possible definitions to systemic risks suggest that there are several assortments of model subject to each different perspective. It is not the purpose of this paper to go into details of these measurement approaches, rather it would like to concentrate on just one aspect of systemic risk, namely the interconnectedness in the global financial system.

Several studies agree that the increase in cross-correlation relationships among the financial system coincides with the high level of systemic risk. This paper interests in the method used by Kritzman et al. (2011), Billio et al. (2012), and Zheng et al. (2012), all of which use Principal Component Analysis (PCA) to capture the connectedness in the financial system. All three papers reach similar conclusion, though came up with different proposed measure, that PCA method can apprehend the interconnectedness of the financial sectors, hence able to capture the high level of systemic risk in the system prior and during the financial crises.

That being said, the main focus of this paper is the application of the absorption ratio, a proposed systemic risk measure from Kritzman et al. (2011) in measuring systemic risk in the global equity markets.

The first part of this paper gives an overview definition and measurement applications of systemic risk used in several financial literatures. Then, it provides a general information of the methodology and data that is being used in this paper. Next it follows the practice of using PCA, notably, the absorption ratio, in identifying the common correlation dynamics in the global equity markets, using data from MSCI sector indexes from 1995 to 2016. After that, it intends to provide some clarification on the source of risks whether it came from a specific economy or sector by observing through two perspectives; sector level and country level. Next, it provides an approximate robustness testing for the choice of data used in the analysis. The next section shows a comparison between average return correlation and average absorption ratio in a sample. Then, it tests the absorption ratio as an early signal by using a probit model to identify the macroeconomic sources of systemic risks. It also briefly addresses the significance of the relationship between credit-to-GDP gap and Debt Service Ratio in the model estimation. Finally, it ends with a conclusion.

Above all, this paper hopes to support the use of the absorption ratio as an early signal model in predicting systemic events in the global equity markets, it also wishes to call for a more comprehensive and larger variety of studies on systemic risk since this topic is still new in a sense that it has just recently attracted close attention from researchers and regulators so there are likely to be a lot of areas we need to examine more closely and thoroughly in order for us to have a better and a more effective risk management frameworks in both individual and policymaker levels.

2. Literature Review

There are several approaches to systemic risk. Smaga (2014) offers a generous overview of the concept of systemic risk, it reviews a multitude of systemic risk definitions that are commonly used in the financial literature. It can be drawn from the paper that the interpretation of systemic risk is usually applies to the significant part of the financial system and impairs the functioning of the system. While Caruana (2010) suggests systemic risk often depicted in two dimensions, cross-sectional and time, and each dimension has a very different policy implication. For the cross-sectional dimension, it relates to how a specific shock can develop and become systemic in the financial system, thus it studies the allocation of systemic risk in a given time period, this usually concerns common exposures and interlinkages within the system. Whereas the time dimension, or the procyclicality aspect, tracks the aggregate building-up of systemic risk overtime.

On the other hand, Hansen (2012) explores a few specific approaches in assessing systemic risk along with its data and modeling challenges, he concludes that although there is not yet a consensus regarding the single measurement of systemic risk and there aren't likely to be one in the near term, we should attempt to measure it anyway using the currently available measures but proceed with caution especially on the impact of model misspecification.

Among the most valuable works in systemic risk, Bisias et al. (2012) perform an incredibly tedious task of collecting popular measurements and conceptual frameworks of systemic risk in economic and finance literature. It reports 31 quantitative measures of systemic risk collected from a variety of perspectives on systemic risk over the past several years. The paper provides different classifications of measures depending on the scope of the user's interest including a concise explanation along with the comparison between each measure. Similarly, Blancher et al. (2013) provide an overview of the current toolbox for systemic risk monitoring. It presents a guideline of how to choose the best set of measures under different circumstances based on the proposed six key questions the policymakers should be asking in the assessment process; these questions concern financial institutions, asset prices, sovereign risk, broader economy, cross-border linkages and crisis risks. Both papers emphasize that we are likely to need more than one measure, in complementary to one another, to deal with systemic risk since it is multifaceted problem in an ever-changing environment.

Alternatively, other notable works concentrate on more specific areas, for instance, some of the most influential works on the firm-level systemic risk propose measures such as Marginal Expected Shortfall (MES) and Systemic Expected Shortfall (SES) by Acharya et al. (2010), Conditional Value at Risk (CoVaR) by Adrian and Brunnermeier (in press), and SRISK by Brownlees and Engle (2016). The common theme in these three papers emphasizes on measuring each bank's contribution to systemic risk, they believe that financial firms lack incentives in limiting their inputs of systemic risks to the system such as excessively risk-taking behaviors or fire-sales which created negative externality in the financial system. Meanwhile, Contagion Index (Cont et al. 2013), and Financial Stress Index or FSI (Lo Duca and Peltonen, 2013) are among the works that examine the network structures of the financial system. These two papers share a goal of providing a framework for assessing systemic risks, though the latter goes one step further in designing a model to predict in and out-of-sample systemic events.

Similarly, Billio et al. (2012) study the interconnectedness of the financial system, they use Principal Component Analysis (PCA) as well as Granger causality tests to measure the correlations of the four financial sectors; banks, brokers/dealers, insurance companies and hedge funds, and the results are that these four sectors have indeed become highly-interrelated over the past decade which presumably increasing the level of systemic risk in the system. Zheng et al. (2012) also use PCA in their study and proposed that the change in cross-correlations, as in the steepest increase in the first component PC1, can effectively act as an indicator of systemic risk. While Kritzman et al. (2011) who also construct a measure based on PCA approach propose the absorption ratio as an early indicator of systemic risk, the authors test the measure with the US housing bubble, financial turbulence and global financial crises and found that the absorption ratio is able to predict the occurrence of systemic events. The common theme of these three papers is using PCA application to the data to find the best linear combinations that can capture the most variation of the data which presumably is when systemic risk level is higher as there is an increase in correlations in the markets. Each of the three papers demonstrated that their indicators performed admirably in predicting the market downturns. As a result, this paper is inspired to follow the pattern with an objective of measuring market concentration in the global equity markets.

In addition, this paper is also interested in identifying the macroeconomic sources of systemic risks. As mentioned earlier, Lo Duca and Peltonen (2013) has taken a step further from creating a systemic risk measure to designing a model for predicting systemic events. They combined domestic and global indicators of macro-financial vulnerabilities in the discrete choice models and found that their framework exhibits a good out-of-sample performance in predicting the global financial crisis in 2008. Similarly, Comelli (2014) compares logit and probit early warning systems in predicting in and out-of-sample currency crises in emerging markets, the paper found that the prediction of crises are very sensitive to the definition of the crisis and the size of the estimation sample.

3. Methodology

The Absorption Ratio

The absorption ratio was originally introduced in “Principal Components as a Measure of Systemic Risk” by Mark Kritzman, Yuanzhen Li, Sebastian Page and Roberto Rigobon in MIT Sloan School of Management working paper 2010. It was aimed to be an “implied measure of systemic risk.” The measure was derived from the application of Principal Component Analysis method (PCA) which is basically a procedure to reduce dimensions of the dataset in order to make them simpler and easier to interpret and able to clearly see the relationships between variables. The PCA is done through an eigen decomposition on a square matrix and the outcomes are the eigenvectors or the loadings and their corresponding eigenvalues, which are essentially the variance of that factor. According to Kritzman et al. (2010), absorption ratio is “the fraction of the total variance of a set of asset returns explained by a fixed number of eigenvectors.” The objective of the absorption ratio is to observe which markets have become tightly connected, ideally if the markets are more tightly coupled then the system is fragile to negative shocks in a sense that shock can spread very quickly in the system. Correspondingly, the higher the absorption ratio, the higher the level of systemic risk. The construction of the absorption ratio is as shown below;

$$AR = \frac{\sum_{i=1}^{n} \sigma_{Ei}^2}{\sum_{j=1}^{N} \sigma_{Aj}^2}$$

N = number of assets
n = number of eigenvectors
σ_{Ei}^2 = variance of the ith eigenvector
σ_{Aj}^2= variance of the jth asset

First, we need to assemble the covariance matrix of asset returns from our dataset, then we apply PCA to the matrix to find the variance of eigenvectors, or eigenvalues so that we can use them as the numerator in our building up of the absorption ratio. In the original paper, the authors used daily MSCI data and a choice of 500-day rolling window, the variance of the assets and the eigenvectors are calculated with exponential weighting average in which the decay rate were set to be half of the window. The authors also set the number of the eigenvectors to be approximately 1/5th of the number of assets in the sample because in principle, if the markets are close connected, only a few eigenvectors will be sufficient in explaining the variation of the data.

Furthermore, the original paper tested the proposed measure with the US stock markets and discovered the inverse relationship between the absorption ratio and the level of stock prices. They also observed that the spike of the absorption ratio coincides with the steepest decline in stock prices in 2008. Further empirical analysis also revealed that the performance of absorption ratio is consistent with the events of US housing bubbles and global financial crises. It is also worth mentioning that the authors supplemented that "a spike of the absorption ratio is a near necessary condition for stock market drawdowns, [but it's] just not a sufficient condition." A sharp increase in the absorption ratio does not always lead to a major stock market drawdown, however, on average, the stock markets perform much worse when there is an increase in the ratio than when there is a decrease in the ratio.

4. Data

Aside from measuring systemic risk in the equity markets, this paper desires to identify the sources of systemic risk in the global equity markets. This is difficult to achieve since there exist several perspectives of systemic risk, however, I decide to settle on the two broad perspectives; sector and country. Here, I expect to observe the similarities and differences between the two perspectives and pinpoint the one that present a better reflection of systemic risk at the global level. For both perspectives, I collected the data from MSCI MXRT Real Time Indices from January 1995 to December 2016.

Through the global sectors perspective, we will see the absorption ratio for each sector and how they each perform in the global market. According to MSCI, the global equity markets are comprised of ten sectors[1] – Energy, Materials, Consumer Discretionary, Consumer Staples, Healthcare, Financials, Information Technology, Telecom and Utilities. On the other hand, through the lens of each country's equity market, I chose a sample of 12 countries consists of United States, United Kingdom, France, Germany, Italy, Spain, Japan, Brazil, China, India, the republic of Korea and Thailand. The choices of the countries in the sample were designed due to the availability of the data. For this perspective, I also conducted an extra figure of the absorption ratio in terms of market development classification to see a broader information in complementary to the country's level. Here, I use the data from MSCI Sector/Industry Indices, of which I compare the World Index (23 developed countries), EMF Index (23 emerging countries), EMU (10 developed member countries in European monetary union) and ACWIF Index (all countries – 46 countries) from January 1995 to December 2016.

For every dataset used in this paper, the absorption ratio is constructed using weekly data with a 100-week rolling window. The number of the eigenvectors is also fixed at 1/5th of the total number of the assets.

[1] The Global Industry Classification Standard (GICS) introduced the Real Estate as the new sector effective September 1st, 2016.

5. Results

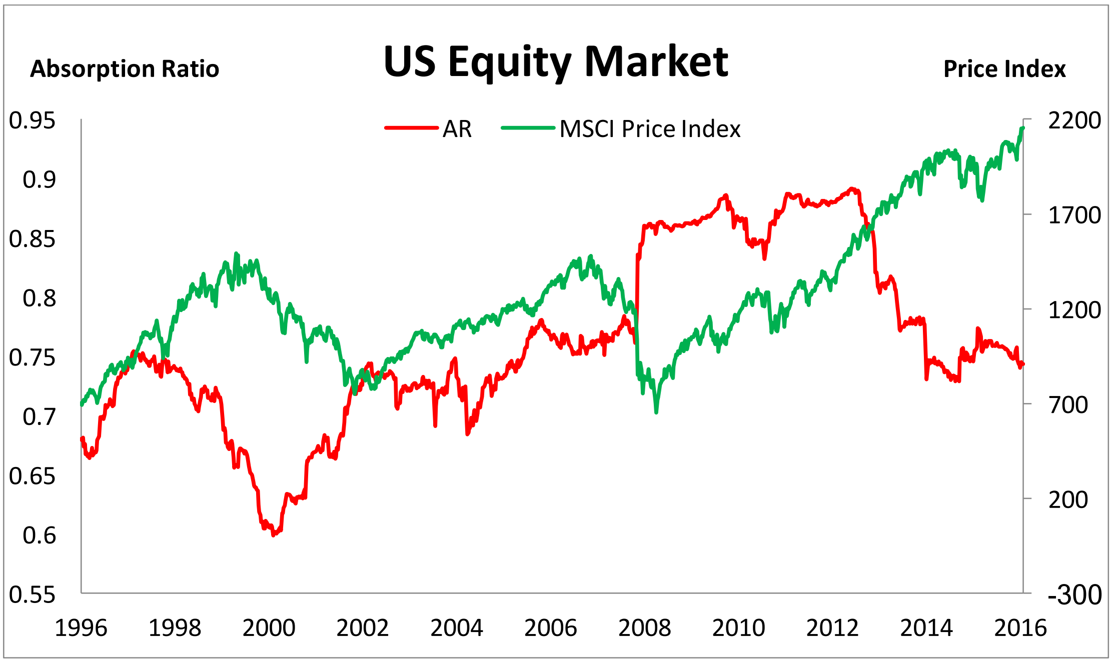

Figure 1 Absorption ratio and the price index of the US Stock market 1995-2016.

Figure 1 shows the inverse relationship between the absorption ratio and the US Stock price index from January 1996 to December 2016.

The purpose of this chart is to visualize the function of the absorption ratio in the stock market. The chart above is consistent with the report from Kritzman et al. (2010), it is clear from the graph that when the stock prices fell sharply during early 2008, the absorption ratio also increased sharply and even when the prices have recovered, the measure remained at the high level which indicates that the market were still fragile to negative shocks and this period also coincided with the European sovereign debt crisis in 2011-2012.

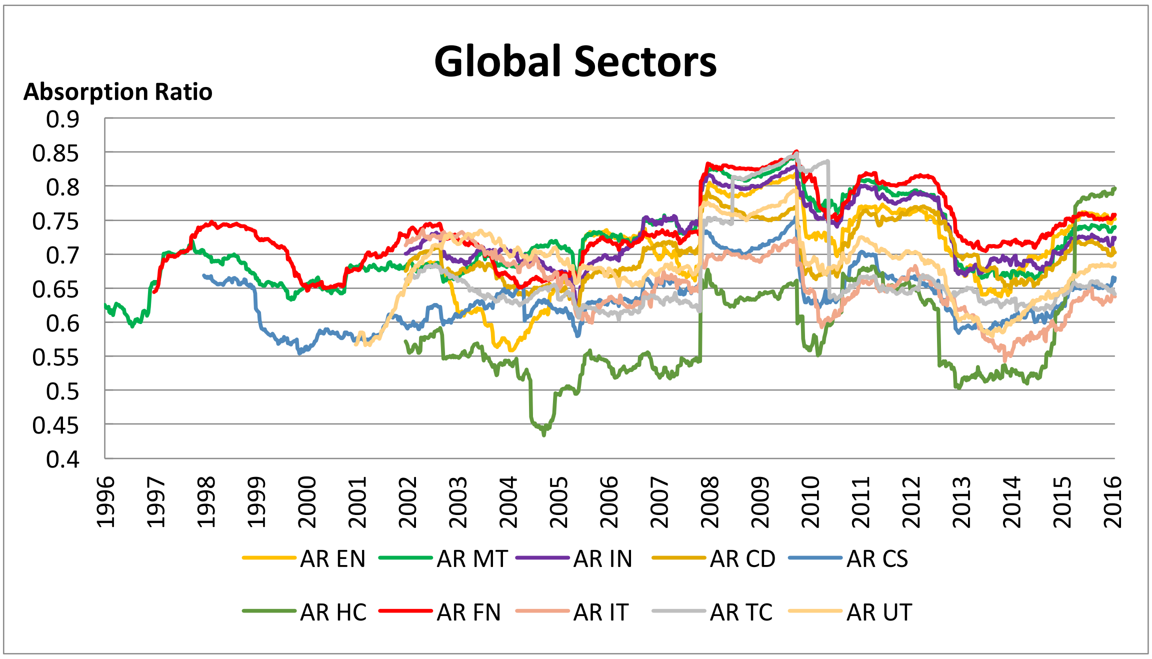

Figure 2 Absorption ratio of the global sectors from 1995-2016

Figure 2 shows the absorption ratio of the ten global sectors from January 1995 to December 2016. It is important to note that due to data availability, some sectors have shorter spans in terms of the beginning of the data than the others. The ten sectors above are classified according to Global Industry Classification Standard (GICS), the sectors are; energy, materials, industrials, consumer discretionary, consumer staples, healthcare, financials, information technology, telecom and utilities.

As can be seen from the graph, the financial sector, red line, generally possesses the highest level of absorption ratio relative to other sectors which is not at all surprising considering that almost all crises are more often than not traced back to the financial sector. The average of the absorption ratio in the financial sector is 0.74 which is decidedly high when compares to the whole sample average of 0.68. Materials and industrial sector are also the two sectors that have considerably higher absorption ratio level than the others, at 0.72 and 0.73 respectively, while consumer staples and health care sector have a fairly low ratio level at 0.63 and 0.58, respectively.

Surprisingly, the level of absorption ratio in the health care sector has climbed up from the relatively low level to a very high level – even higher than the financial sector, during 2014-2015 and still remains high at the latest data available. According to Bennett (2016), the health care sector often led the stock market for the past five years due to the introduction of new treatments by the innovative drug makers to generate tremendous sales – hence great returns, as well as the huge premiums big companies paid to have smaller rivals with intriguing pipelines. The demand from the growing and aging population is also factored in the growth of the health care sector, however, as demand rises, the pressure to reduce costs becomes intensified – heating the competition in the market (Deloitte, 2015). In addition, the US presidential election in 2016 had also generated fears and uncertainty regarding the government intervention into drug pricings which clearly affected the expected performance of the sector (Bennett, 2016). In fact, the health care sector has tumbled from being the safe haven of private equity investors to the worst-performing industry as ranked by Standard & Poor's 500 index in 2016 (ibid). Correspondingly to the fast pacing and uncertainty surrounding the health care sector, the absorption ratio of the sector from the graph shows that the sector has become decidedly fragile to negative shocks in recent years.

In brief, observing the global systemic risk through the lens of the ten global sectors gives us a general idea of what is going on in the economy – which sector is the most vulnerable at a given time period. We might able to gleam from looking at this graph which sector to start and to avoid investments. Policymakers may also use this information to review the appropriate policies and regulations for their own economies.

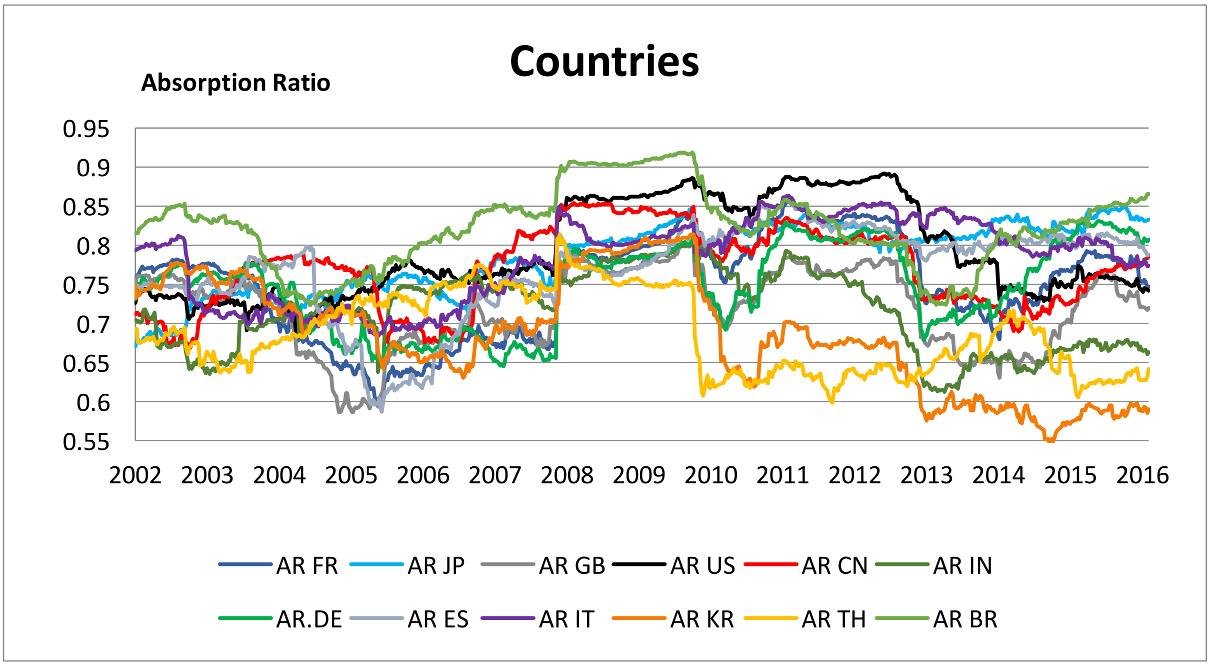

Figure 3 Absorption Ratio in a sample of 12 countries 2001-2016

On the other hand, the global systemic risk can also be observed from the perspective at country level. Figure 3 shows absorption ratios in a sample of 12 countries from January 2001 to December 2016.

As can be seen from the graph, Brazil, as represented by the light green line, exhibited a very high level of systemic risk in comparison to other countries in the sample prior and during the global financial crisis then the ratio declined for a few years but recently it has been rising again which may in some parts due to the crash of its commodity prices and corruption scandals in 2015 (Gillespie, 2016). Whereas, The US, as represented by a black line, also displays a very high level of systemic risk which is not surprising considering that it played a major role in global financial crisis in 2008, though it's interesting to see that the absorption ratio in the US equity markets has been steadily decreasing since the end of 2012 from a high level of almost 0.90 in 2012 to a moderate level at around 0.75 in 2015, which perhaps contribute to a better understanding of systemic risk as well as an improvement in enforcing efficient market regulations. It's also pleasing to see that during the period of European sovereign debt crisis in 2011-2012, all the European Union countries in the sample – Germany (DE), France (FR), Spain (ES), Italy (IT), and Great Britain (GB), exhibited a decidedly high level of absorption ratios, considering that at other time periods, some of these countries such as Spain had quite a low level of the ratio. It is pleasing because the results of the measure are consistent with the events in the real world.

However, it's not clear from the graph from which markets does the systemic risk originated or in which region does the systemic risk is most concentrated. Hence, I decided to expand to a broader perspective – instead of focusing on a country level, we may look at the market development level as it's possible that developed markets will possess a higher level of systemic risk due to the greater complexity of their financial systems and I tested this hypothesis in Figure 4.

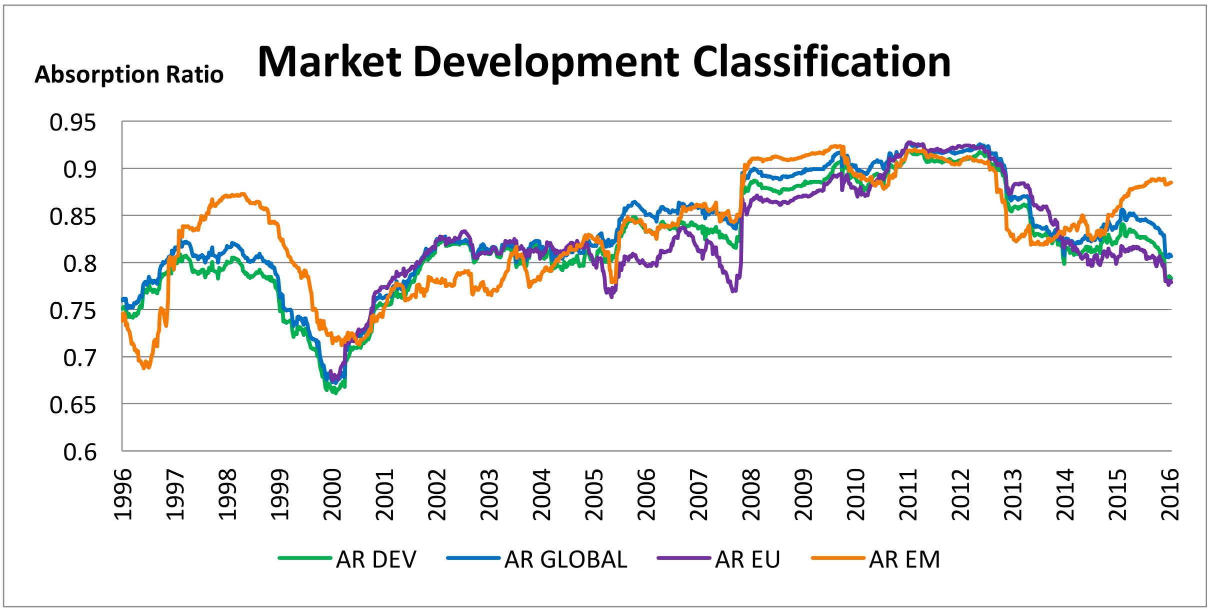

Figure 4 Absorption ratio in the global equity markets, categorized by the level of market development, from January 1995 to December 2016.

Figure 4 shows the absorption ratio in the global equity markets sorted by the level of market development as classified by MSCI Sector/Industry Indices from January 1995 to December 2016.

The blue line represents the absorption ratio at the global level for all the 46 countries in the MSCI ACWIF Index. And this index is dissected into 3 sub-indices – MSCI World Index for 23 developed markets, MSCI EMF for 23 emerging markets, and the extra one, MSCI EMU for 10 developed markets in the European monetary union.

In contrary to my hypothesis, the developed markets do not have higher absorption ratio level than emerging markets, rather that the opposite is true – emerging markets appear to have higher absorption ratio than developed markets according to figure 4.

It can be seen from the graph that the trends of the 4 lines generally move in tandem with one another. Though, the emerging markets, depicted in orange, seem to deviate slightly from the general trend from time to time. One explanation for this slight divergence from the trend during 1997-1999 was that the time period happened to coincide with the events of the 1997 Asian financial crisis as well as the 1998 Russian financial crisis and since these two crises originated from, mainly involved and affected the emerging markets. These should then justify the high level of absorption ratio, or in other words, high level of systemic risk, for this type of market development in comparison to others in the same time period. Interestingly, the emerging markets seemed to carry the highest level of systemic risk during the 2008 global financial crisis, and while the level had been declining after the period of crisis recovery, it has recently been rising to almost reaching 0.90 which is quite disconcerting as this implies the markets are very vulnerable to negative shocks and if this information proved to be correct then attentions should be drawn to this problem immediately before it can develop into a crisis. Furthermore, this rising ratio is noticeably different from the trend of the other three indices which suggest that there must be something going on, possibly terribly wrong, in the emerging markets.

Yet, if we're to look at this graph alone, we would have concluded that emerging markets appeared to carry a very high systemic risk, therefore we should focus solely on emerging markets, and this would be a mistake. From earlier analysis of a country perspective in figure 3, we can see that the US and other developed markets such as Japan also held a high systemic risk level and we would have missed this information were we to ignore the developed markets. That being said, I would suggest we look at the market development level to assess the general trend of the global markets then we can narrow down to a country level to have a more detailed explanation of where might be the sources or which markets are the most troubling in terms of their implied incapability to be resilience to negative shocks.

As illustrated in figure 2, 3 and 4, the observation of the absorption ratio can be realized though several perspectives. Despite my efforts to compare the differences and similarities between all these three perspectives, I failed to draw a meaningful connection as well a contraction between sector and country perspectives. I can only conclude that each perspective is useful in its own merits and subject to the preferences of the users. An individual investor or an asset manager may interest in the sector perspective because it gives a convenient view of the global equity markets so that they can, by some extent, assess which sectors are particularly vulnerable to shocks hence implies risky investment prospects. Whereas policymakers may interest in the country perspective in complementary with the market development classification perspective as a benchmark in assessing the systemic risk in their own countries.

Here, I also observed limitation in the use of absorption ratio as a measure of implied systemic risk. It is not clear whether at what level the absorption ratio is considered to be "high" or "low" or "on average", a ratio of 0.90 is definitely very high but does 0.75 considered as high, too? As the question remained unanswered, I took the liberty and choose to label the level of the absorption ratio in terms of comparison to one another – 0.75 is low if the average is 0.85, 0.85 in country a is high if compares to 0.70 in country b, etc.

6. Robustness Tests

Summary of the Absorption Ratio by data frequency			
	MAX AR	**MIN AR**	**AVERAGE AR**
Daily (500-day)	0.906 AT 13/8/2010	0.585 AT 15/12/2000	0.774
Weekly (71-week)	0.902 AT 07/09/2012	0.593 AT 09/03/2001	0.763
Monthly (17-month)	0.859 AT 10/2011	0.548 AT 01/2000	0.737

Table 1 shows the summary of the absorption ratio in the US stock market using three different data frequency from January 1995 to December 2016

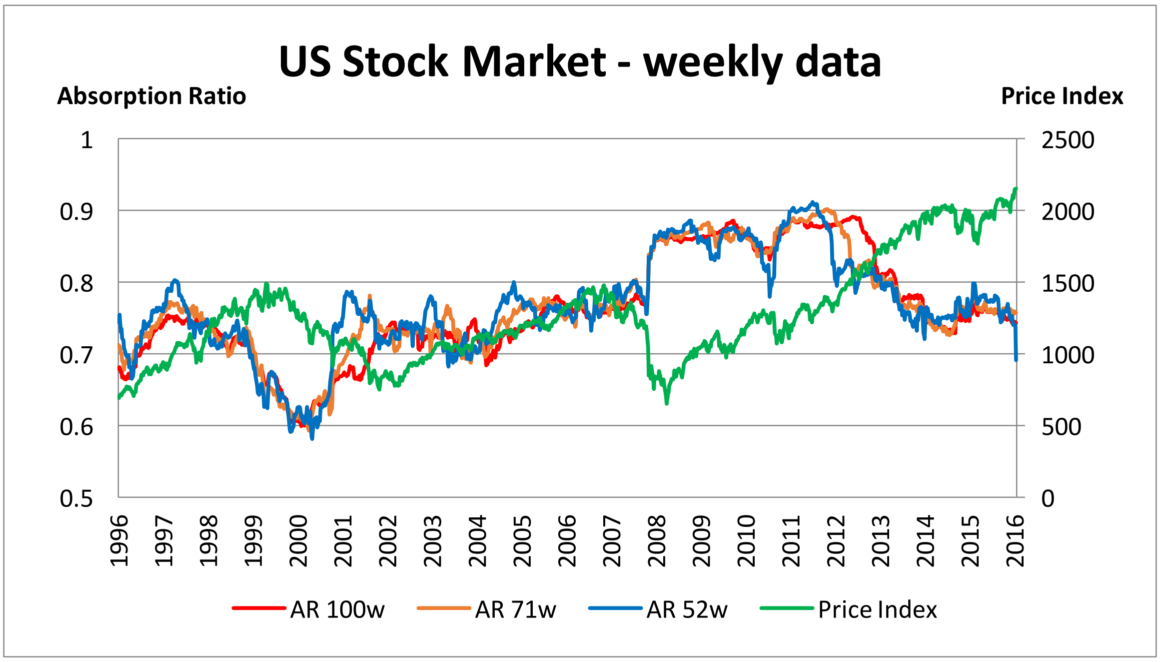

Figure 5 compares size of rolling window for a weekly data in the US stock markets.

Table 1 and Figure 5 above show the results of the robustness tests of the data used in this paper. Both figures formed the absorption ratio from the US stock market beginning at January 1995 to December 2016, though with slight modifications.

The original paper on absorption ratio by Kritzman et al. (2011) used daily data from the equity markets and applied 500-day rolling window in forming the absorption ratio, and I was interested to see if using different data frequency or different choices of window size would yield different results. Therefore, I conducted an approximate robustness testing on these choices. In Table 1, we can see that on average the summary statistics of the absorption ratio from the three data frequencies were not openly different, these statistics are comparable as they were tested over the same rolling window length (500 days). On average, the daily data gives the highest value follow by weekly then monthly data.

Figure 5 displays the graph of the absorption ratio composed by using weekly data but with different choices of window size against the stock price index. As can be seen from the graph, the three data frequencies appear to move in the same directions and all were seen to have inverse relationship with the price index. However, the time period where the maximum value and the minimum value appeared are slightly different – for the monthly data, the longer the window, the sooner the maximum value to appear while for the daily and weekly data, the shorter the length of the window, the sooner the maximum value to appear.

7. Average return correlation and absorption ratio

One may wonder, why should we bother going through all these troubles constructing the absorption ratio to measure the interconnectedness of the markets when we can simply use the average correlation approach to capture this relationship. However, my hypothesis was that the average return correlation approach underestimates the risks in the markets. Thus, I tested my hypothesis with the sample of 12 countries previously used in the analysis.

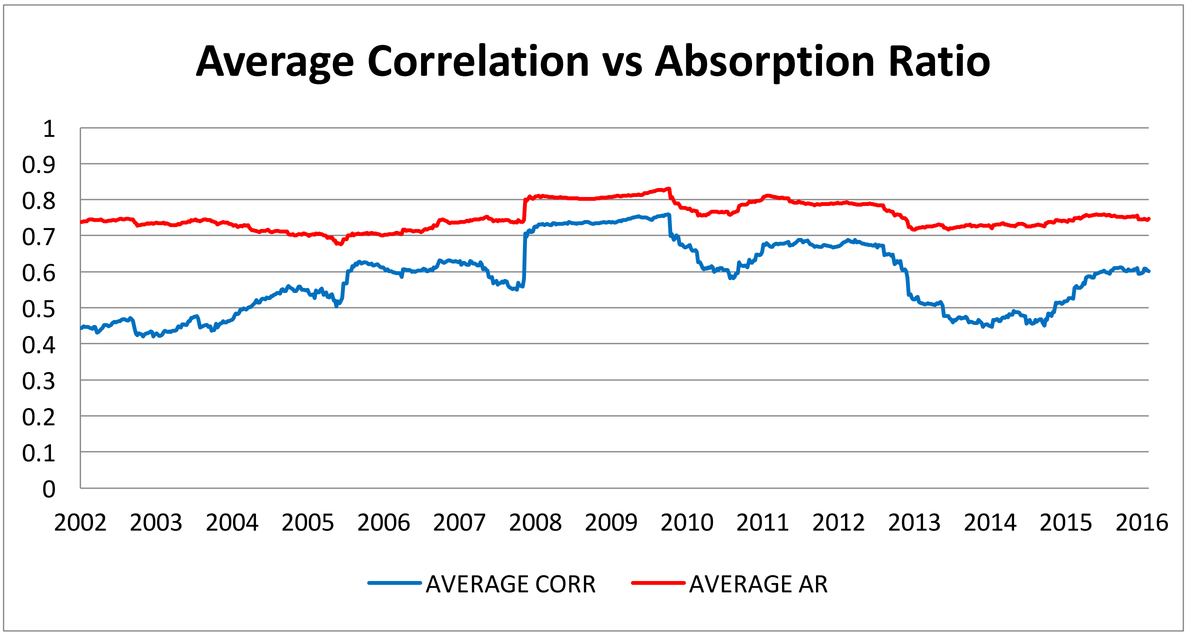

Figure 7 Average Return Correlation and the Absorption Ratio for the 12 countries from January 2001 to December 2016

Figure 7 compares the results between average return correlation and average absorption ratio in a sample of 12 countries during January 2001 to December 2016.

Pollet and Wilson (2010) assumes aggregate risk is related to market risk premium and proposes that the interdependence among observable equity returns came from the true market risk, hence an increase in average correlation between stock returns when the stock markets has a positive sensitivity to aggregate market shocks should reflect an increase in aggregate risk by some degrees.

In this paper, the average return correlation is calculated by finding the correlation of each unique pair in the sample using 100-week rolling window then taking the average out of all the possible pairs. Whereas the average absorption ratio is computed from taking the average out of each and every 12 countries' absorption ratios in the sample.

As can be seen from the graph, the return correlation and risk correlation are perhaps similar in some regards but they are not the same. Risks as measured by the absorption ratio appear to be higher than the return correlations at any time periods. Thus, average return correlation can only partially reflect aggregate risk in the market but the absorption ratio seem to yield a more meaningful result. Kritzman et al. (2011) suggests that the two approaches are different because the absorption ratio accounts for the relative importance of each asset's contribution to systemic risk while average return correlation does not.

8. Absorption Ratio as an early warning signal for systemic risk

The works by Lo Duca and Peltonen (2013) and Comelli (2014) are the main motivation for this part of the paper. Lo Duca and Peltonen use multivariate logit models to predict the systemic events as measured by the Financial Stress Index (FSI), while Comelli (2014) compares the performance of logit fixed effects model and probit early warning system (EWS) in predicting currency crises in the emerging markets.

In this paper, I use the absorption ratio to derive the crisis binary variable,

$$SE_{it} = \begin{cases} 1 & if\ AR_{it} > 0.75 \\ 0 & otherwise \end{cases} \qquad (1)$$

As shown in condition (1), the variable SE_{it} stands for Systemic Events in country i at time t which will assume the value of 1 if the absorption ratio in the country at time t is higher than a threshold of 0.75 and will assume the value of 0 if otherwise. Note that the crisis variable here does not necessarily signal a systemic crisis, it merely is a signal for the vulnerability of the equity market. In addition, the choice of the threshold is set to equal to the average of the absorption ratio of the whole sample. I realized that the chosen threshold may not present the best possible results because as mentioned earlier there is no baseline model available for us to compare the level of the absorption ratio – we have no suggestion at what level it considered to be high or low, yet I presume that by setting the threshold to equal to the average score of the whole sample should at least provide a general idea of the level of systemic risk in each country when compare to other countries in the same sample. Nonetheless, I have also tested two other different choices of the threshold, one is set at 0.8 while another is set at the average of country i.

Furthermore, I also compare between the absorption ratio at the end of the quarter – noted as EQ, and the average of the absorption ratio in a quarter – noted as AQ. Hence, there will be altogether six models in my paper.

After deriving the crisis binary variable, I then converted SE_{it} into the forward-looking crisis variable Y_{it},

$$Y_{it} = \begin{cases} 1, & if\ k \ni 1,2,\ldots,8\ s.t.\ SE_{it} = 1 \\ 0, & otherwise \end{cases} \qquad (2)$$

If there is a systemic event occurs within the next eight quarters in country i at time t, then Y_{it} will assume the value of 1 and 0 if otherwise. Both Lo Duca and Peltonen (2013) and Comelli (2014) suggest that on average the best forecasting horizon is achieved over the eight quarter periods, hence the suggested forecasting span is used in this paper.

Then, I estimate the probability of country i to experience a systemic event at time t ,PR(Y_{it}=1) as a function of a selected macroeconomic variables X, using a probit model as shown below.

$$(\mathrm{Pr}Y_{it}=1) = \phi(X'\beta) = \int_{-\infty}^{X'\beta} \phi(Z)dz \qquad (3)$$

Results

The first three models use the absorption ratio at the end of the quarter to derive the crisis binary variable, however each uses different thresholds; model (1) uses threshold of 0.75, model (2) uses threshold of average in country i, while model (3) uses threshold of 0.8. On the other hand, model (4), (5), and (6) use the average of the absorption ratio from each quarter to derive the crisis variable at three different thresholds – 0.75, average of country i, and 0.8, respectively.

The explanatory variables are collected from the OECD and the BIS websites using the data from Q1 2003 to Q4 2016 for the 11 countries in the sample (excluding Thailand). The six variables are as follow; real GDP growth, Long-term interest rate, Short-term interest rate, CPI price level, credit-to-GDP gap and Debt Service Ratio (DSR). Note that in this paper, the credit variable used in the estimation is the credit-to-GDP gap as defined by BIS, which is a deviation of the private sector's credit-to-GDP ratio from its long-term trend. Whereas the debt service ratio reflects the share of income used to service debt.

Initially, I included the Private Consumption Expenditure, Public Consumption Expenditure, Imports and Exports in estimates but these four variables were not statistically significant in any of the models, so I dropped them out from the estimation.

The inclusion of the credit-to-GDP gap variable in the estimation is primarily due to the widespread recognition of the role of credit in the financial system. Taylor (2015) uses correct classification frontier (CCF) based on a fixed effect logit model to confirm the robustness of credit signal, particularly the change in private credit relative to GDP, as a forewarning signal for impending financial crises in advanced economies at 95 percent significance level. He concludes that the recurrent episodes of financial instability in recent years have more often than not been a result of atypical credit expansion, moreover, credit booms often lead to a debt overhang which makes both normal and financial recessions more painful (ibid).

Interestingly, in all of the six models shown in table 2, credit-to-GDP gap appears to be statistically significant only when Debt Service Ratio (DSR) is also presence in the estimation. Drehmann and Juselius (2012) compare the performance of DSR and credit-to-GDP gap to identify the best early warning indicator for systemic banking crises and find that both indicators provide complementary information; while credit-to-GDP gap starts to signal impending vulnerabilities in the system well in advance, a rapid rise in DSR is a very strong indication that a crisis is near. This would perhaps explain why the models perform better with the presence of the two variables alongside. In addition, a recent work from Juselius and Drehmann (2015) argues that while credit-to-GDP ratio is decidedly useful in predicting the credit booms, oftentimes economists are unable to distinguish between the long-run and short-run increases in the credit-to-GDP ratio, hence they were unable to understand the divergence between output and credit growth prior to the crisis. They conclude that the relationship between leverage and debt service determines the long-run value of the credit-to-GDP ratio (ibid)

Table 2. Coefficient estimates from probit models

	Models					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	EQ075F	EQAVRGF	EQ08F	AQ075F	AQAVRGF	AQ08F
Real GDP Growth	0.727***	0.775***	0.787***	0.709***	0.771***	0.809***
	(0.0573)	(0.0592)	(0.0576)	(0.0570)	(0.0592)	(0.0584)
Long-term Interest Rate	1.063	1.146**	1.306***	1.089	1.144**	1.298***
	(0.0689)	(0.0723)	(0.0805)	(0.0719)	(0.0720)	(0.0793)
Short-term Interest Rate	0.826***	0.899**	0.799***	0.817***	0.909*	0.799***
	(0.0446)	(0.0480)	(0.0438)	(0.0449)	(0.0484)	(0.0435)
CPI	0.997	1.012**	1.039***	0.998	1.011**	1.037***
	(0.00498)	(0.00514)	(0.00788)	(0.00496)	(0.00516)	(0.00754)
Credit to GDP gap	1.008*	1.004	1.023***	1.010**	1.002	1.019***
	(0.00498)	(0.00483)	(0.00535)	(0.00501)	(0.00482)	(0.00521)
DSR	0.968*	0.980	0.860***	0.970*	0.978	0.861***
	(0.0163)	(0.0162)	(0.0160)	(0.0164)	(0.0162)	(0.0159)
Constant	5.448***	0.597	0.138**	4.700***	0.648	0.172**
	(3.124)	(0.344)	(0.107)	(2.696)	(0.373)	(0.128)
Observations	495	495	495	495	495	495

Pseudo R-squared	0.181	0.181	0.181	0.181	0.181	0.181

seEform in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2 above shows the coefficient estimates from the six probit models.

From table 2, model (3) and model (6) outperform other models in terms of identifying the important macroeconomic sources of systemic risk. All of the six macroeconomic variables appear to be statistically significant at the 1 percent significance level in both models. However, only the real GDP growth are consistently statistically significant in all of the six models, perhaps if I include more macroeconomic variables and able to deliver a more solid threshold level, the models may generate even more meaningful results.

Nevertheless, using the available results I then proceed to observe the ROC curve or the Receiver Operating Characteristic curve for each of the six models to identify the model that is best applicable to be an early warning signal of systemic events. The area under the ROC curve (AUROC) is generally a good measure for comparing performance of early-warning models, it depicts the trade-off between true positives (correctly classified) and false positives (incorrectly classified). As a result, the larger the ROC statistics, the more accurate classification test between systemic events and non-systemic events.

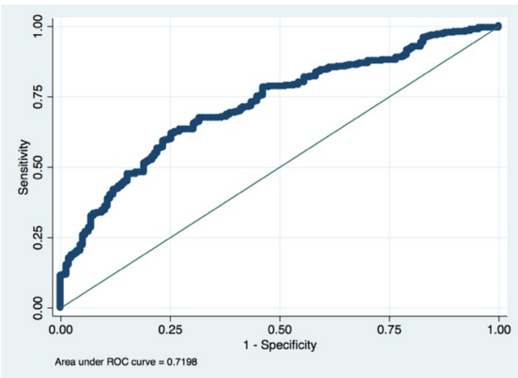

Figure 8.1 Model (1) ROC EQ075F

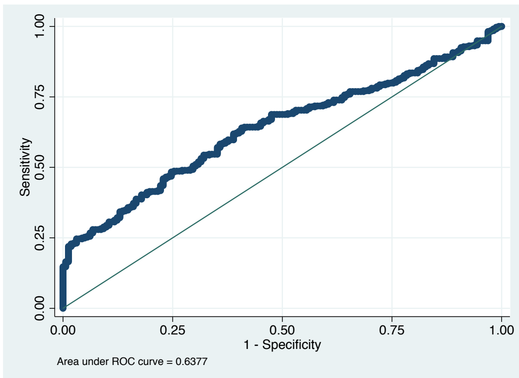

Figure 8.2 Model (2) ROC EQAVRGF

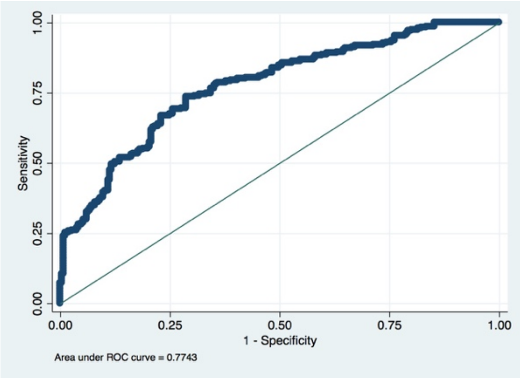

Figure 8.3 Model (3) ROC EQ08F

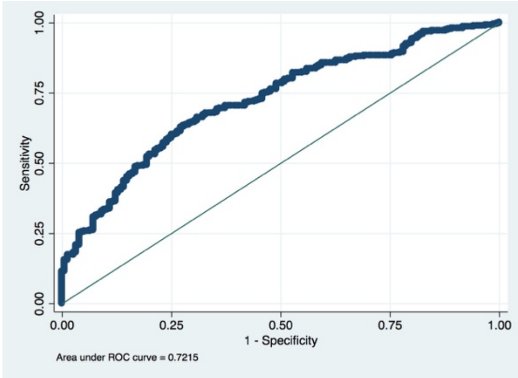

Figure 8.4 Model (4) ROC AQ075F

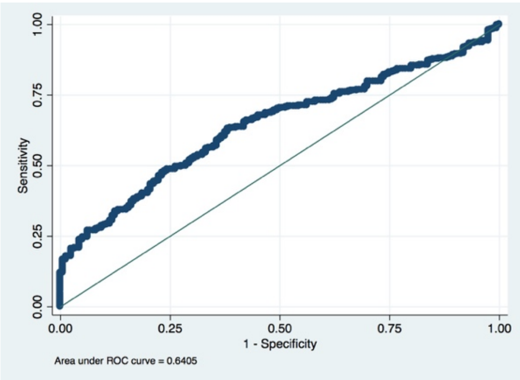

Figure 8.5 Model (5) ROC AQAVRGF

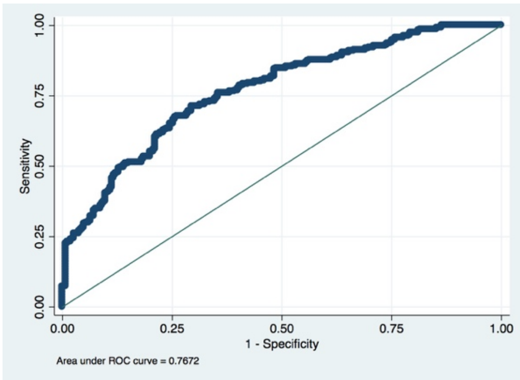

Figure 8.6 Model (6) ROC AQ08F

Figure 8.1 to 8.6 shows the ROC of the six models. Of all the six models, model (3) possesses the highest area under the ROC curve at 0.7743 follows by model (6) at 0.7672. Hence, I choose to present model (3) of which deriving the crisis variable from the absorption ratio at the end of each quarter with a threshold of 0.8 as my best model for predicting systemic events because it is shown to classify more accurate events more often than not.

Furthermore, I compare the ROC curves from model (3) to test the significance of credit-to-GDP gap and DSR variables in the estimation using the first four variables (real GDP growth, Long-term and Short-term interest rate and CPI) as control variables. Figure 9 below shows the result of ROC curve comparison between the four choices of estimation. The first estimation, as represented by the blue line, is done without the inclusion of credit-to-GDP gap nor DSR in the model. The second estimation, as depicted by the red line, includes credit-to-GDP gap but not DSR. The third estimation, as shown in green, includes DSR but not credit-to-GDP gap. Whereas, the last estimation, as shown in orange, is the model that include both variables in the estimation.

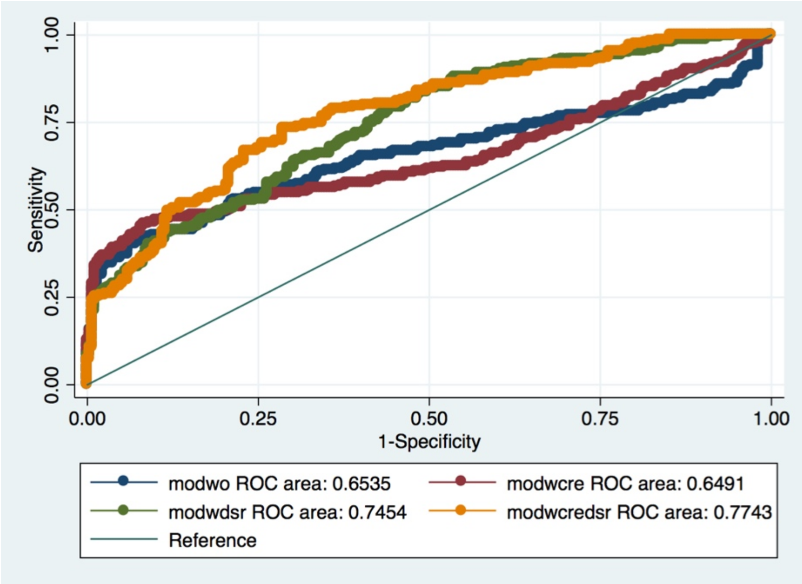

Figure 9 ROC Curves comparison from different estimation of Model (3)

As shown above, the inclusion of both credit-to-GDP gap and DSR significantly increases the performance of the predictor. Note that having credit-to-GDP gap in the estimation does not necessarily increase the performance of the predictor unless DSR is also presence in the estimation. Whereas, including DSR in the model does improve the performance but the model still performs much better with the presence of the two variables together. This result further supports the works of Drehmann and Juselius (2012) and Juselius and Drehmann (2015) whose studies point out that DSR and credit-to-GDP gap provide complementary information about the impending systemic crises albeit at different time horizons.

9. Conclusion

Despite a greater development of literature on systemic risk in recent years, most researches continue to fixate on a specific sector or a specific group of economies. In fact, none to my knowledge have attempted to measure the systemic risk at the global level and whether this is a deliberate intention or not I cannot presume. Nevertheless, I believe that the systemic risk assessment at the global level can provide meaningful implications for the risk management purposes in the interests of investors and policymakers alike.

First, I have demonstrated that the absorption ratio is able to reflect the activities of the global equity markets, for example, the spike in the absorption ratio which implies a high level of systemic risk usually coincides with the financial distress events in the global financial markets. Then, I examined the sources and the concentration of the global systemic risk between two perspectives;

sector and country, I found that each of the two are equally useful in portraying risks in the markets albeit depending on the interests of the users. I suggest that the sector perspective is more beneficial to the ones who seek information on investment opportunities as well as the regulators who are overseeing the outlook of the markets. On the other hand, the perspective at the country level along with the market classification types may prove to be more useful to the central banks of the country or the government officials who are more concerned about the vulnerability of the economy as a whole. I also provided a simple robustness tests for the data frequency and choice of window size, and I found that there are no significant differences between the choices. Then, I illustrated that the using average return correlation in the stock markets alone is not sufficient in capturing the risk in the market, while the average absorption ratio has proved to apprehend the risks because it considers the relative importance of each asset's contribution to systemic risk. Finally, I transformed the absorption ratio into an early warning signal of systemic events to identify the macroeconomic sources of systemic risk as implied by the absorption ratio. I acknowledged that there are some limitations to the model, particularly the choices of threshold and the choice of the variables as well as the coverage of the sample. Hence, I encourage future works to design a more complete form of the model. Nevertheless, I observed from my ROC statistics that the model that uses the absorption ratio at the end of each quarter and a threshold of 0.8 to derive the crisis binary variable outperformed the other five proposed models. I also found that the inclusion of credit-to-GDP gap alongside Debt Service Ratio in the estimation significantly improves the performance of the predictor, thus highlights the significant of credit-to-GDP gap and DSR as macroeconomic determinants of systemic crises in the economy.

While the purpose of this research is to propose the measure of systemic risk at the global level, it also acknowledges that identifying the vulnerable parts of the markets to systemic risk is only one of the many steps in managing financial stability in the VUCA world. The absorption ratio may prove to be one of the many useful tools in understanding the Complexity element of the financial system, but other elements particularly the Uncertainty and Ambiguity remain for a much needed further researches and studies.

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