A Thesis presented as part of the requirements for the Award of a Master Degree in Finance from the Nova School of Business and Economics.

Using CoVaR to model Cross-border Connections in Financial Markets

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A Thesis for the Master in Finance Program
Supervised by: Afonso Eça

January 6, 2017

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Abstract

This paper will examine how the conditional value at risk of the United States financial market can be calculated using exposure to foreign financial markets. Whether import or export partners have more of an effect on a country's financial markets and the results of how both are strongly significant, yet how exports play a slightly larger role, will be examined. The paper will also examine how the US financial market has become more interconnected over the last 21 years. These calculations have been conducted using the conditional value at risk measure via quantile regressions.

Keywords: Financial interconnection, Value at risk, Conditional Value at Risk, Risk Management

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Introduction

Globalization is here. It has provided us with access to many products and services that we previously would not have had through an increase in foreign trade. Additionally, it has brought an increase in the interconnectedness of the global economy and led to links between countries' financial systems all around the world.

On September 17, 2015, we observed the US Federal Reserve leaving rates unchanged due to fears within emerging market economies. This serves as proof of how the system is becoming more and more interconnected. A major decision in the world's largest economy, the United States, was made based on the effect it could have on a global scale.

The majority of value at risk measures focus primarily on domestic firms and their effect on the national economy. This is very important for risk management and measurement although it provides a limited view in terms of the measurement of international contagion of distress in financial markets. This paper will explore a new measure which uses a risk matching approach to measure how a country's risk exposure can be derived from its trading partners.

The research focus is primarily on the effects of the major trade partners of the US on its financial markets. This is done using Adrian and Brunnermeier's CoVaR measure to examine how changes in a major trade partner's financial markets affect the US markets, and how this relationship has evolved over time.

Through increased foreign trade you would expect an increase in the connectedness of countries' economies and financial markets. This research focuses on how markets are connected when the US market is in a period of crisis. Intuitively, if a partner's economy is struggling it should have a contagious effect through trade on its partner's economy. I find both import and export partners' financial indexes to provide the best risk matching profile in stress times. The addition of commodity returns proves to even further improve this risk match.

This research uses CoVaR to measure cross-border contagion of financial events and determine the effects major market movements in one country have on another country. I will also show how there is a negligible difference upon whether the partner country is a major import or export partner, it is simply the connection through trade which is important.

Finally, I examine the interconnectedness of the global financial system over the last 20 years. I find that we have seen a significant increase in the risk matching across countries' financial markets. This is used as the basis to show how we are observing a period of growing global connectedness within the financial system.

The paper is organized in 5 sections. Section 1 is an overview of the recent financial crises, which have occurred over the last 40 years, and a look into their causes. Section 2 will be an analysis of the literature on topics related to my research. Some of the covered literature is also used to show the motivation behind this study. Section 3 will be an overview of the analytical process, focusing on the methodology used and the research design. Section 4 will have a presentation of the research results. The final 5th section will cover further research and the conclusion.

1. Recent financial Crises

1.1 Latin American Debt Crisis (the 1970s)

In the 1970s, drastic fluctuation in the oil price caused deficits within the current accounts of several countries within Latin America. The US government urged large US banks to act as intermediaries providing oil-exporting countries a reliable and liquid place to store their surpluses and the banks then lent those funds to Latin America. The borrowing from US banks was initially slow, with the Latin American countries owing foreign creditors $29 billion in 1970. By 1978, the debt had grown to $159 billion and by 1982 it had skyrocketed to $327 billion. In 1982, the finance minister of Mexico informed the International Monetary Fund (IMF) and US Treasury secretary that Mexico could no longer maintain its debt payments on the outstanding $80 billion. Several other countries followed Mexico's lead and, in the end, 16 Latin American countries needed to restructure their debt payments. This led to a cessation of overseas bank lending as the focus switched to collecting outstanding debts. (Sims & Romero, 2013)

1.2 Savings and loan crisis (the 1980s)

As interest rates rose in the early 1980's, many firms in the savings and loans business struggled. The deposit rate which was set by the federal government was low, which resulted in customers withdrawing funds to put elsewhere where they could earn a better rate of return. Additionally, savings and loans firms had made significant loans for long-term fixed rate mortgages. As the interest rates rose, the mortgage values plummeted causing the firms to lose almost everything. Regulators did not have enough capital to sustain the losses the firms were suffering. This ultimately resulted in a bailout provided by the taxpayers. (Robinson, 2013)

1.3 Stock Market Crash (1987)

Later to become famously known as "Black Monday", the crash in the fall of 1987 was the first global financial crisis. A series of events sent the stock market, as well as the futures and options markets, crashing downward to their worst single-day loss in market history. The Dow Jones Industrial Average dropped 22.6% while the S&P 500 fell over 20%. It showed how the trading systems in place could be pushed to the point of almost breaking in extreme conditions. This event was a prime demonstration of how interconnected our financial markets have become through technology. (Bernhardt & Eckblad, 2013; Carlson, 2007)

1.4 High-yield Bond Crash (1989)

Many companies throughout the 1980's were engaged in aggressive restructuring and mergers. Most of these transactions were principally financed through debt. This led to an aggressive boom in the high-yield bond market, also known as the "Junk Bond Market". In

1989, the amount of defaults began to skyrocket and defaults were in excess of $8 billion, with default rates being just under double the usual average of 2.2% coming in at 4.3%. The high risk in the market led to a large credit spread which grew to over 700 basis points. One investment bank which was responsible for a large number of these issuances, Drexel Burnham Lambert, filed for bankruptcy and its figurehead, Michael Milken, was indicted. (Altman, 2000)

1.5 Mexican Financial Crisis (1994 - 1995)

The 94/95 crisis which originated in Mexico is better known as the "Tequila Crisis". It originated upon the devaluation of the Mexican peso in the later part of 1994. The crisis led to a severe depreciation of the peso and a drastic recession ensued. In 1995, Mexico's GDP fell over 6%. The weak regulation in the financial system and over-excited foreign investors are considered to be the primary causes of the crash. (Musacchio, 2012)

1.6 Asia Crisis (1997 - 1998)

There are 3 main causes of the Asian crisis. Firstly, the amount of foreign money which was flowing into Asia due to the low-interest rates led investors to seek new investment opportunities. The large inflow led to significant price appreciation in housing, and the stock market, this then led to even further inward flows. Unfortunately, the Asian firms were unable to efficiently use the funds, and their lack of financial transparency temporarily hid this fact from investors. The second main cause were the fixed exchange rate systems which the countries had in place. This provided investors with a false sense of security making the countries appear more stable than they truly were. The third and final cause was the establishment of increased trade within North America which was created through the foundation of the North American Free Trade Agreement. (Aghevli, 1999; Carson & Clark, 2013)

1.7 Dot-com Bubble (Mid 1990's - 2002)

During this time, the way investments were analyzed changed, and investors were no longer relying on business fundamentals. Investors were overly optimistic about the future potential of technology and the many newly created companies which were operating in the online space. The investors were relying on newly created measures which attempted to forecast future earnings. Due to popular demand, companies began releasing "Pro-forma" financial statements with did not have to follow previously set accounting guidelines. This period led to the famous quote by the chairman of the US Federal Reserve at the time, Alan Greenspan, who warned investors about "irrational exuberance". This asset price bubble began deflating in early 2000 and continued to do so until near the end of 2002, with the terrorist attacks in New York City on September 11, 2001 having an accelerating effect on the bubble deflation. (Morris & Alam, 2008)

1.8 Global Financial Crisis (2007 - 2009)

The global financial crisis began in 2007 and had a ripple effect around the world. This is another great example of how interconnected our financial systems have become and how globalization has increased financial linkage between countries. The 2007 crisis was a banking crisis which affected the money supply and threatened the economy as a whole. In examining the 2007 crisis, Lastra and Wood attempt to determine whether it was a liquidity or capital caused crisis, and conclude that it is difficult to tell due to the speed with which the crisis took place. They go on to mention how several key factors led to the crisis, with some of the main culprits being macroeconomic imbalances with foreign countries, failures of regulation, a belief that some institutions were "too-big-to-fail", excessive use of the securitization markets, poor risk management and several other causes. (Lastra & Wood, 2010) The 2007 crisis led the US Federal Reserve to use unconventional monetary policy which has had a lasting effect on the US economy and has led to interest rates remaining low over the last 9 years.

1.9 Sovereign Debt Crisis (2009 - Present)

The most recent crisis arose in Europe. The primary cause of this crisis was governments' attempts to stabilize their banks during the global financial crisis. Banks play a major role in any economy and it is in the government's best interest to ensure their country's banks remain operational. This led to many European governments overleveraging themselves in order to maintain stability within the banking sector. This unfortunately led to a financial sector banking problem bleeding into a fiscal sector problem, which then presented itself in the sovereign debt markets. (Correa & Sapriza, 2014) Large amounts of debt from countries such as Portugal, Italy, Ireland, Greece and Spain were at risk as the countries could no longer sustain their debt. This led to the European Central Bank stepping in and taking unprecedented measures in an attempt to regain financial stability in the Eurozone.

2. A Review of Relevant Literature

The basis for this research is a 2011 paper in which Adrian and Brunnermeier outline their CoVaR measure. This measure was created as an extension of the pre-existing VaR measure with the addition of "Co" to represent conditional, contagion and comovement. The measure represents the VaR of the financial system conditional on one institution being in a state of stress. In addition, they create a ΔCoVaR measure which denotes the change or marginal contribution one institution has upon the system. This measure can be used to denote one institution's contribution to overall systemic risk. They use the measure to find how much systemic risk commercial banks, insurance companies, real estate and broker-dealers contribute to the US financial markets. They also create a forward measure of ΔCoVaR which they use to monitor and predict the buildup of systemic risk in the financial system. The main benefit of this measure is its ability to predict risk counter-cyclically. (Adrian & Brunnermeier, 2011)

Forbes and Rigobon look at comovement and attempt to determine the difference between contagion and interdependence. They note how the definition of contagion in itself has many different uses within literature. Thus they create their own definition "contagion as a significant increase in cross-market linkages after a shock to one country (or group of countries)"(Forbes & Rigobon, 2002). Their definition acknowledges that some markets will always contain a large amount of comovement. They find that it's only when an event can trigger and increase in this comovement that contagion is present. When a country's financial market has a link with another this is denoted as interdependence. Similar to previously noted literature and one of the main research points of this paper the authors note how one of the main potential sources of transmission of financial stress from one country to another is through international trade. They also note how in general, correlations increase throughout the markets during crisis times. It must be noted that in order to be deemed contagion, there is one relationship between a pair of countries which increases more than the others. Their research finds that daily data with no lags provides the best result. They focus primarily on only the larger markets, the 10 largest in their case, due to the fact that liquidity can disappear during a crisis. They also note how contagion tests can be biased when the market is experiencing a large swing in the amount of volatility observed. Within their research they perform a correction to account for bias in the coefficient of correlation. In order to perform this correction, they make the assumption of no omitted variables or endogeneity. I find these unrealistic assumptions. I am working with only country returns and a small sample of commodity returns, so the assumption of no omitted variables is unlikely as the entire basis for this research is that markets are highly interconnected; thus, I do not perform their correlation correction. Secondly, Adrian and Brunnermeier note that there is endogeneity in systemic risk which translates into the CoVaR measure. (Adrian & Brunnermeier, 2011) The central conclusion is that the markets do not exhibit contagion but higher comovement via increased interdependence in times of crisis. (Forbes & Rigobon, 2002)

Looking at cross-listed stocks from US and Japan, how they move from a daily and intraday perspective, Karolyi and Stulz examine why markets move together. Their study focuses on a time frame from 1988 to 1992. The stocks which they observed are Japanese listed stocks which are cross-listed with American Depository Receipts (ADR) that are traded on the New York Stock Exchange (NYSE). Their study finds that several factors which we may initially think have an effect on the return covariance do not. US macro news, foreign exchange shocks and changes in US treasuries do not present a measurable effect. They do find that large shocks to major market indices, the Nikkei and S&P 500 Index, have a positive effect on increasing the magnitude and also on the persistence of correlation observed between the two markets. Within their research, they also report a couple other useful findings relevant to the research conducted in this paper. Firstly, they note that global shocks are generally associated with higher return covariance, which demonstrates a spillover effect on market return covariance. Additionally, when we observe competitive shocks within an individual market, the result is generally a lower covariance. Looking at the weekly returns they find that covariance is generally higher on Mondays than other days during the week. Finally, they note how monthly unexpected changes in macro variables do not prove to be informative for explaining changes in monthly returns. They note how there is a problem when using daily returns due to the non-synchronous trading cycles all over the world. (Karolyi & Stulz, 1995)

The Financial Stress Spillover Index (FSSI) was created by Chau and Deesomsak; the index's purpose is to measure financial stress transmission. FSSI is used to monitor for conditions which could create the possibility for excessive spillover, which in turn would lead to instability in the financial system. Their index is measuring spillovers across US debt, equity, banking and foreign exchange markets. Backtesting using their index, they find how generally as the crisis intensified so too did their index. They note how financial stress is the most systemic risk because its instability spreads easiest across the global system. Their index shows the debt market appears to be the market which contributes most to spillovers with equity being second, and then foreign exchange and banking markets being a distant third and fourth. The banking system usually receives the brunt of the stress and its stress leads to spillovers. (Chau & Deesomsak, 2014)

2.1 Contagion from the Latin American and Asian Crises

Baig and Goldfain look at contagion amongst financial markets during the Asian crisis. There is evidence that within currency and equity markets, cross-border contagion is present. They look at several possible sources of transmission including: trade linkages, third party competition spillovers and change in financial market sentiment. They note that in a period of crisis, it is ideal for an investor to divest themselves from an entire group of related markets at the same time and not simply one or a few of the markets. Within their research they use a three-month rolling window. They use a shorter window so that they are able to observe interactions amongst markets which only have a quick effect. Whereas if they used the entire sample these effects would be smaller. (Baig & Goldfajn, 1999)

An IMF paper on contagion of equity markets makes several relevant discoveries to my research. Their findings address the way in which contagion spreads. It can differ from one region to another and even within one region. This is observed using their contagion measure and historical evidence from the Asian and Latin American crises. Looking at the 1998 Russian and Brazilian crises, they conclude that contagion is generally higher for negative events and market returns than positive ones. Based on the assumption that financial integration increases the possibility of contagion, they believe the developing markets are the most exposed as they have a higher reliance on more mature global markets. Their study uses a five-year rolling window to examine how inter-market dynamics are changing over time. This was used as motivation for the examination across time in my research. Prior to 1998, there had been minimal contagion from other foreign markets with the US, although from 1998 through to 2001 there was an observed increase in contagion. After the Latin and Asian crises, we observe increased contagion across the world as prior crises had been more geographically focused. This was observed through the contagion from Argentina and Korea, Chile and Hong Kong amongst others having increased. (Chan-Lau, Mathieson, & Yao, 2004)

Bordo and Murshid's paper on financial contagion looks at contagion over a longer time frame, from pre-World War 1 through the Asian and Latin American crises. They use weekly returns from bond prices and interest rates. Their research finds that there does not appear to be drastic increases in cross-market correlations in war times versus in the more recent Asian and Latin market crises. In fact, they actually note that the evidence is contrary to the belief that globalization has increased market co-movement, and they note how the co-movement was stronger during unstable periods in earlier war times. This is directly in opposition to the hypothesis of my research that increased globalization has led to an increase in financial market connections. Their analysis reveals crisis periods are not required to increase comovement and that there is significant comovement across markets during both calm and crisis periods. They find several explanations for how international crises spread, with trade linkages being one of the main sources. Lending to peripheral countries, stock markets and commodities markets are also sources of spread. They note how countries that have high correlations with one another may not necessarily denote contagion as they could simply have a dependence upon one another. They use Canada and the UK as an example. These countries have high correlation, which the authors believe arises due to their strong trade linkages creating a dependence upon one another. Similarly, they find that there is a surprisingly small link between Canada and the US given their strong trade with one another. They find the US market has stronger correlations with advanced countries in pre-crisis periods. While during crisis periods the correlations between advanced and emerging economies increase with the US, meanwhile correlations with Canada still remain relatively weak. (Bordo & Murshid, 2000)

2.2 Quantitatively Intense Research

From a quantitative technical level two papers further delve into the issue. One study looks at the interconnectedness of markets through changes in comoments of asset returns looking further than volatilities and correlations changing. In their study they use option pricing models. They note how asset markets are interconnected and that they are connected beyond correlation and volatility. Their findings conclude that the current asset pricing models do not take into account the fact that there are higher order moments in times of financial crisis which can lead to poorly priced assets. (Fry-McKibbin, Martin, & Tang, 2014)

Allali, Oueslati and Trabelsi also examine financial market interactions using a partial directed coherence model. They are looking at ten major stock market indexes. Their results find that there are strong connections between the world's major financial markets, and they note how investors may not be receiving the diversification benefit they seek by investing in several of these markets. In particular, they note how the US, UK, Germany and Hong Kong have a particularly strong impact on the major market index movements. (Allali, Oueslati, & Trabelsi, 2011)

2.3 Financial Markets in Emerging Economies

Calvo and Mendoza create a model in which they analyze herd behavior in financial markets. Their research finds that portfolios are more likely to change their allocations as the assets that they are invested in become globalized. So as we have seen a large increase in the ability to invest capital in smaller emerging markets, we are creating a greater potential for herd inflows and outflows to these markets. This is an issue because herd behavior with an outflow from a country due to fear in credit worthiness or slow growth can be a self-fulfilling prophecy. From the perspective of the countries, this is dangerous as it can take them a significant amount of time to regain their reputation and attract foreign investments. The authors observe how when investors are comparing their returns to a benchmark and they have a reputational benefit for beating the benchmark they are more susceptible to herd behavior. (Calvo & Mendoza, 1998)

In emerging economies, the capital inflow and outflow are very sensitive to their ratings, which are generally volatile. A country is deemed to be integrated once the return it is providing relative to its risk is the same as a country in another geographic area. (Bekaert & Harvey, 2003) When the markets are not fully integrated, we can see large swings in foreign markets which have little effect on trade partners. This is primarily caused by their lack of financial integration.

With their research from the Johannesburg Stock Exchange, Dicle and Levendis note that increasing the technology of an exchange is not enough to make it globally competitive. In order for it to be truly appealing to foreign investors, they also need to increase the information provided. This decreases the information asymmetry between foreign and domestic investors, which ultimately makes it more appealing to foreign investment. (Dicle & Levendis, 2013)

2.4 Policy Implications

Chang and Majnoni have a model which they use to analyze financial crises. Their model relies on two conditions which are necessary for a crisis: weak fundamentals and adverse self-fulfilling expectations. Contagion can be created from a crisis if investors change their ideology on the fundamentals of another country. For example, if Greece defaulting on their debt makes a US investor reconsider the likelihood of Portugal defaulting on their debt despite Portuguese fundamentals remaining unchanged, we would observe contagion in the markets. Similarly, to the previously mentioned herd behavior (Calvo & Mendoza, 1998), contagion can arise as an outcome of a combination of fundamentals and a self-fulfilling belief. Chang and Majnoni note how the contagiousness of a crisis is dependent upon the withholding or release of information to the public. Based on their predictive model, there have been some backtested crises which could have been prevented if more information had been released, and there have been others which would have been unavoidable. The authors note that when creating policy and trying to prevent the contagiousness of a crisis, transparency should be increased to provide the public with more information. (Chang & Majnoni, 2001)

Peckham examines how policy should be adapted from a much different angle. In his research on pandemic and financial crises, he finds that tracing the path of financial contagion is not unlike tracing that of biological contagion. He argues how society has a wide array of analytical tools which we use for examining how biological contagion spreads from one country to another and we could use these tools as a predictive measure for the spread of financial contagion. Historically, the spread has been quite similar with one central event, which then radiates outwards as the outbreak grows. He views trade linkages and financial interconnections, through common creditors and lenders, as the main methods of transmission of financial crises. (Peckham, 2013)

VanHoose examines how the international interconnection amongst markets provides regulators an opportunity to coordinate their policies. He notes how the interconnection creates the possibility for conflict among policies to be created. The policies which have been attempted in Europe are used to show how, thus far, coordination of financial policies has failed. VanHoose notes how the coordination between countries could take place via monetary policy and also via fiscal policy. The main challenge which he sees preventing the development of regulation coordination is the incentive for one country to cheat. There is also the ideological differences which cause regulators to have different goals. (VanHoose, 2015)

3. Analysis

3.1 Method

Quantile Regressions

The research conducted is primarily focused on left tail behavior, looking at which factors drive the returns from average to several standard deviations away and deeper into the tails.

As I am looking at the effects of other countries' financial markets conditional on the US market, the method selected for this analysis is a quantile regression because it is easy of use and the results are easily interpreted.

For a traditional Ordinary Least Squares Model we would look at the relationship between the independent variables (X1, X2, X3 etc.) and the conditional mean of the dependent variable Y.

Here, I am interested in looking at the relationship from the opposite direction. Looking at the relationship X has on Y, conditional on the quantile of Y, rather than simply the conditional mean. This allows us, by changing the quantile level, to see the effect that X has on Y at various points throughout the curve, allowing us to better examine how X affects Y in the tail versus closer to the mean. For an unbiased result in the regression, X must be non-zero and continuous.

The quantile regression operation is as follows. You select the quantile which you would like to observe. For this example, we will use the 90th percentile. This means we are interested in seeing what effect the independent variables have on the dependent variable when the dependent variable is at or above its 90th percentile. So, from the perspective of stock returns, as is the application use for this thesis, we are observing the effect which certain variables have when stock market index X has returns that are at or above the 90th percentile. For daily data, this threshold would be breached once every ten trading days, with the best trading day of the 10 being the event which is the primary focus of the quantile regression.

This regression begins by setting the US financial market as the dependent variable and observing how it is distributed. For clarification I note that a quantile is the same as a percentile meaning the 85th percentile is equivalent to the 85th quantile. Similarly, the most well-known quantile/percentile would be the 50th, which is also known as the median.

The equation for the quantile regression is as follows:

$$y_i = x_i\beta_q + e_i \qquad \text{(Equation 1)}$$

Such that β_q is a vector containing all unknown parameters associated with the qth quantile for the independent variables. The quantile regression minimizes the sum in an asymmetrical sense such that when there is an over prediction, the error is penalized with a factor of q, and when there is an under prediction, it is penalized with a factor of 1-q.

Which looks like:

$$\sum_i q|e_i| + \sum_i (1-q)|e_i| \qquad \text{(Equation 2)}$$

In its entirety, the quantile regression is performing the following:

$$Q(\beta_q) = \sum_{i:y_i \geq x_i\beta}^{N} q|y_i - x_i\beta| + \sum_{i:y_i < x_i\beta}^{N} q|y_i - x_i\beta| : while\ 0 < q < 1 \qquad \text{(Equation 3)}$$

The standard conditional quantile can be specified as:

$$Q_q(y_i|x_i) = x_i\beta_q \qquad \text{(Equation 4)}$$

which is linear. Looking at the rate of change we see when the first derivative is found with respect to j, we observe a marginal effect of:

$$\frac{\partial Q_q(y|x)}{\partial x_j} = \beta_{qj} \qquad \text{(Equation 5)}$$

This is the effect of the dependent variable on the independent variable conditional on the independent variable remaining in the same quantile. It is important to note that the regression results are only applicable when the independent variable is in the same pre-specified quantile. (Katchova, 2013)

Variance

The variance for the portfolio is calculated using a factor return method used by MSCI Barra; this method uses the following equation:

$$\sigma^2 = h^T(X^T F X + \Delta)h \qquad \text{(Equation 6)}$$

Where h is the vector of the holdings in the portfolio, X is the matrix of exposures, F is the covariance matrix of returns, and Δ is a diagonal matrix of the specific return variances. Note that a superscript of T denotes the transpose of the respective matrix. (Barbieri et al., 2009)

Diversification Effect

As commonly known, the normal variance equation is:

$$\sigma^2_{portfolio} = w_1^2\sigma_1^2(asset\ 1) + w_2^2\sigma_2^2(asset\ 2) + 2w_1w_2cov(asset\ 1, asset\ 2) \quad \text{(Equation 7)}$$

When working with a multi-asset portfolio, this expands to:

$$\sigma^2_{portfolio} = \sum_{i=1}^{n} w_i^2\sigma_i^2 + \sum_{i=1}^{n}\sum_{j=i+1}^{n} 2w_iw_jcov(asset\ i, asset\ j) \quad \text{(Equation 8)}$$

And when the weights are equal, as is the case applied in my research, variance is further simplified to:

$$\sigma^2_{portfolio} = \frac{\sigma^2_{average}}{n} + \frac{n-1}{n}cov_{average} \quad \text{(Equation 9)}$$

This is the basis of the widely-known fact that diversification can decrease risk exposure. By looking at the previously presented equations, it becomes evident that the risk will decrease as the number of assets included in the portfolio grows. Thus when looking at the results in the coming sections, we need to be aware of how our four data-set-created variances will be significantly smaller than that of the US market variance. The lower variance will, in turn, lead to the CoVaR levels being lower.

Conditional Value at Risk (CoVaR)

$CoVaR_q^{j|i}$ is the Value at Risk (VaR) of institution j, conditional on a state which institution i is in $C(X^i)$; this conditional event is chosen when i is in a "stress" situation such that $X^i = VaR_q^i$. So we then arrive to

$$\Pr\left(X^j \leq CoVaR_q^{j|i} \middle| X^i = VaR_q^i\right) = q \quad \text{(Equation 10)}$$

This will show us the VaR for institution j when institution i is in distress, at or below its pre-defined q% VaR level. (Adrian & Brunnermeier, 2011)

In the case of this research, I consider institution i to be the US financial market, represented by the S&P 500 index, and institution j to be a bundle of various countries' stock market indexes. This will be further explained in the methodology section.

3.2 Data Set

Several data sets are used for this research. The 25 major trade partners of the US from January 1, 2004, to the end of December 2015 are used as the base sample. These 25 are derived from all countries which were, at one point, either a top 15 importer or exporter of trade goods with the US over the 2004 to 2015-time period. This was determined from the annual year-to-date trade numbers reported on the US census in December of each year. For each of the countries, in the 25 country sample, a major market index for that country was selected. The indexes were selected based on a couple criteria. Firstly, the market index needed to be composed primarily of companies which were based in the country. For example, in the US the S&P 500 was chosen as all companies belonging to this index are based in the US. This is important as the assumption of using a market index for the country's economic activity would need to be reflected in the underlying financial result of those companies, which in turn represent either a growing or shrinking economy. Secondly, indexes with the largest time span were selected. If a country had two major market indexes, and one was an older and more established index, this one was selected. This criteria is included because one calculation uses a 21 year time-frame; the index would need to have been in existence since at least January 1, 1995, to be included in the long time-frame calculation. A quick overview of each of the market indexes selected is shown in Appendix 1.

Based on the aforementioned criteria, a sample of the 25 countries' indexes is created. Several data sets are then created using this data. One is created from the start of 1995 through the end of July 2016. This data set will be used to evaluate whether globalization and increasing international trade are leading to further linkages through trade between the US markets and foreign trade partners' markets. Another data set is created with data from 2004 through the end of 2015. This is a composite cross-sectional index, where the country's import/export trade rank is used to create a return series. This is done by examining one country's trade rank and then using the country's major return in that year for the index. For example, in 2008, Germany was the 5th largest export partner of the US, so for the export rank 5th index from January 1, 2008, through December 31, 2008, the returns are equal to that of the German index. While in 2015, Germany fell to the 6th largest exporter and so from January 1, 2015, through December 31, 2015, Germany's market returns are in the export rank 6th index. Next, returns are examined to see what behavior the trade partners' indexes have on the US markets. The research I conducted focuses solely on various quantiles in the left tail, the worst 10%, 5% and 1% of daily returns and the worst 10% of monthly returns.

Lastly, several key commodities are used to see if the returns on these commodities have an effect on the US market when observing tail behavior. All returns are total returns composed of index and currency returns. All market price, currency value and commodity price data is collected from Bloomberg. The rankings of the top 15 import and export partners have been assembled in a table presented in Appendix 2.

3.3 Research execution

The price data is transformed into return data using logarithmic returns. Due to the varying trading days, a couple market indexes needed to be modified. Four countries' indexes required an adaptation due to slightly different trading days throughout the year. The countries affected by the modifications are: South Korea, Taiwan, India and Saudi Arabia. The modification was performed by making the price which the index closed at equal to the price from the previous close, representing a return of zero for the days which the index was not traded.

Quantile regressions were then used to analyze the index return data sets. These regressions were performed using Matlab. The quantile regression function used was created by Shapour Mohammadi from the University of Tehran in 2008. (Mohammadi, 2008)

The quantile regressions are run in a rolling window, a 60-day roll frequency is used for daily data and a 2-month roll frequency for monthly data. The time width of the rolling window varies in order to accommodate the number of exceedances that occur within the window. For the daily data, this number is set at 10. For example, when looking at the 90th quantile, 100 days are used as the rolling window time frame which gives a sample of 10 days that are deemed to be in exceedance of the 90th quantile. This is done so that no one day plays too much of a role in the determination of the regression coefficients.

Unfortunately when working with a monthly time frame, the number of exceedances needs to be reduced due to the smaller sample size of only 144 months. This leads to the number of observed exceedances decreasing to 5 when using the monthly timeframe. Additionally, due to the shorter timeframe the 95th and 99th quantiles cannot be used for the monthly return series. This is due to the fact that the 2008 financial crises falls within the initial window and remains within the window for the entire sample, which leads to the same exceedances being used throughout the entire rolling window. Thus, such analysis does not present results which are of any use.

At each point in the rolling window, a quantile regression is performed with 4 data sets: the import composite index, export composite index, the sample of 25 countries, and lastly the 33 commodities. From each point, using the result of the respective quantile regression, a variance is found for each data set. The variance is then used to calculate the conditional value at risk level for that data point. The sample of each data set composed CoVaR is then regressed on the actual US market CoVaR. This is done to see which measure is best for comparison with the CoVaR found in the US market. Each of the 4 Portfolio CoVaRs is regressed individually against that of the US. In addition, the Export/Import/Country in combination with the commodity Portfolio CoVaR are regressed against that of the US. An examination of the results using this methodology will be explored in the next section.

To examine how the relationships between markets are changing over time, a similar approach to that discussed in the previous section is used. A time frame from the beginning of

1995 until the end of July 2016 is used. For this time frame, a sample of 21 countries is used. These are all from the previous sample of 25 countries used minus Italy, Nigeria, Russia and Vietnam. These four countries are excluded as they did not have a uniform and continuous return index for the entire time frame.

Only one time frame, monthly, is used due to the fact that several indices had different trading cycles for the earlier time portion. For example, some only traded every two days or did not trade on Fridays. This was a concern that Karolyi and Stulz expressed with their research when dealing with return data across many countries in the 1990s. (Karolyi & Stulz, 1995) When looking at which quantile to use the 90^{th}, quantile was selected. A rolling window with a length of 50 months was set-up and the roll frequency was every 4 months. This rolling window length is selected such that there are 5 exceedances in each window observation. This leads to 53 data points being collected. These 53 data points are then converted into CoVaR measures, which are then regressed against the US market CoVaR. The regressions are run on a rolling window basis where 25 CoVaR calculated data points are included in each regression, and the points are rolled over one at a time. This leads to 28 regressions being run with the country calculated CoVaR against the actual CoVaR observed in the US market over the same period. The figures found from this analysis are presented in the following results section.

4. Results

4.1 Daily Time Frame

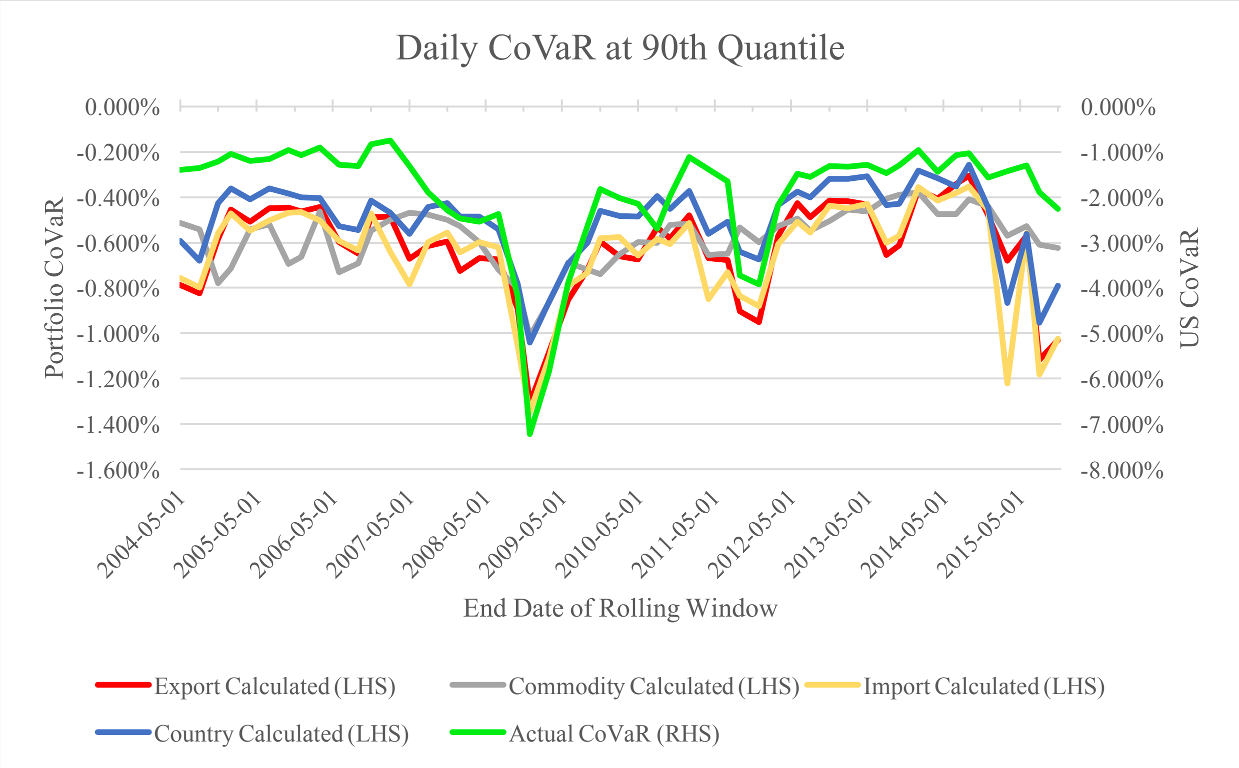

Figure 1 (Daily CoVaR at 90th Quantile)

Looking at figure 1 we can see that the "Portfolio CoVaR" which is created as a composition of either Exports/Imports/Country/Commodity returns has a shape which closely resembles that of the actual CoVaR in the US stock market. There is an increase in early 2007 which every data set picks up. The major market crash in 2008 is significantly larger in the US. This is to be expected as it was primarily a US caused crash thus it makes sense that we see it have the largest effect on the US in addition to there being no real signs in other markets of the crash prior it happening. In early 2011 we can see that foreign markets had an increase in their CoVaR. Seeing as how the foreign credit crisis was taking place during this time and its origination was in Europe this makes sense. We can see how the European markets fell first, triggering what should have been a fall in the US markets, although it took a little long for the crisis to be felt in the US.

Looking at the regression results found in appendix 3, we see when each Portfolio

CoVaR is regressed on the US market CoVaR that the export composite index combined with the commodity results create the best match of Daily US CoVaR at the 90% threshold as they match around 64.3% of the risk. Meanwhile, the composite import and commodity falls short of the export measure with 53.7% of risk matched.

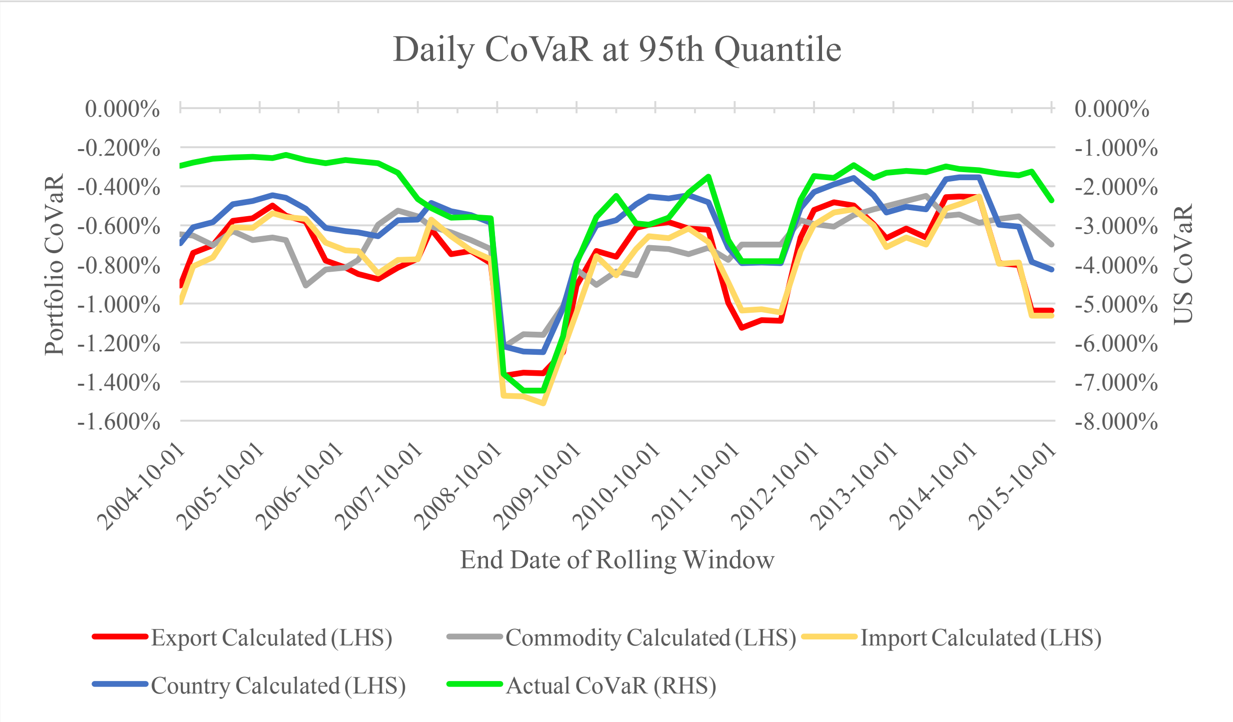

Figure 2 (Daily CoVaR at 95th Quantile)

Looking at figure 2 we can see the daily CoVaR at the 95th quantile level. There is slightly less movement and the CoVaR level tends to persist a little longer. This is due to the longer time frame in the rolling window to accommodate the number of exceedances observed. Similar to the 90th quantile results we see that there is change in foreign CoVaR prior to the 2008 crisis although for 2011 yet again all Portfolio CoVaRs are lower.

The regression results of the daily Portfolio CoVaRs on that of the US at the 95% level, found in appendix 4, have two items of note. Firstly, the import composite index combined with the commodity returns provide the better risk match for that of US CoVaR as they correspond to 75.8% match of the risk. Meanwhile, the export composite with the commodity returns accounts for slightly less, 72.5% of the risk. Secondly, we see how the overall matching of the composite CoVaRs with the actual US CoVaR increases. This is in line with the current theory proposed by Forbes and Rigobon of how inter-market correlations increase in times of troubled markets. (Forbes & Rigobon, 2002)

Moving on to the daily CoVaR at the 99% level, seen in figure 3, the first item of note is how there is significantly less movement in the CoVaR of the US market. Again this is due to the modification in the time window to accommodate for setting the minimum number of exceedances to 5. Again, Portfolio CoVaR has a similar shape to that of the US market CoVaR. There is a noticeably prolonged period of significantly higher CoVaR during the 2008-11 period to 2012-11. This is due in large part to the exceedance values in the 99th quantile remaining unchanged during the time frame. This causes the flat shape of the graph during this observation period. Baig and Goldfajn noted in their research how as the length of the rolling window increases the effects will be smaller. (Baig & Goldfajn, 1999)

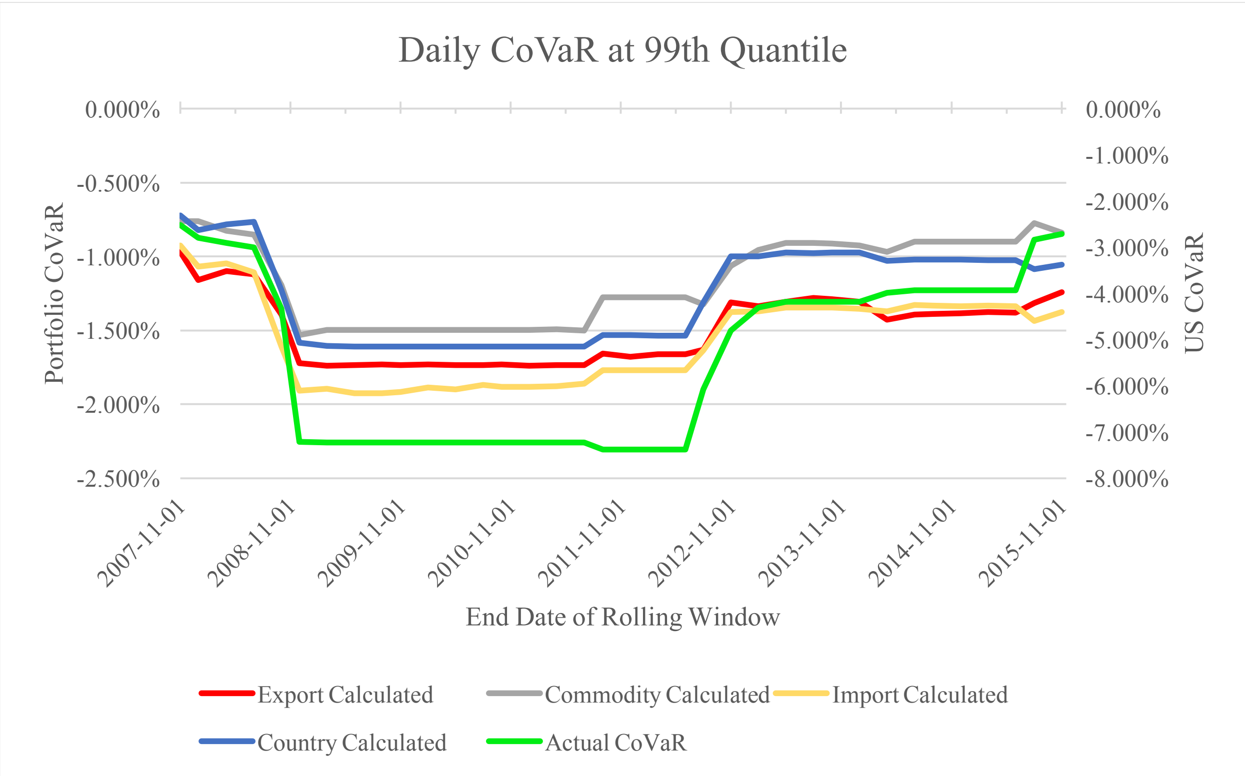

Figure 3 (Daily CoVaR at 99th Quantile)

Yet again we see an increase in the matching of our Portfolio CoVaRs with the US portfolio this is similar with the aforementioned interconnectedness during tumultuous times. The export composite combined with the commodity returns provide the best risk matching as they are matching 93.7% of the US market risk. While the import composite and commodity account for a 92% match of US market risk.

4.2 Monthly Time Frame

The final chart which looks at the import vs export relation is figure 4. The time frame for this final figure is one month at the 90th quantile. A similar trough is observed from the end of 2008 through to the end of 2012 as in the previously examined daily CoVaR at 99%. Once again this is due to a lack of turnover in the exceedance points which remained low from the 2008 crisis until they exit the rolling window in the end of 2012.

From a risk matching perspective, the import versus export comparison is close yet again. The import composite with commodity returns provides a slightly better match to that of the US, accounting for a 57.7% match. While the export composite and commodity returns provide a 55.9% match to the tail risk of the US market.

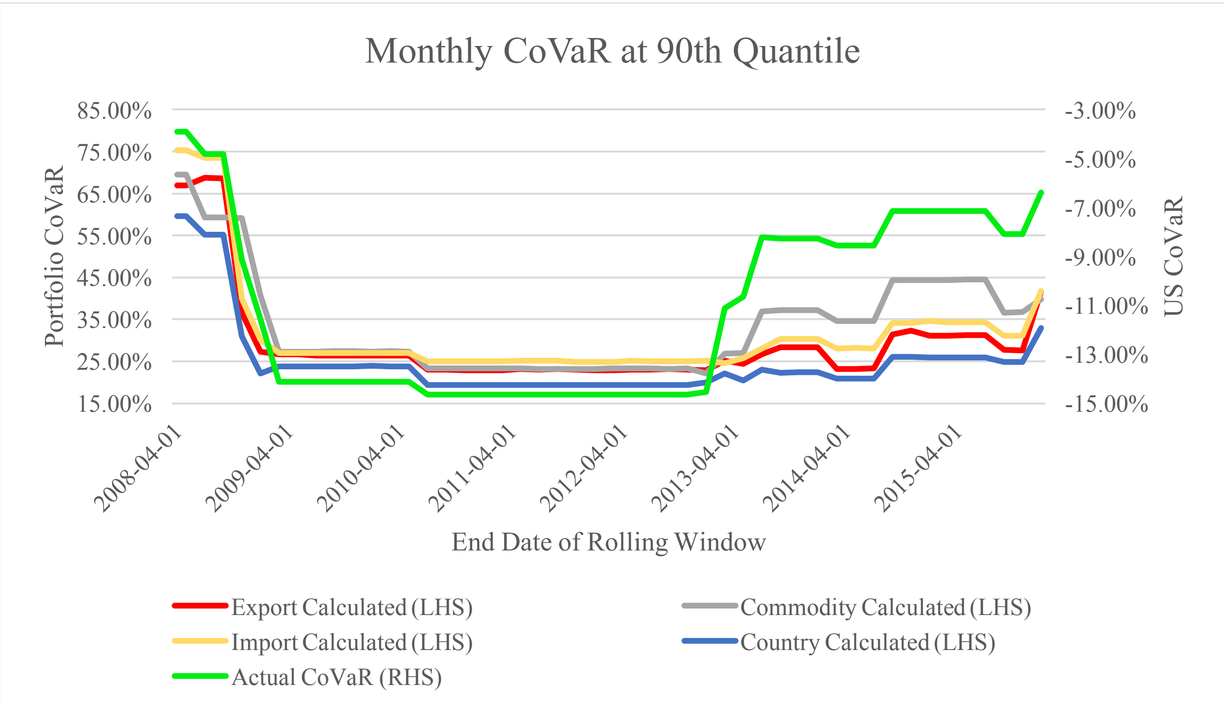

Figure 4 (Monthly CoVaR at 90th Quantile)

4.3 Import vs Export

The question as to whether import or export partners provide a better matching of market risk remains muddled. It appears to depend upon the time frame and quantile chosen. The lack of a definitive answer leads to the conclusion that both play an important role in risk management and countries should be cautious when engaging in a trade relationship with one another as their financial markets do become more interconnected. Within each time frame and quantile set the import composite with commodity or export composite with commodity return provides the dominant risk match. This further demonstrates how current trade relationships are the most important and historical trade relations are dwarfed in comparison to those which are currently taking place.

4.4 Rolling Window over time

A process similar to that previously discussed in the Portfolio CoVaR calculation was used. The sole component for the Portfolio CoVaR calculation over the 1995 to the end of July 2016 is the Country calculated CoVaR.

Each rolling window data point has a total time frame of 50 months, 25 rolling window data points are then used in the regression so each point on the graph represents the relation between the financial markets over the last 150 months, or 12 and a half years. So the first data point runs from the start of 1995 through the end of June 2007, with the second taking place 4 months later from April 1995 through the end of October 2007. This regression is run advancing one observation at a time which results in 28 observations comparing how well the country Portfolio CoVaR does at matching to the US market CoVaR.

The key results from the 28 regressions have been plotted in figure 5. Looking at this figure there are a few key items of note. Firstly, we see how over time the fit of the country Portfolio CoVaR is increasing its risk match with the US market. This is a demonstration of how the financial markets are becoming more interconnected. The results are highly significant, after the first 6 observations, which from a date perspective corresponds to the end of 1996, all data points remain significant to the 95% confidence level.

As shown a portfolio of 21 stocks is going to have a much lower calculated standard deviation due to the diversification effect. We note that over the sample the coefficient required to multiply this deviation converges to approximately a factor of 3.5. This shows when the US markets experience a monthly return which would be in exceedance of their 90th quantile the CoVaR of the US markets should be roughly 3.5 times greater than the 21-country Portfolio CoVaR.

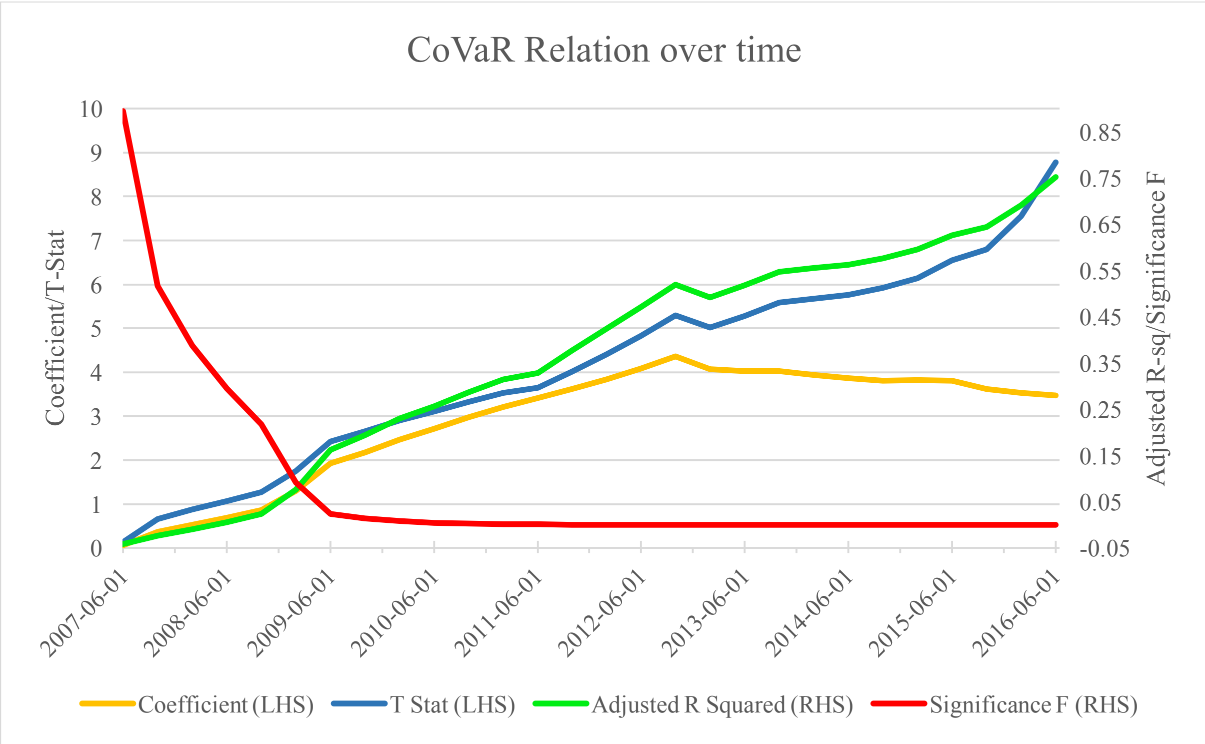

Figure 5 (CoVaR Relation over time)

5. Further research and Conclusion

Further Research

This thesis focused on using current market data to match risk exposures. One potential area of future research could attempt to use current market exposure to forecast the future CoVaR. This would be similar to Adrian and Brunnermeier's (Adrian & Brunnermeier, 2011) Forward-CoVaR measure except using various country market index and debt data which is much higher frequency than monthly or quarterly reported macroeconomic data. This would allow risk managers to forecast or nowcast their risk measures in real time based on historical financial market relations.

Institutional investors could delve further into the individual country by country exposures which arise out of the US market. They could create an alternative hedging strategy which is only enacted when market returns approach the tails since the interconnectedness of financial markets increases in times of crisis.

Policy makers could look at other countries and their financial markets and make more proactive decisions with the knowledge that their decisions will be affecting other economies. With increased communication between regulators further steps could be taken to ensure the stability of the global financial system recognizing its increasingly interconnected nature versus the current country by country management. This is similar to a combination of the idea of increased transparency to decrease crisis effects, expressed by Chang and Majnoni, and the idea of VanHoose to increase the cooperation amongst regulators. (Chang & Majnoni, 2001; VanHoose, 2015) With increased transparency on the part of regulators there's less incentive for regulators to cheat one another as they can work together to achieve mutually beneficial optimal solutions for financial system stability.

Conclusion

Based on the previously determined definition of contagion by Forbes and Rigobon (Forbes & Rigobon, 2002) this research does not satisfy the conditions to conclude that there is contagion. It does satisfy their definition of increasing interconnectedness, which they also determine to be present in financial markets. I also find that there has been an increase in the interconnectedness of financial markets in times of turmoil over the last 21 years, from the start of 1995 through the end of July 2016. This result is consistent with that of Chan-Lau et al. who found that from 1998 through 2001 interconnections were increasing among countries. (Chan-Lau et al., 2004) The result is contrary to that of Bordo and Murshid who found that from World War 1 through the end of the Asian crisis, there was no noticeable increase in the interconnection of financial markets. (Bordo & Murshid, 2000)

In terms of determining the source of the interconnection, I find that trade linkages do increase the likelihood of interconnectedness amongst financial markets. This is seen as the Portfolio CoVaR of import/export composite indexes with commodity returns provides a dominant risk match to that of the US financial market. This result is found at the 90^{th}, 95^{th} and 99th quantiles during the daily time frame and 90^{th} quantile during the monthly time frame. This reaffirms the ideas of trade being a source of financial stress transmission. (Baig & Goldfajn, 1999; Bordo & Murshid, 2000; Forbes & Rigobon, 2002; Peckham, 2013)

Appendices

Appendix 1: Index Description

Country	Index Ticker	Index Description
Canada	SPTSX	The S&P/Toronto Stock Exchange Composite Index is a capitalization-weighted index designed to measure market activity of stocks listed on the TSX.
China	SHCOMP	The Shanghai Stock Exchange Composite Index is a capitalization-weighted index. The index tracks the daily price performance of all A-shares and B-shares listed on the Shanghai Stock Exchange.
Mexico	MEXBOL	The Mexican IPC index is a capitalization weighted index of the leading stocks traded on the Mexican Stock Exchange.
Japan	NKY	The Nikkei-225 Stock Average is a price-weighted average of 225 top-rated Japanese companies listed in the First Section of the Tokyo Stock Exchange. The Nikkei Stock Average was first published on May 16, 1949, where the average price was ¥176.21 with a divisor of 225.
Germany	DAX	The German Stock Index is a total return index of 30 selected German blue chip stocks traded on the Frankfurt Stock Exchange. The equities use free float shares in the index calculation.
United Kingdom	UKX	The FTSE 100 Index is a capitalization-weighted index of the 100 most highly capitalized companies traded on the London Stock Exchange.
South Korea	KOSPI2	The KOSPI 200 Index is a capitalization-weighted index of 200 Korean stocks which make up 93% of the total market value of the Korea Stock Exchange.
Taiwan	TWSE	The TWSE, or TAIEX, Index is capitalization-weighted index of all listed common shares traded on the Taiwan Stock Exchange.
France	CAC	The CAC 40, the most widely-used indicator of the Paris market, reflects the performance of the 40 largest equities listed in France, measured by free-float market capitalization and liquidity.
Malaysia	FBMKLCI	The FTSE Bursa Malaysia KLCI Index comprises of the largest 30 companies by full market capitalization on Bursa Malaysia's Main Board.
Italy	FTSEMIB	The Index consists of the 40 most liquid and capitalized stocks listed on the Borsa Italiana.
Ireland	ISEQ	The ISEQ Overall Index is a capitalization-weighted index of all Official list equities in the Irish Stock Exchange but excludes UK registered companies.
Venezuela	IBVC	The IBC Index from the Caracas Stock Exchange (Venezuela), also known as the General Index, is a capitalization-weighted index of the 15 most liquid and highest capitalized stocks traded on the Caracas Stock Exchange (Bolsa de Valores de Caracas).
Brazil	IBOV	It is a gross total return index weighted by market value to the free float & is comprised of the most liquid stocks traded on the Sao Paulo Stock Exchange.
Saudi Arabia	SASEIDX	This is the Tadawul All Share Index (TASI). It is disseminated by the Saudi Stock Market.
Nigeria	NGSEINDX	The Nigerian Stock Exchange All Share Index was formulated in January 1984 with a base value of 100. Only ordinary shares are included in the computation of the index. The index is value-relative and is computed daily.
India	SENSEX	The S&P BSE Sensex Index is a cap-weighted index. The index members have been selected on the basis of liquidity, depth, and floating-stock-adjustment depth and industry representation.
Russia	INDEXCF	MICEX Index is cap-weighted composite index calculated based on prices of the 50 most liquid Russian stocks of the largest and

		dynamically developing Russian issuers presented on the Moscow Exchange.
Switzerland	SMI	The Swiss Market Index is an index of the largest and most liquid stocks traded on the Geneva, Zurich, and Basel Stock Exchanges.
Vietnam	VNINDEX	The Vietnam Stock Index or VN-Index is a capitalization-weighted index of all the companies listed on the Ho Chi Minh City Stock Exchange.
Netherlands	AEX	The AEX-Index is a free-float adjusted market capitalization weighted index of the leading Dutch stocks traded on the Amsterdam Exchange.
Singapore	STI/STIOLD	The Straits Times Index (STI), maintained & calculated by FTSE, is the most globally-recognized benchmark index and market barometer for Singapore. It tracks the performance of the top 30 largest and most liquid companies listed on the Singapore Exchange.
Belgium	BEL20	The BEL 20 Index is a modified capitalization-weighted index of the 20 most capitalized and liquid Belgian stocks that are traded on the Brussels Stock Exchange. The equities use free float shares in the index calculation.
Hong Kong	HIS	The Hang Seng Index is a free-float capitalization weighted index of a selection of companies from the Stock Exchange of Hong Kong. The components of the index are divided into four sub-indices: Commerce and Industry, Finance, Utilities, and Properties.
Australia	AS51	The S&P/ASX 200 measures the performance of the 200 largest index-eligible stocks listed on the ASX by float-adjusted market capitalization. Representative liquid and tradable, it is widely considered Australia's preeminent benchmark index. The index is float-adjusted.

*Definitions are taken from Bloomberg

Appendix 2: Import and Export Rank Data

Import	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	Canada	Canada	Canada	China	China	China	China	China	China	China	China	China
2	China	China	China	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada
3	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico
4	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan
5	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany	Germany
6	United Kingdom	United Kingdom	United Kingdom	United Kingdom	United Kingdom	United Kingdom	United Kingdom	Korea, South	Korea, South	Korea, South	Korea, South	Korea, South
7	South Korea	South Korea	Korea, South	Korea, South	Saudi Arabia	Korea, South	Korea, South	United Kingdom	Saudi Arabia	United Kingdom	United Kingdom	United Kingdom
8	Taiwan	Taiwan	Taiwan	France	Venezuela	France	France	Saudi Arabia	United Kingdom	Saudi Arabia	Saudi Arabia	France
9	France	Venezuela	Venezuela	Venezuela	Korea, South	Taiwan	Taiwan	Venezuela	France	France	France	India
10	Malaysia	France	France	Taiwan	France	Venezuela	Ireland	Taiwan	India	India	India	Italy
11	Italy	Malaysia	Malaysia	Saudi Arabia	Nigeria	Ireland	Venezuela	France	Taiwan	Italy	Italy	Taiwan
12	Ireland	Italy	Italy	Italy	Taiwan	Italy	Saudi Arabia	Ireland	Venezuela	Taiwan	Taiwan	Ireland
13	Venezuela	Ireland	Saudi Arabia	Malaysia	Italy	Malaysia	Nigeria	India	Italy	Venezuela	Ireland	Vietnam
14	Brazil	Saudi Arabia	Ireland	Nigeria	Ireland	Saudi Arabia	India	Russia	Ireland	Ireland	Switzerland	Malaysia
15	Saudi Arabia	Brazil	Nigeria	Ireland	Malaysia	India	Italy	Italy	Brazil	Switzerland	Vietnam	Switzerland

Export	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
1	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada	Canada
2	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico	Mexico
3	Japan	Japan	Japan	China	China	China	China	China	China	China	China	China
4	United Kingdom	China	China	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan	Japan
5	China	United Kingdom	United Kingdom	United Kingdom	Germany	United Kingdom	United Kingdom	United Kingdom	United Kingdom	Germany	United Kingdom	United Kingdom
6	Germany	Germany	Germany	Germany	United Kingdom	Germany	Germany	Germany	Germany	United Kingdom	Germany	Germany
7	Korea, South	South Korea	Korea, South	Korea, South	Netherlands	Netherlands	Korea, South	Korea, South	Brazil	Brazil	Korea, South	Korea, South
8	Netherlands	Netherlands	Netherlands	Netherlands	Korea, South	Korea, South	Brazil	Brazil	Korea, South	Netherlands	Netherlands	Netherlands
9	Taiwan	France	Singapore	France	Brazil	France	Netherlands	Netherlands	Netherlands	Hong Kong	Brazil	Hong Kong
10	France	Taiwan	France	Taiwan	France	Brazil	Singapore	Hong Kong	Hong Kong	Korea, South	Hong Kong	Belgium
11	Singapore	Singapore	Taiwan	Singapore	Belgium	Singapore	France	Singapore	Australia	France	Belgium	Brazil
12	Belgium	Belgium	Belgium	Belgium	Singapore	Belgium	Hong Kong	Belgium	France	Belgium	France	France
13	Hong Kong	Hong Kong	Brazil	Brazil	Taiwan	Hong Kong	Taiwan	France	Singapore	Singapore	Singapore	Singapore
14	Australia	Australia	Australia	Hong Kong	Australia	Australia	Belgium	Australia	Belgium	Switzerland	Taiwan	Taiwan
15	Brazil	Brazil	Hong Kong	Australia	Switzerland	Taiwan	Australia	Taiwan	Switzerland	Australia	Australia	Australia

Appendix 3: Regression Results: Daily at 90^{th} Quantile

Regression Results: Daily at 90th Quantile

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.009678579	0.003464429	2.793700796	0.00741499
Export Calculated	4.615541999	0.523190984	8.821906608	1.08806E-11
	Observations	R Square	Adjusted R Square	Significance F
	51	0.613644	0.605759184	1.08806E-11

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.005007094	0.003934691	1.272550894	0.209182883
Import Calculated	3.739382039	0.571606178	6.541885273	3.40136E-08
	Observations	R Square	Adjusted R Square	Significance F
	51	0.466209207	0.455315517	3.40136E-08

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.005571589	0.00396603	1.404827786	0.166380469
Country Calculated	4.922284784	0.742460359	6.629693725	2.48652E-08
	Observations	R Square	Adjusted R Square	Significance F
	51	0.472850958	0.462092814	2.48652E-08

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.016226229	0.00642398	2.525884017	0.014823442
Commodity Calculated	6.113305688	1.079542699	5.66286604	7.7057E-07
	Observations	R Square	Adjusted R Square	Significance F
	51	0.395569538	0.383234222	7.7057E-07

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.018653385	0.004903801	3.803862627	0.000402907
Export Calculated	3.723138943	0.61495641	6.054313581	2.0713E-07
Commodity Calculated	2.508021444	1.01448251	2.472217528	0.017023971
	Observations	R Square	Adjusted R Square	Significance F
	51	0.657282375	0.643002474	6.89405E-12

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.018203298	0.005585863	3.258815796	0.002059034
Import Calculated	2.639277915	0.634901572	4.156987528	0.000132165
Commodity Calculated	3.500683173	1.126838508	3.106641411	0.003174474
	Observations	R Square	Adjusted R Square	Significance F
	51	0.555569549	0.537051614	3.52607E-09

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.017519739	0.00562065	3.117030767	0.003083079
Country Calculated	3.474094615	0.862685289	4.02707066	0.000200095
Commodity Calculated	3.31463869	1.171419595	2.829591295	0.006784547
	Observations	R Square	Adjusted R Square	Significance F
	51	0.548211105	0.529386567	5.22942E-09

Appendix 4: Regression Results: Daily at 95th Quantile

Regression Results: Daily at 95th Quantile

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.013337507	0.004494719	2.967372627	0.004712151
Export Calculated	4.941249947	0.557118168	8.869303195	1.32724E-11
	Observations	R Square	Adjusted R Square	Significance F
	49	0.625988363	0.618030669	1.32724E-11

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.015314364	0.004011665	3.817458349	0.000393611
Import Calculated	5.072626136	0.485033465	10.45830134	7.39216E-14
	Observations	R Square	Adjusted R Square	Significance F
	49	0.699442498	0.693047658	7.39216E-14

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.011777313	0.003596361	3.274786346	0.001989254
Country Calculated	5.993457466	0.557984384	10.74126379	3.02941E-14
	Observations	R Square	Adjusted R Square	Significance F
	49	0.710546125	0.704387532	3.02941E-14

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.022962009	0.00600407	3.824407056	0.000385255
Commodity Calculated	6.783694126	0.830524333	8.167965534	1.43172E-10
	Observations	R Square	Adjusted R Square	Significance F
	49	0.586688416	0.577894552	1.43172E-10

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.026924842	0.004903904	5.49049118	1.66778E-06
Export Calculated	3.175182117	0.619717005	5.12360011	5.79921E-06
Commodity Calculated	3.868947739	0.878824634	4.402411572	6.32213E-05
	Observations	R Square	Adjusted R Square	Significance F
	49	0.736858179	0.72541723	4.61708E-14

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.025878912	0.004573609	5.65831362	9.38789E-07
Import Calculated	3.563238468	0.594492437	5.993749029	2.95892E-07
Commodity Calculated	3.198360973	0.868064485	3.684473939	0.00060199
	Observations	R Square	Adjusted R Square	Significance F
	49	0.7679301	0.757840105	2.56586E-15

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.02101886	0.004706676	4.465754693	5.14708E-05
Country Calculated	4.354411002	0.783258598	5.559352958	1.31783E-06
Commodity Calculated	2.735209797	0.975632776	2.803523891	0.007377293
	Observations	R Square	Adjusted R Square	Significance F
	49	0.752786094	0.742037663	1.09819E-14

Appendix 5: Regression Results: Daily at 99th Quantile

Regression Results: Daily at 99th Quantile

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.059080341	0.005814856	10.16024129	7.75208E-12
Export Calculated	7.570295375	0.386262625	19.59882961	4.20235E-20
	Observations	R Square	Adjusted R Square	Significance F
	36	0.918682488	0.916290797	4.20235E-20

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.036036977	0.005204646	6.924001071	5.58163E-08
Import Calculated	5.741819935	0.327587094	17.5276134	1.34304E-18
	Observations	R Square	Adjusted R Square	Significance F
	36	0.900356732	0.897426048	1.34304E-18

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.016083134	0.003434454	4.682879291	4.41038E-05
Country Calculated	5.543449194	0.265197727	20.9030796	5.53468E-21
	Observations	R Square	Adjusted R Square	Significance F
	36	0.927803773	0.925680354	5.53468E-21

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.016739336	0.003919444	4.270844447	0.000148023
Commodity Calculated	6.086133373	0.329544854	18.46830042	2.6762E-19
	Observations	R Square	Adjusted R Square	Significance F
	36	0.909352217	0.906686106	2.6762E-19

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.04241133	0.00689604	6.150098947	6.20693E-07
Export Calculated	4.2247143	1.004410103	4.206164682	0.000186726
Commodity Calculated	2.866567763	0.811626777	3.531879238	0.001242395
	Observations	R Square	Adjusted R Square	Significance F
	36	0.940988965	0.937412539	5.25289E-21

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.027023307	0.005342619	5.058064115	1.55458E-05
Import Calculated	2.607521132	0.9962055	2.617453056	0.013267752
Commodity Calculated	3.453890766	1.050708087	3.28720299	0.002406623
	Observations	R Square	Adjusted R Square	Significance F
	36	0.92493608	0.920386751	2.78366E-19

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.017705095	0.003277169	5.40255688	5.62232E-06
Country Calculated	3.49396501	0.876234463	3.987477275	0.000348627
Commodity Calculated	2.369552373	0.971725783	2.438499023	0.020296187
	Observations	R Square	Adjusted R Square	Significance F
	36	0.938826618	0.935119141	9.5122E-21

Appendix 6: Regression Results: Monthly at 90th Quantile

Regression Results: Monthly at 90th Quantile

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.028310425	0.018003525	1.572493478	0.122689874
Export Calculated	4.654473585	0.591469231	7.869341877	4.61124E-10
	Observations	R Square	Adjusted R Square	Significance F
	48	0.573784175	0.564518613	4.61124E-10

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.045695816	0.019460509	2.34813051	0.02322295
Import Calculated	4.870433942	0.596724585	8.161946175	1.70872E-10
	Observations	R Square	Adjusted R Square	Significance F
	48	0.591537239	0.582657614	1.70872E-10

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.018967472	0.016799279	1.129064656	0.264724376
Country Calculated	5.084056282	0.644430923	7.889218378	4.30959E-10
	Observations	R Square	Adjusted R Square	Significance F
	48	0.575017561	0.565778812	4.30959E-10

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.012530218	0.031956713	0.392099697	0.69679537
Commodity Calculated	3.672930619	0.942821535	3.895679598	0.000315329
	Observations	R Square	Adjusted R Square	Significance F
	48	0.248075066	0.231728872	0.000315329

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.039870751	0.02463152	1.618688234	0.112502967
Export Calculated	4.356808109	0.733986498	5.935815059	3.88803E-07
Commodity Calculated	0.609788993	0.880872295	0.692255843	0.492333532
	Observations	R Square	Adjusted R Square	Significance F
	48	0.578275245	0.559531922	3.65725E-09

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.055586582	0.024691503	2.251243323	0.02930031
Import Calculated	4.58810348	0.738146984	6.21570443	1.49275E-07
Commodity Calculated	0.565254934	0.859582181	0.657592662	0.514149738
	Observations	R Square	Adjusted R Square	Significance F
	48	0.595425008	0.577443897	1.43707E-09

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.029880608	0.024362079	1.226521283	0.226381752
Country Calculated	4.786800084	0.805623836	5.941730955	3.81025E-07
Commodity Calculated	0.551468764	0.886101921	0.622353648	0.536850329
	Observations	R Square	Adjusted R Square	Significance F
	48	0.578644255	0.559917333	3.58592E-09

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