Financial Market Stress: Measuring Spillover Effects Across Countries

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Abstract

The wide-spread effects of the Global Financial Crisis reignited interest in the ability to measure financial market stress along with the ability to analyze the transmission of financial stress across markets. Building off of methods of Kliesen & Smith (2010) and Klößner & Sekkel (2014), this thesis measures financial market stress for five prominent countries in the form of financial stress indexes and estimates spillovers of financial stress between these indexes. I find that spillovers account for just above ten percent of the dynamics of financial stress in these countries, with spillovers peaking towards the end of the Global Financial Crisis. The United Kingdom and United States are responsible for larger portions of financial stress spillover, while the others are net receivers of spillover effects. Within the past two years, financial stress has been slowly increasing while spillover measures have been declining.

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1 Introduction

Since the early 2000s with the dot-com crisis and the widespread effects later on from the Global Financial Crisis (Guillén, 2009), there has been renewed interest in the measurement of financial stress with emphasis placed upon how the transmission of stress through markets. Several papers build upon techniques discussed in the creation of financial stress indexes (FSI) as seen in Illing & Liu (2003); Hakkio et al. (2009); Kliesen & Smith (2010); Grimaldi (2010); Monin (2019).. In part to analyzing stress and the effects there of, global interconnectedness is becoming greatly apparent. Global market interconnectedness is stressed as Monin (2019) incorporates various global financial data in the OFR FSI for the United States, and Danninger et al. (2009) found that financial stress spreads "rapidly to emerging economies" during times of financial crisis. This raises the question, does financial stress in one advanced economy affect financial stress in other advanced economies? Are shocks to financial markets in one nation transmissible across the global financial system to markets in other nations, and if so, how much will these shocks affect financial stress levels in other markets?

To answer these questions, my research utilizes the same methodology as used by Kliesen & Smith (2010) in the creation of the St. Louis Financial Stress Index. After replicating this index, I construct FSIs for the United States, Germany, India, Japan and the United Kingdom, while maintaining the same techniques and consistent data series across countries. Keeping data consistent is important as to capture stress in the same market sectors within each national economy. Then, by applying the Diebold & Yilmaz (2008) spillover model, as adapted by Klößner & Sekkel (2014), I measure spillover between FSIs, creating a total spillover index (SOI) and construct a rolling measure of spillover over time. Lastly, it is important to note that as in Diebold & Yilmaz (2008) and Klößner & Sekkel (2014), I do not attach a causal interpretation to the word spillover. Spillover and the creation of the spillover index highlight the overall and directional pairwise connectedness across all FSIs constructed.

I find lower levels of spillover between financial stress indexes than expected. The total spillover index, which explains variance among the FSIs, is approximately 11%. Furthermore, I find that spillover between FSIs are relatively uncorrelated to large changes in financial stress itself, while still significantly varying over time. Within the past few years, financial stress is increasing while spillover measures have been decreasing, implying resiliency of financial markets to shocks from foreign financial stress.

This paper proceeds as follows. First, in Section 2 we discuss financial stress and methods utilized to capture stress from market data and other indicators. In Section 2.1 and 2.2, I replicate the St. Louis Financial Stress Index (STLFSI) and then apply the same technique to construct a new FSI for the United States, incorporating data that is consistent across foreign FSI. Section 3 discusses the FSI constructed for Germany, India, Japan and the United Kingdom, and compares all five indexes together. Section 4 describes my spillover model and further discusses spillover results. Section 5 concludes my thesis.

2 Measuring Financial Stress

Although financial stress is a common topic of discussion that concerns policymakers and investors, financial stress is not directly observable. It manifests itself through market trends and shocks over periods of time. Generally, financial stress is defined as a "mix of market conditions, in which 'market participants experience increased uncertainty or change their expectations about future financial losses, fundamental value of assets, and economic activity" (Kliesen et al., 2012). Thus, financial stress is very multidimensional and implies various exogenous shocks from banks and financial markets (Kliesen et al., 2012). Prior to the creation of financial stress indexes, certain variables were used as indicators of market conditions, such as the yield curve, the federal funds rate, stock indexes, real Money2 (M2), the three month commercial paper rate spread, and real GDP growth (Manamperi, 2015). The issue with attempting to measure financial stress with individual variables alone is that they don't capture trends across the market as a whole. Single variables are not the only indicators plagued with this problem of a narrow focus.

Early attempts of measuring financial stress through indexes were also found to focus on specific market sectors. The financial stress index created by the Bank of Credit Analyst (BCA FSI) only captures stress in the banking sector, as it focuses its measure on the "composition of banking shares to total market shares" (Manamperi, 2015). In addition, the Volatility Index (VIX) created by the Chicago Board of Exchange (CBOE) only captures stress in the exchange market (Manamperi, 2015). Variables capturing different aspects of the financial market must be evaluated together to capture a broader understanding of financial stress throughout financial markets.

To understand what is meant by financial stress indexes, there are two main types of indexes created to measure stress in financial markets. Financial stress indexes (FSI) and financial conditions indexes (FCI) are very similar in some ways but different at their core in others. FSIs generally consist of financial variables only, and aim to capture a "snapshot of the level of fragility in the financial market." They look for evidence of shocks as opposed to directly measuring factors and shocks themselves. On the other hand, FCIs tend to incorporate financial and non-financial variables and map financial conditions onto macroeconomic conditions. For example, the Macroeconomic Advisors Monetary and Financial Conditions Index (MAFCI) constructed in 2003 maps directly into changes in real GDP. Thus FCIs like the MAFCI produce an observable relationship with the macroeconomy. Since FSIs don't produce an observable relationship, so they can only be measured relative to themselves (Kliesen et al., 2012). What is comparable between FSIs is their common trends and their abilities to capture shocks, and over the years, researchers have found different ways to improve their methods to measuring financial stress.

There are a variety of methods to create FSIs and FCIs, but two of the most common methods to create financial stress indexes are through the weighted sum method and through principal component analysis (Manamperi, 2015). Illing & Liu (2003) discussed how they improve their accuracy in their financial stress index for Canada's financial markets. They compared their index to results from a Bank of Canada survey concerning the the top ten severe events over the prior 25 years. They then narrowed down their number of variables to ten, from 150 potential market variables, covering 3 broad categories: Expected loss, Risk, and Uncertainty. They then constructed their index using the weight sum methodology. Each of their variables were weighted by their sample cumulative distribution function and then again by their relative market share.

Illing & Liu (2003)then summed the variables by date to create their daily index. Their index was fairly accurate when compared back to their list of severe events, and thus provided an example for others to follow in the creation of future financial stress indexes.

Shortly after Illing & Liu (2003), four of the United States' federal reserve banks created their own comprehensive financial stress indexes for US financial markets: the Chicago Federal Reserve Bank's Financial Conditions Index (NFCI) in 2006, the Kansas City Federal Reserve Bank's Financial Stress Index (KCFSI) in 2009, the St. Louis Federal Reserve Bank's Financial Stress Index (STLFSI) in 2010, and the Cleveland Federal Reserve Bank's Financial Stress Index (CFSI) in 2011, which was later discontinued due to uncovered calculation errors in the creation of the CFSI. Each of these indexes were created with their own individual focus. The Chicago Fed's NFCI was created by integrating 100 different financial variables that covered three market segments: the Money Market, the Debt and Equity Market, and the Banking system. Instead of using survey results, the researchers at the Chicago Fed used dynamic factor analysis to calculate appropriate weights for their data, which was then summed by date to create their index (Manamperi, 2015).

Research at the Kansas City Fed took a slightly different approach in the creation of the KCFSI. Hakkio et al. (2009) aimed to identify the key phenomena that occur during financial crises and selected data that capture these phenomena as opposed to data that capture shock from specific events in time. They incorporated 11 variables that were associated with at least one or more of their five identified key phenomena. Based upon the assumption that financial stress was the factor most responsible for co-movements between these variables, principal component analysis, which will be discussed further in depth in Section 2.1, was performed to capture this factor for the construction of the KCFSI. After normalizing the data, by subtracting the respective mean from each variable and then dividing it by its standard deviation, eliminate units from affecting co-movements within the data, the first principle component is capture and then applied to the dataset then the weighted dataset is summed by date to create the index(Manamperi, 2015).

The St. Louis Fed's STLFSI was created to improve upon the KCFSI. As noted by Kliesen & Smith (2010), the KCFSI was constructed using monthly data. To create a better real-time measurement of financial stress, the STLFSI incorporated 18 weekly variables that are split into three categories: Interest Rates, Yield Spreads, and Exchange Rates. Principal component analysis was performed and applied to the normalized data, just as done in the construction of the KCFSI. This paper further discusses the construction of the STLFSI in Section 2.1 along with the replication of this index.

Also building off of the KCFSI, Monin (2019) constructed the Office of Financial Research's Financial Stress Index (OFR FSI) in 2019, in part to fulfilling duties mandated by the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010. Using the same phenomena as Hakkio et al. (2009) identified for the construction of their index, the OFR FSI improved upon the KCFSI's calculation based upon monthly data by using a dynamic approach, consisting of both a dynamic factor model and principal component analysis. This allowed Monin (2019) to create a "real-time summary of the level of financial stress" and to use an evolving dataset, since the "financial system may evolve to a point where certain indicators are no longer appropriate and should be removed or even replaced." The OFR FSI incorporated 33 variables that cover five categories: Credit, Equity Valuation, Funding, Safe Assets, and Volatility. It also incorporated global data, citing the 2007-09 Global Financial Crisis as an illustration of a "highly interconnected" global financial system (Monin, 2019).

In addition to further measurements for financial stress in the United States, such as the Bloomberg Financial Conditions Index, CITI Group's Financial Conditions Index, and Goldman Sachs' Financial Conditions Index, research was also focused towards financial stress in financial markets in other parts the globe (Manamperi, 2015). The Organisation for Economic Co-operation and Development (OECD) constructed financial soundness indicators for different countries , and Danninger et al. (2009) at the International Monetary Fund (IMF) created financial stress indexes for both advanced economies and emerging economies.

2.1 Replication of the St. Louis Financial Stress Index

As mentioned previously, the St. Louis Financial Stress Index (STLFSI) was originally published by Kliesen & Smith (2010) at the Federal Reserve Bank of St. Louis. In order to create a better "real-time" snapshot of financial conditions than currently existed in the form of the monthly KCFSI, Kliesen & Smith (2010) takes into account 18 different weekly variables that are described by three categories: interest rates, yield spreads, and exchange and inflationary pressures. This index begins 1993 and is updated on a weekly basis. To help understand the STLFSI, positive values represent elevated levels of financial stress. Values of zero represent "normal" financial conditions. Lastly, negative values represent healthy financial conditions with less financial stress.

I choose to focus my research towards the methods used to construct the STLFSI. Their data, goals, and methods are relatively straightforward. Unlike a few other indexes, they do not use their own constructed banking or financial "betas" and all their data is rooted in financial markets. I start by collecting the same data as they report, as seen in Table 1. Of their 18 variables, the dataset consists of seven interest rates, seven yield spreads, and four exchange and inflationary pressures. I gather 13 of these variables from the St. Louis FRED database and proceed with their methods for the construction of their index.

Unable to gather the other five variables, I move forward with my replication because I feel confident that the effects of these five variables are relatively captured within the dataset that I have constructed. I believe that the effects of the Three Month London Interbank Offering Rate Minus Overnight Index Swap (LIBOR Minus OIS) Spread are partially captured by and associated with the Three Month Treasury Eurodollar (TED) Spread. The Merrill Lynch One Month Bond Market Volatility Index and the Vanguard Financials Exchange Traded Fund may have effects similar to those captured by the various corporate bond yields, corporate minus government bond yield spreads, as well as the Three Month Commercial Paper Minus Three Month Treasury Bill Spread. Lastly, as for the J.P. Morgan Emerging Markets Bond Index and the 10 Year Nominal Treasury Yield Minus 10 Year Treasury Security Yield Spread, I do not substitute in new variables as to not compromise the replication of the STLFSI. New variables to capture the effects of emerging markets and inflation on financial stress are incorporated in Section 2.2, as I adapt my model with data found to be consistent across national markets.

Table 1: St. Louis Financial Stress Index Replication Dataset

	STL FSI Data	My Replication Data
Interest Rates	Federal Funds Rate	Federal Funds Rate
	Two Year Treasury Yield	Three Year Treasury Yield*
	Ten Year Treasury Yield	Ten Year Treasury Yield
	Thirty Year Treasury Yield	Thirty Year Treasury Yield
	BAA-Rated Corporate	Moodys Seasoned BAA Corporate Bond Yield
	Merril Lynch High-Yield Coporate Master II Index	ICE BofAML US High Yield Master II Index (Effective Yield)
	Merrill Lynch Asset Backed Master BBB-Rated	ICE BofAML US Corporate BBB Index (Effective Yield)
Yield Spreads	Yield curve: Ten Year Treasury minus Three Month Treasury	Yield curve: Ten Year Treasury Minus Three Month Treasury
	Merrill Lynch High Yield Corporate Master II Index minus Ten Year Treasury	ICE BofAML US High Yield Master II Index minus Ten Year Treasury
	Three Month London Interbank Offering Rate Overnight Index Swap Spread	NA
	Three Month Treasury-Eurodollar Spread (TED Spread)	TED Spread (Three Month LIBOR Minus Three Month Treasury)
	Three Month Commercial Paper Minus Three Month Treasury	Three Month AA Financial Commercial Paper Rate Minus Three Month Treasury
	Ten Year Nominal Treasury Yield Minus Ten Year Treasury Security Yield	NA
	Corporate BAA Rated Bond Minus Ten Year Treasury	Moodys Seasoned BAA Corporate Bond Yield Minus Ten Year Treasury Yield
Exchange & Inflation Measures	J.P. Morgan Emerging Markets Bond Index	NA
	CBOE Market Volatility Index (VIX)	CBOE Market Volatility Index (VIX)
	Merril Lynch One Month Bond Market Volatility Index	NA
	Vanguard Financials Exchange Traded Fund	NA

* Three Year Treasury Yield is used in place of Two Year Treasury Yield in replication of the St. Louis Fed's Finanial Stress Index.

The STLFSI is one of the FSIs that is constructed by using principal component analysis (PCA). PCA is mathematical analysis aimed to capture co-movements between variables within a set of data. Rather than looking at the effects of movements from individual variables, PCA identifies times when the data moves together, and this simultaneous co-movement data is where we capture financial stress. Take for example change in stock indexes. With PCA, our analysis doesn't just focus on the movements within the stock index data, but it focuses how this data moves together simultaneously with other data. This captures the effects of not just the stock index, but also bond yields, yield spreads, volatility and uncertainty measures. Our analysis assumes that the first principal component, the component that captures maximum variance within the dataset, is driven by financial stress.

At its core, PCA is a linear orthogonal transformation of the dataset. First, the data must be normalized. Each variable is demeaned by subtracting the mean value of its data series from each data value, and then standardized by the division of each value by the standard deviation of the data series the value belongs to. Then, using different decomposition methods based in linear algebra, PCA creates a covariance matrix from the dataset and then extracts eigenvectors of the matrix. When researchers note that they are extracting the first principal component, this means they are extracting the first eigenvectors of the matrix. These explain the first directions of the maximum variance, capturing as much of the variance in the dataset as possible. The second principal component captures as much of the variance that remains after the first component. Then the third captures as much variance as possible from what remains after the second component, and so forth. For my replication, my principal component analysis focuses solely on extracting the first principal component of nine to ten total components.

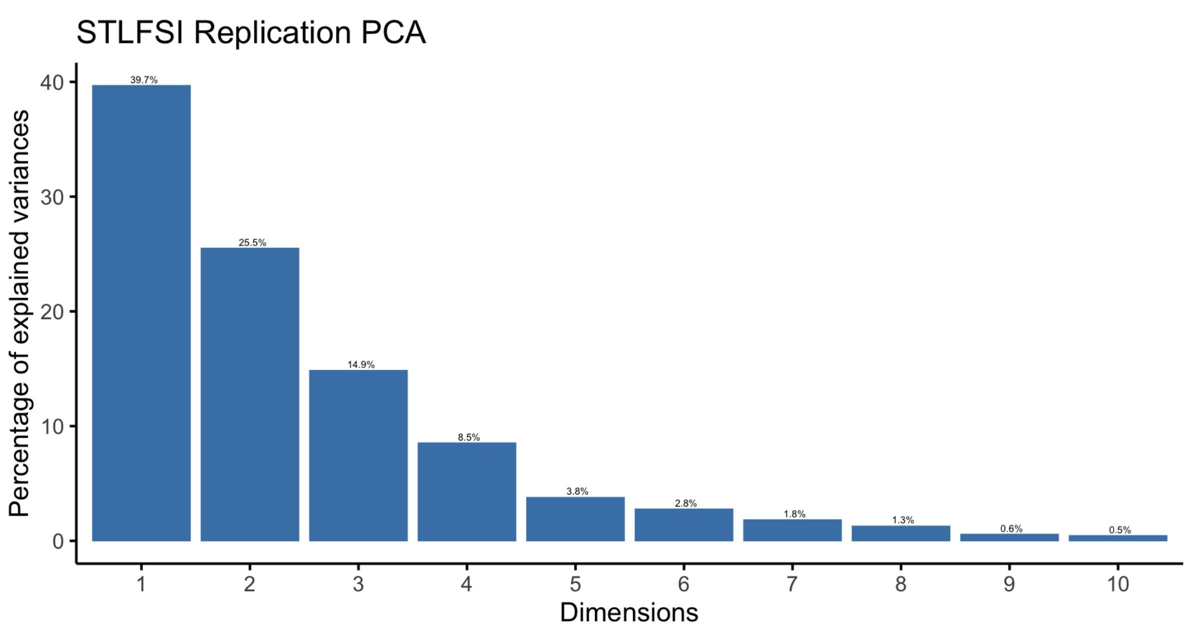


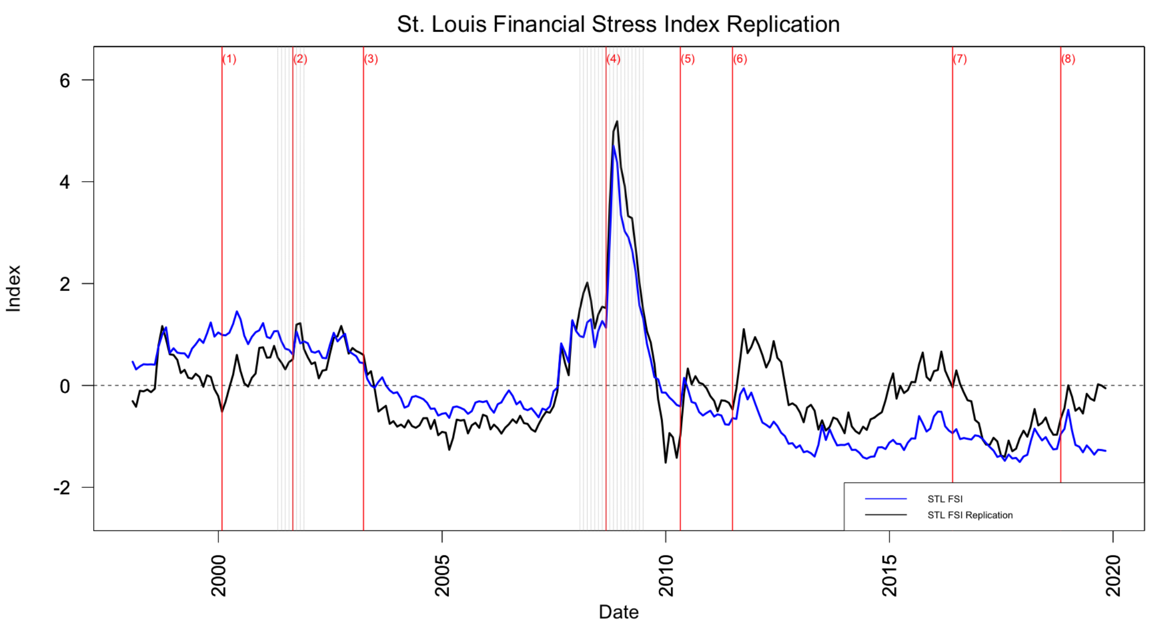
Figure 1: St. Louis Financial Stress Index Replication Principal Components

As seen in Figure 1, financial stress explains approximately 39% of the variance within the STLFSI replication dataset, as it is represented by the first principal component dimension. After PCA is performed and appropriate weights are applied to each data series, I sum the data together by date to create my replication index. In Figure 2, I plot my replication index with the STLFSI and include periods of recession in the United States, as well as lines to indicate dates (or starting dates if events develop over longer periods of time) that are noted as significant events. In chronological order, these events are listed below in Table 2. Due to restrictions in available data, my replication and the STLFSI are plotted on a monthly basis.

Table 2: Significant Shock Inducing Events

	Event	Start Date
(1)	Y2K/Dot-com Crises	Approx. 2000
(2)	Attack on September 11th	Sep. 11, 2001
(3)	Invasion of Iraq	Mar. 19, 2003
(4)	Fall of Lehman Brothers	Sep. 15, 2008
(5)	First Bailout of Greece	May 2010
(6)	Second Bailout of Greece	Jul. 2011
(7)	Initial Brexit Vote	Jun. 2016
(8)	Iran Crude Oil Sanctions	Nov. 4, 2018

*Note: The bailouts of Greece are two separate events within the European Sovereign Debt Crisis, when the European Union (EU) worked together the International Monetary Fund (IMF) to rescue Greece from severe financial stress caused by their debt holdings.



Note: This plot compares the St. Louis Fed's Financial Stress Index (black) with my replication of such index (blue) while using data that is available. This chart spans the period from January 1998 through October 2019.

Figure 2: STLFSI Replication

When comparing these two indexes, as mentioned earlier, they must be measured in respect to themselves. Thus, we can only compare trends and responses to stressful events and periods rather than comparing magnitudes. This is due to the fact that these indexes are proxies for stress in financial markets and do not produce real-observable relationships in the macroeconomy (Kliesen et al., 2012). In Figure 2, the STLFSI and my replication trend closely together at important periods surrounding severe events. They both show increases in stress coinciding with the start of the year 2000, as well is in response to market shut downs after 9/11, the collapse of Lehman Brothers at the beginning of the Global Financial Crisis, both bailouts of Greek debt, and the United States sanctioning of Iranian crude oil. Both indexes show similar decreases in financial stress coinciding with the periods surrounding the invasion of Iraq in 2003. Also, both show very subtle responses around the initial poll results deciding that Britain should exit the European Union. With this understanding of FSIs and a working model, I create a new index for the United States by substituting for new data that is commonly reported in other national markets while still capturing stress within as many of the same financial sectors represented in the STLFSI.

2.2 Adaptation with Data Consistent Across Foreign Economies

In an effort to construct a new United States Financial Stress Index (USA FSI), I build off my model from replicating the STLFSI. In order to maintain a dataset that is consistent across foreign financial markets, I must make appropriate substitutions and exclusions from the dataset which was used for the replication. I maintain the use of variables that are commonly used in other measures of stress. In the dataset, I keep the Federal Funds Rate, the three month Treasury Eurodollar (TED) spread, the ten year minus three month government bond yield spread, and the Chicago Board of Exchange's volatility index (CBOE VIX). These are important measures that cover current bank lending, uncertainty, and stock volatility. During a period of slower economic growth and higher levels of financial stress, the federal funds rate will be lowered to as part of accommodative monetary policy. In periods of greater uncertainty, the yield curve will decline and potentially become negative. A negative yield curve, otherwise referred to as a yield curve inversion, is often used as a warning sign that a recession may occur within the next four to six quarters after the date of inversion (Estrella, 2005). During times of financial stress and stock volatility, VIX measures will increase, and the TED spread also increases, as we see how our standardized data behaves over time in Figure 3.

The STLFSI incorporates the Vanguard Financials Exchange Traded Fund, which was eventually substituted out for the S&P 500 in 2010 (Manamperi, 2015). In my new index for the United States, I incorporate the S&P 500 as well as the NASDAQ Composite Index. I incorporate both stock indexes for two reasons. The first is that some countries, for which I create indexes in Section 3, do not have one main stock index or stock exchange. For example, India has the Bombay Stock Exchange as well as the National Stock Exchange of India. To capture as complete of a measure of stock volatility as possible, two indexes allows me to capture fluctuations of more corporations on a given nation's stock exchanges. The second reason is that there was not an exchange market volatility index similar to the CBOE VIX for all countries, so incorporating two stock indexes allows me to capture more volatility in lieu of the absence of a stock volatility index. To capture stock market volatility, I take the annual log change of each stock market index. During periods of stress, we can expect their to be negative growth in stock indexes.

The STLFSI originally incorporates "exchange and inflationary pressures" (Manamperi, 2015), but I am unable to collect the exact data that the STLFSI used to capture their effects on financial stress. Thus, I substitute in new data to for this task. First is the measure of exchange pressures, defining exchange here as foreign exchange rates as opposed to stock exchange markets. I use real broad effective exchange rates and take the annual log difference of this indexed data. The real broad effective exchange rate is calculated as weighted averages of bilateral exchange rates adjusted by relative consumer prices by the Bank of International Settlements. In periods of recession and stress, a nation's exchange rate will be relatively lower, as exchange rates decrease as interest rates are lowered.

For inflationary pressures, I incorporate the consumer price level inflation rate. This economic indicator is not necessarily a financial variable, but it is a measure that helps explain the health of a nation's markets. It is also a common method to measure price level stability, which allows me to keep my data consistent for each national financial stress index that I create. Another economic indicator that I include in my dataset is the Organisation for Economic Co-operation and Development's (OECD) Composite Leading Indicator (CLI). The OECD constructs their monthly CLI for several different nations using economic time series that have similar fluctuations to that as the business cycle while also leading the business cycle. This allows them to construct a model that provides "early signals of turning points of economic activity"(Gyomai & Wildi, 2012). I include this in my model is an indicator of future outlook, similar to that provided by inversions of the yield curve.

Lastly, I exclude corporate bond data, since different measures mix different sources of indexed data over time and are unreliable. With the inability to find consistent measures for different nations, I exclude corporate bond data from my indexes all together. By excluding corporate bond yields and spreads that include corporate bond yields, I no longer capture that risk and uncertainty provided by that data. Stock indexes give a snapshot of investor confidence and performance of corporations, but it doesn't capture the same uncertainties that bonds capture. Thus, I substitute another measure for uncertainty with the Economic Policy Uncertainty (EPU) index created by Baker et al. (2015). EPU is a news based measurement of uncertainty consistent across nations. This captures mentions of uncertainty paired with national governments, economic policy and conditions, and constructs the index based upon the ratio of articles with uncertainty to total articles per given nation. Baker et al. (2015) keep their model consistent for different countries, with the only change being news coming from specific new sources within the country of focus.

With this new dataset, here are plots of each data series after the normalization process. The data no longer has different units, but the trends and deviations are still captured from January 1995 to August 2019. Figure 3 shows each data series plotted independently over this timespan. After the construction of the new index, the USA FSI, Figure 4 provides a plot containing the USA FSI and its ten individual factors. Lastly, Figure 5 provides a plot comparing the STLFSI, the STLFSI replication, and the USA FSI.

Note that, in Figure 4, much variance is explained by the United States' Composite Leading Indicator constructed by the OECD, the CBOE VIX, as well as the NASDAQ and S&P 500. During the 2001 recession and the attacks of September 11th, the stock markets appear to capture the large rise in financial stress. During the Global Financial Crisis, each data series captures some level of stress except for the CPI inflation rate, which doesn't deviate from zero much throughout the entire span of time that I focus on. Lastly, increases in financial stress surrounding the sovereign debt crisis (events five and six), Brexit (event seven), and sanctions on Iranian crude oil (event eight) appear to be captured mainly by the economic policy uncertainty index as well the CBOE VIX.

In Figure 5, although magnitudes differ from index to index, the same general trends as well as most sharp increases and decreases in stress. There are subtle differences. For example, in 2007 there is a peak in financial stress just before the fall of Lehman Brothers that isn't captured by the USA FSI but is captured by both the STLFSI and my replication. There is also an increase in financial stress measured by the USA FSI several months after the initial Brexit vote, but this is not captured by either the STLFSI or my replication. These subtle differences are from slightly different datasets. Even with these subtle differences, the USA FSI moves along with the trends of the STLFSI and my replication.

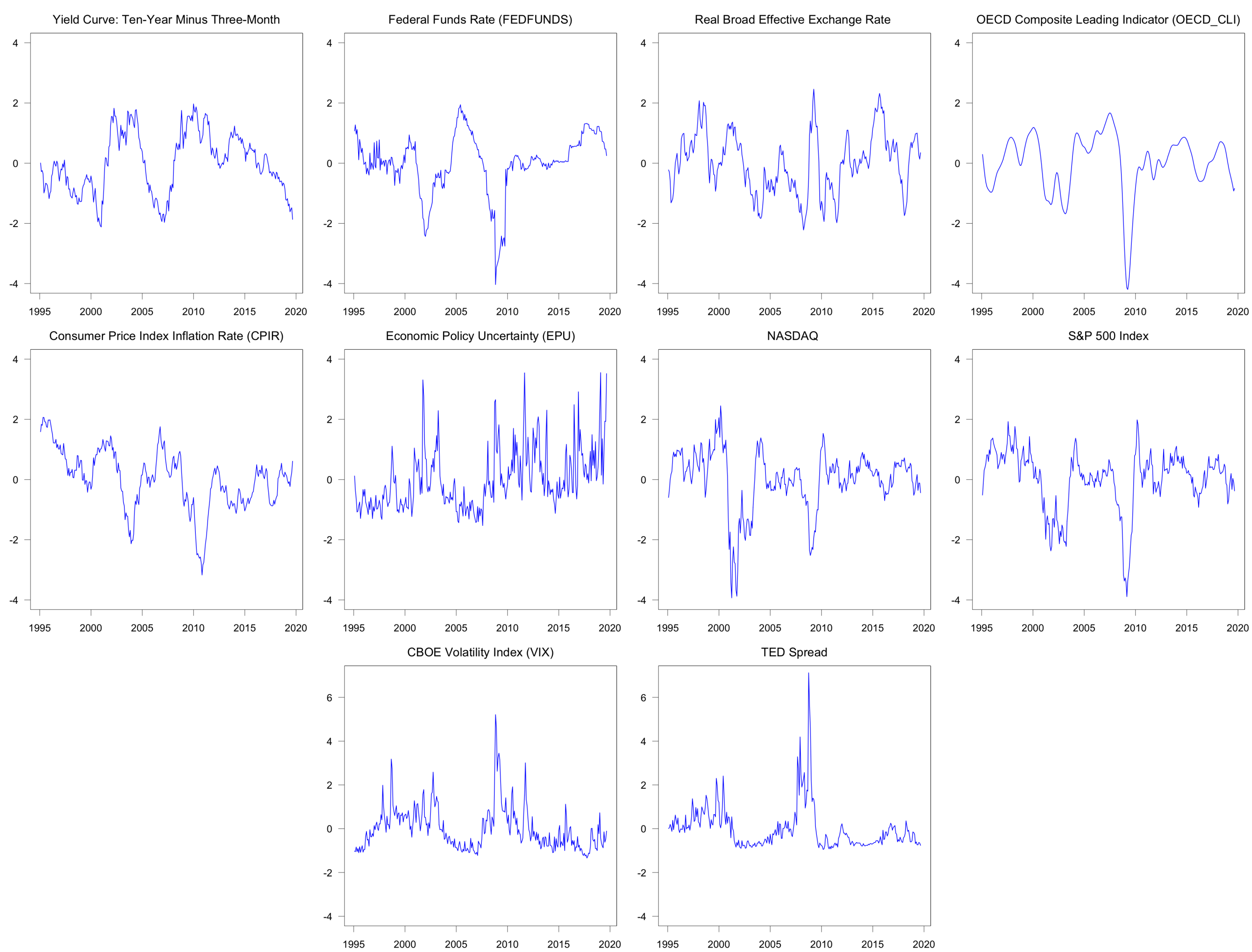
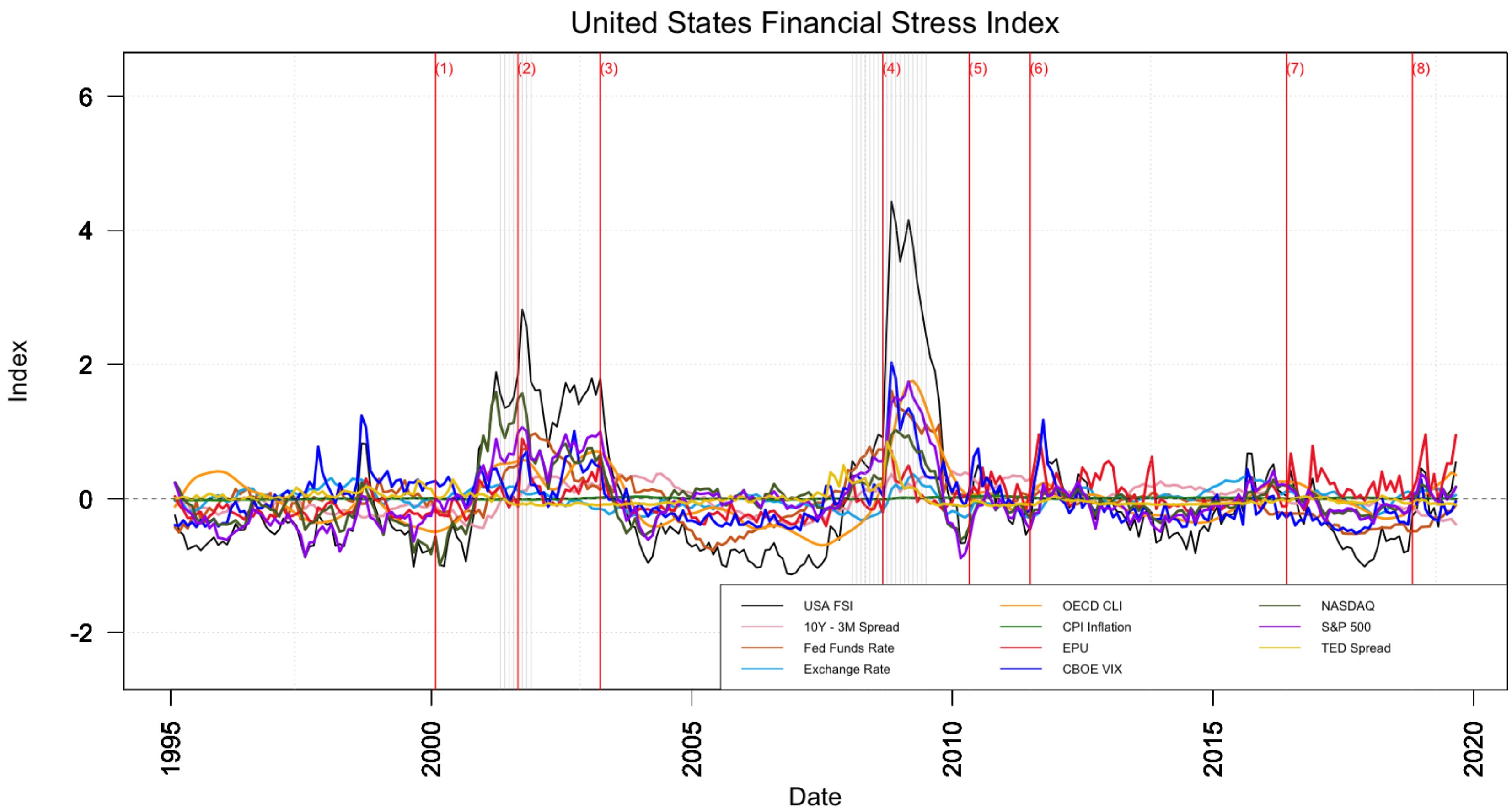


Figure 3: Visualizing Raw Components of the USA Financial Stress Index



Note: The USA FSI and the weighted factors used to construct the USA FSI are of the same unit. Thus, the USA FSI in this figure is not the direct sum of the individual plotted factors, but stands to represent the trend of the USA FSI in comparison to the trend of the individual factors. This is for the purpose to create a visual that compares the trends of the individual factors to the overall trend and deviations of the USA FSI. The plot covers the period from January 1995 through August 2019.

Figure 4: United States Financial Stress Index

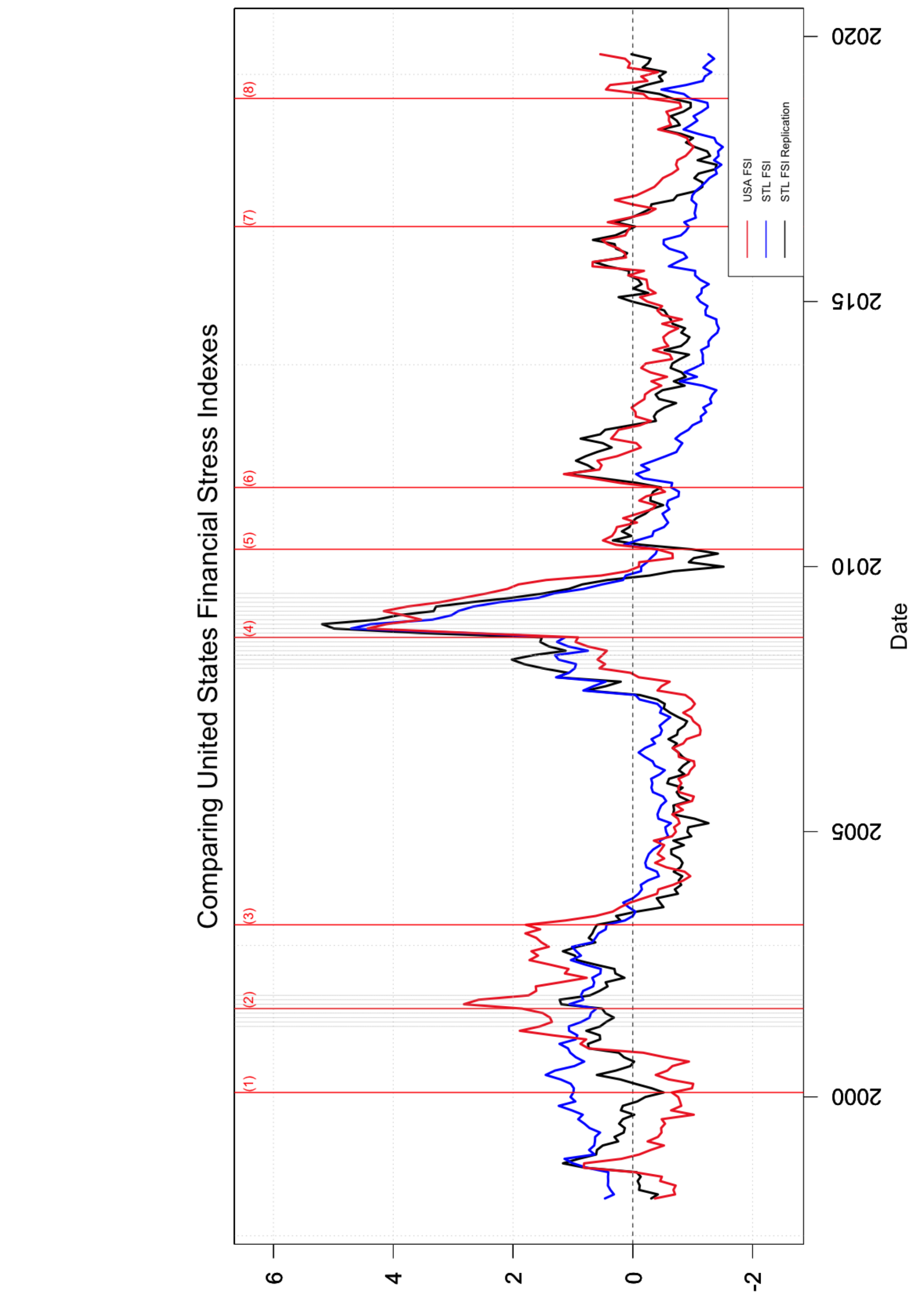


Figure 5: Financial Stress Index Comparison

3 Creation of FSIs for Foreign Economies

After the creation of the USA FSI, I construct four more datasets for four new FSIs. The countries of focus are: Germany, India, Japan, and the United Kingdom. I maintain consistent datasets to capture stress across the same market sectors within each economy. Below, Table 3 provides a breakdown of the datasets compared to that used for the construction of the USA FSI. Stock indexes will differ from nation to nation, but as done for the USA FSI, I maintain two indexes per nation, and I use the annual logged difference to measure change in stock indexes. I also use the annual log difference to measure the rate of inflation based upon the consumer price index, and the change of the indexed real broad effective exchange rate. As the federal funds rate and other 24 hour interbank lending rates are already in percent units, I take the annual difference in percent for these variables to capture how they move in response to stressful events and conditions over time. I incorporate VIX and the VJX, stock volatility indexes for the United States and Japan respectively. I was unable to collect similar measures for Germany, India, or the United Kingdom, but I continue to include these measures as they provide deeper insight to the stock exchange markets. Also, the STLFSI incorporated both the CBOE VIX and the S&P 500 (after substituting the S&P 500 in for the Vanguard Financials Exchange Traded Fund), so it is not unheard of for slightly overlapping data series to be used to provide deeper insight to market trends.

Table 3: Financial Stress Index Variables Across Country Index Datasets

Data Type	United States USA FSI	Germany GER FSI	India IND FSI	Japan JPN FSI	United Kingdom UK FSI
Consumer Price Level Inflation Rate	✓	✓	✓	✓	✓
Economic Policy Uncertainty Index	✓	✓	✓	✓	✓
Fed Funds or Equivalent	✓	✓	✓	✓	✓
OECD Composite Leading Indicator	✓	✓	✓	✓	✓
Real Broad Effective Exchange Rate	✓	✓	✓	✓	✓
Stock Index One	NASDAQ	DAX	BSE Sensex	NIKKEI 225	FTSE 100
Stock Index Two	S&P 500	MDAX	NSE 50	TOPIX	FTSE All Share
Ten-Year Minus Three Month Treasury	✓	✓	✓	✓	✓
TED Spread or Equivalent	✓	✓	✓	✓	✓
CBOE Volatility Index (VIX) or Equivalent	✓	NA	NA	✓	NA

3.1 Germany Financial Stress Index

As the largest economy in Europe and the fourth largest economy in the world by nominal GDP, Germany's Deutsche Börse exchange is also amongst the top stock exchanges in the world. Noting Germany's prominence in the global market, I construct an index to capture stress in its financial markets. Following the same method as before, I am able to construct a financial stress index for Germany (GER FSI) and analyze its different components. Germany's first principal component explains approximately 34% of co-movements through the dataset. The data series that explain most of the simultaneous co-movements through the data are Germany's DAX and MDAX stock indexes, the composite leading indicator constructed for Germany, and Germany's 24 hour interbank lending rate.

In Figure 6, the GER FSI trends closely with the USA FSI. It responds very similarly surrounding several of the listed events except for the fifth listed event: the first bailout of Greek debt during the European Sovereign Debt Crisis. This defies expectations, as it is expected that financial stress within the European Union (EU) would affect financial markets in Germany, one of the EU's largest economies. We learn in Figure 7 that the measured decline in stress is captured by the composite leading indicator constructed by the OECD. This indicator along with the DAX, MDAX and the 24 hour interbank rate imply market conditions with less stress during this period.

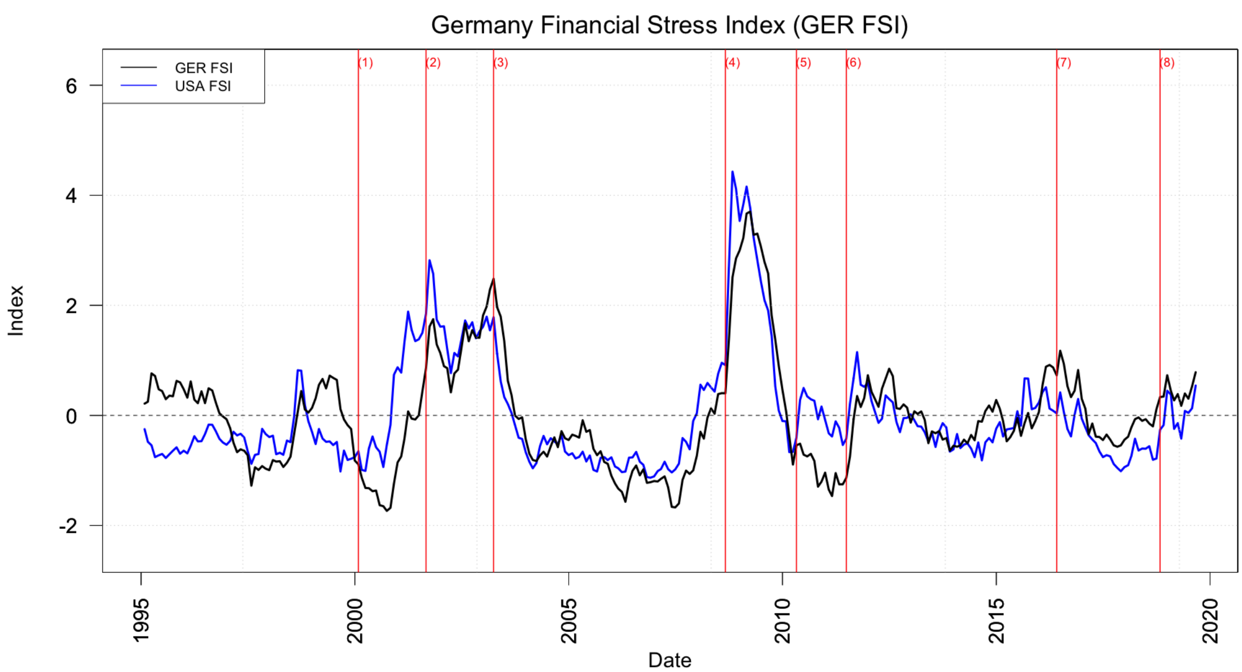
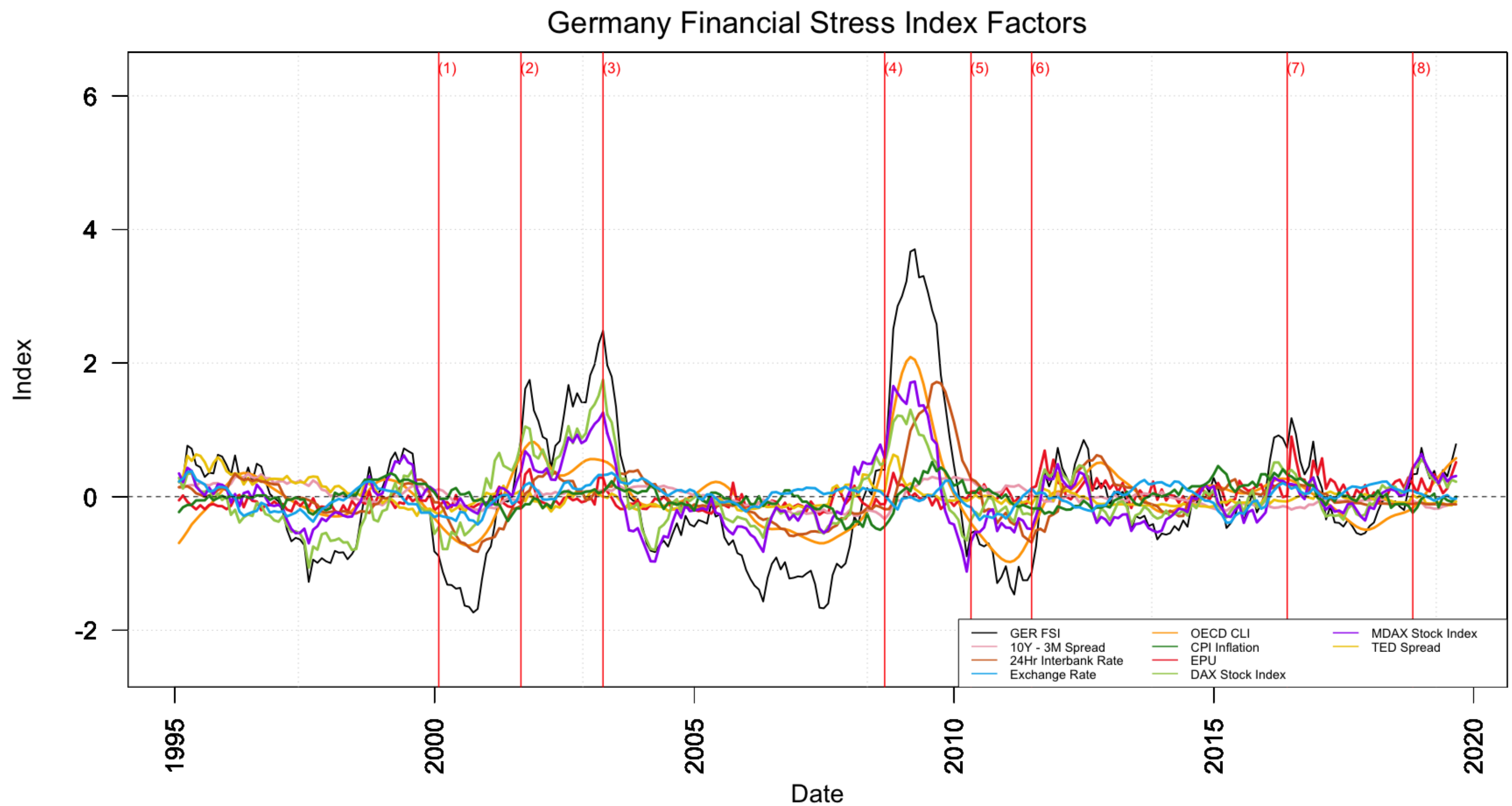


Figure 6: Germany Financial Stress Index



Note: The GER FSI and the individual factors used to construct the GER FSI are of the same unit. Thus, the GER FSI in this figure is not the direct sum of the individual plotted factors, but stands to represent the trend of the GER FSI in comparison to the trend of the individual factors. This is for the purpose to create a visual that compares the trends of the individual factors to the overall trend and deviations of the GER FSI. The plot covers the period from January 1995 through August 2019.

Figure 7: Plotting the GER FSI and Individual Factors

3.2 India Financial Stress Index

With the fifth largest economy in the world by nominal GDP, second largest population at 1.31 billion people, and two of the world's largest stock exchanges in the Bombay Stock Exchange (BSE) and National Stock Exchange of India (NSE), India's financial stress is very important to monitor, as stress in India's markets may be connected with others. As done for Germany, I construct a financial stress index for India and compare its individual factors. India's first principal component explains approximately 37% of co-movements through the dataset. The data series that explain most of the simultaneous co-movements through the data change over time, as seen in Figure 9. Unlike Germany, there does not appear to be any single large magnitude driving factor, such as the composite leading indicator in Figure 7.

In Figure 8, the IND FSI moves closely with the USA FSI until approximately 2012. This happens to coincide with the second negotiated deal to bail out Greece of financial debt. Between 2012 and 2015, the two indexes trend apart and have few similarities. In Figure 9, the increased level of financial stress during this period is captured by economic policy uncertainty, broad effective exchange rates, the 24 hour interbank lending rate, and the NSE 50 and BSE Sensex plots.

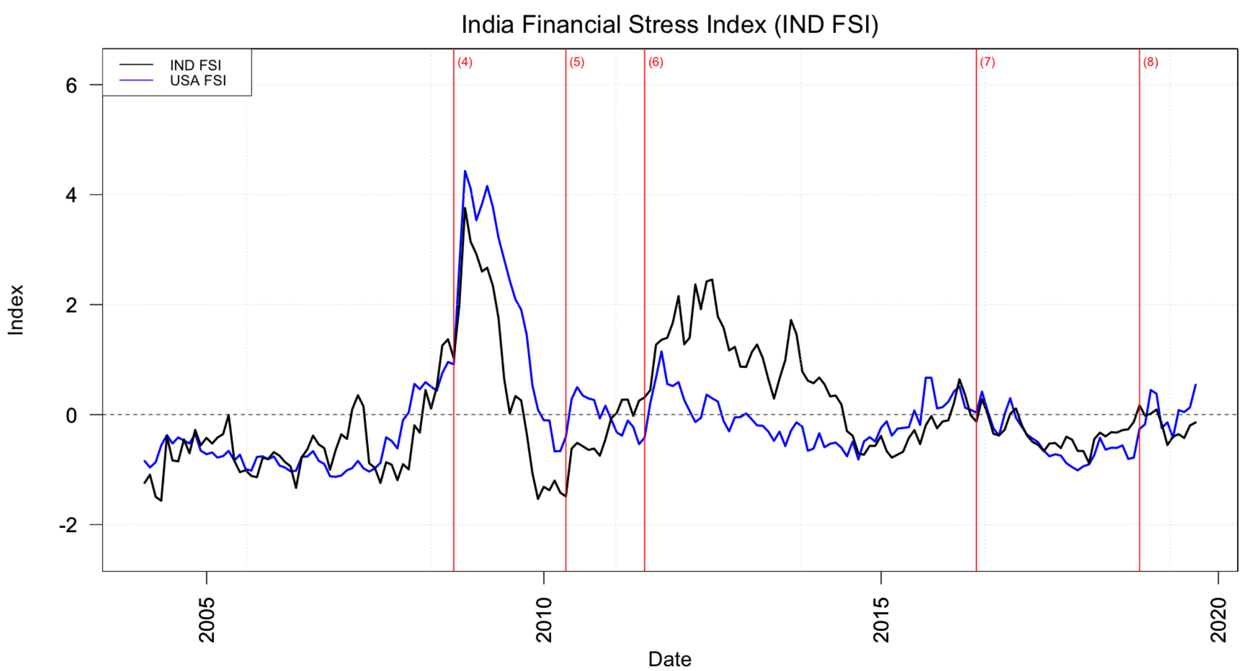
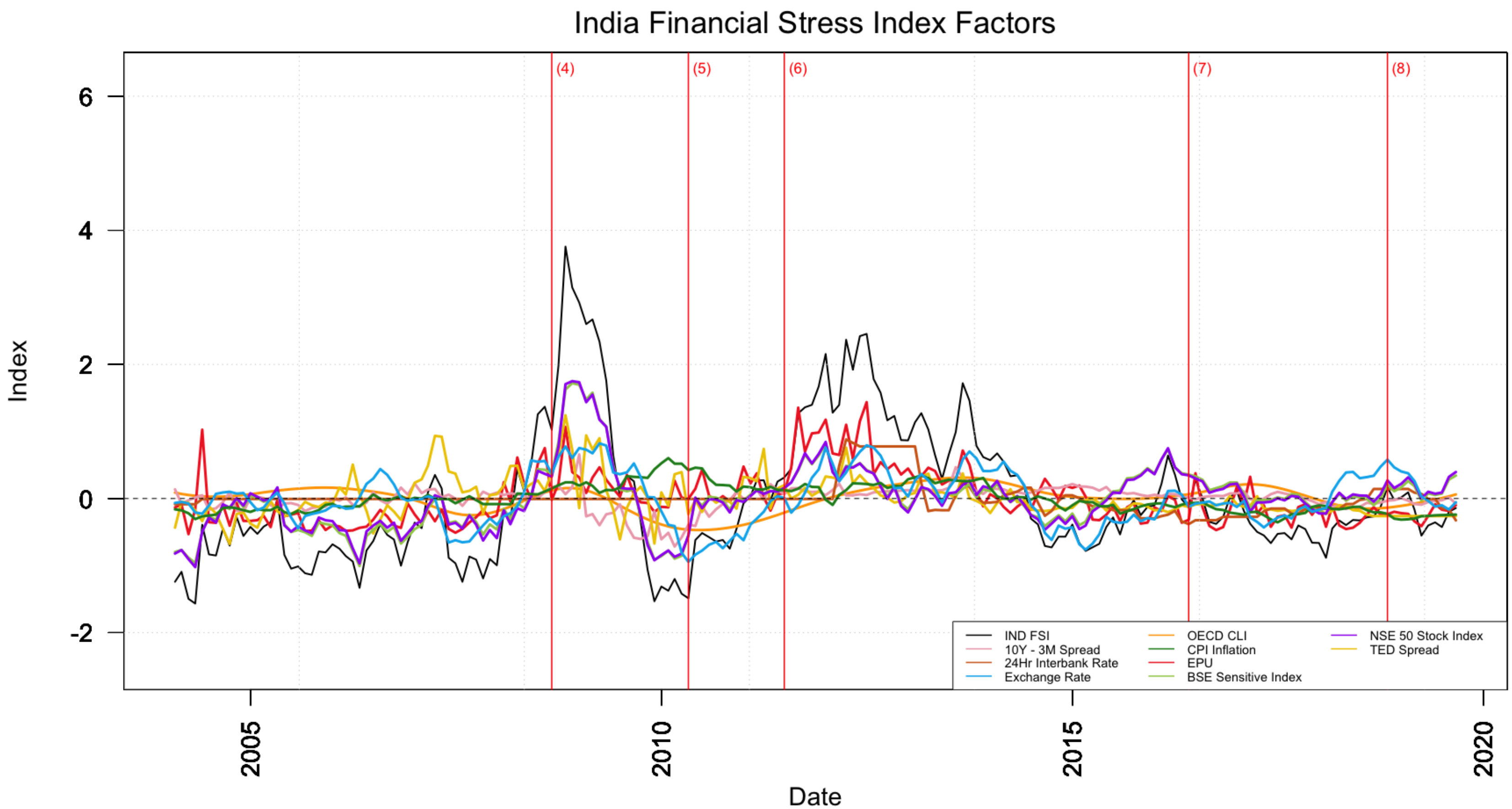


Figure 8: India Financial Stress Index



Note: The IND FSI and the individual factors used to construct the IND FSI are of the same unit. Thus, the IND FSI in this figure is not the direct sum of the individual plotted factors, but stands to represent the trend of the IND FSI in comparison to the trend of the individual factors. This is for the purpose to create a visual that compares the trends of the individual factors to the overall trend and deviations of the IND FSI. The plot covers the period from January 2004 through August 2019.

Figure 9: Plotting the IND FSI and Individual Factors

3.3 Japan Financial Stress Index

Since Japan is the third largest economy in the world in terms of nominal GDP, has one of the largest stock exchanges in the Japan Exchange Group (JPX), and is our fourth largest trade partner according to the U.S. Census Bureau, it is imperative to construct a financial stress index for Japan. Using the same technical methods, I apply PCA and construct a model that captures financial stress in Japanese markets. Japan's first principal component explains approximately 44% of co-movements through the dataset.

In Figure 10, the JPN FSI and the USA FSI move together closely from 1999 through 2019. There are instances, such as the period from 2001 through 2003 and from 2014 through late 2015, where the JPN FSI and USA FSI separate. In the first period, the two indexes maintain similar trends with two large increases of stress measured and preceding a leveling off of financial stress before financial conditions improve after the beginning of 2003. I focus on similarity in trend, which is important when comparing FSIs as opposed to the magnitude of the index. However, during the second period mentioned, the two indexes do not trend together. The the JPN FSI captures healthier financial conditions as the JPN FSI produces two decreases in measured stress while the USA FSI remains around the same value just below zero.

Using Figure 11, we understand the JPN FSI further by analyzing its individual factors. The factors that have the largest influence on the trend of the JPN FSI are the volatility index (VJX) and Japan's composite leading indicator, as well as the Nikkei 225 and TOPIX stock indexes. The VJX rises sharply surrounding the attacks on September 11th and after the fall of Lehman Brothers. After both bailouts of Greek debt in the years following the Global Financial crisis, economic policy uncertainty and the VJX rise sharply. During the decrease of financial stress captured prior to 2015, Japan's stock indexes, the broad effective exchange rate, and the composite leading indicator capture healthy conditions, while the other factors remain around zero. Lastly, the index captures a rise in financial stress around the Brexit vote. This is driven by many factors and does not appear to be in response to the event itself. Other conditions in 2016 must explain this rise in stress, which is also not captured by the USA FSI in Figure 10.

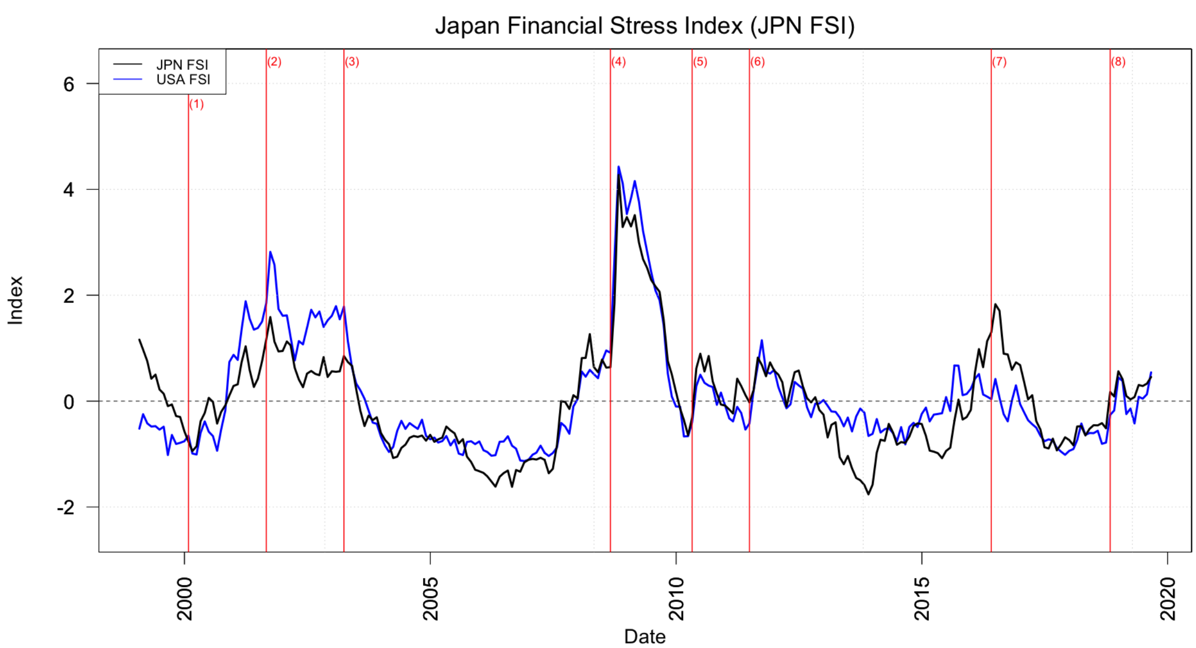
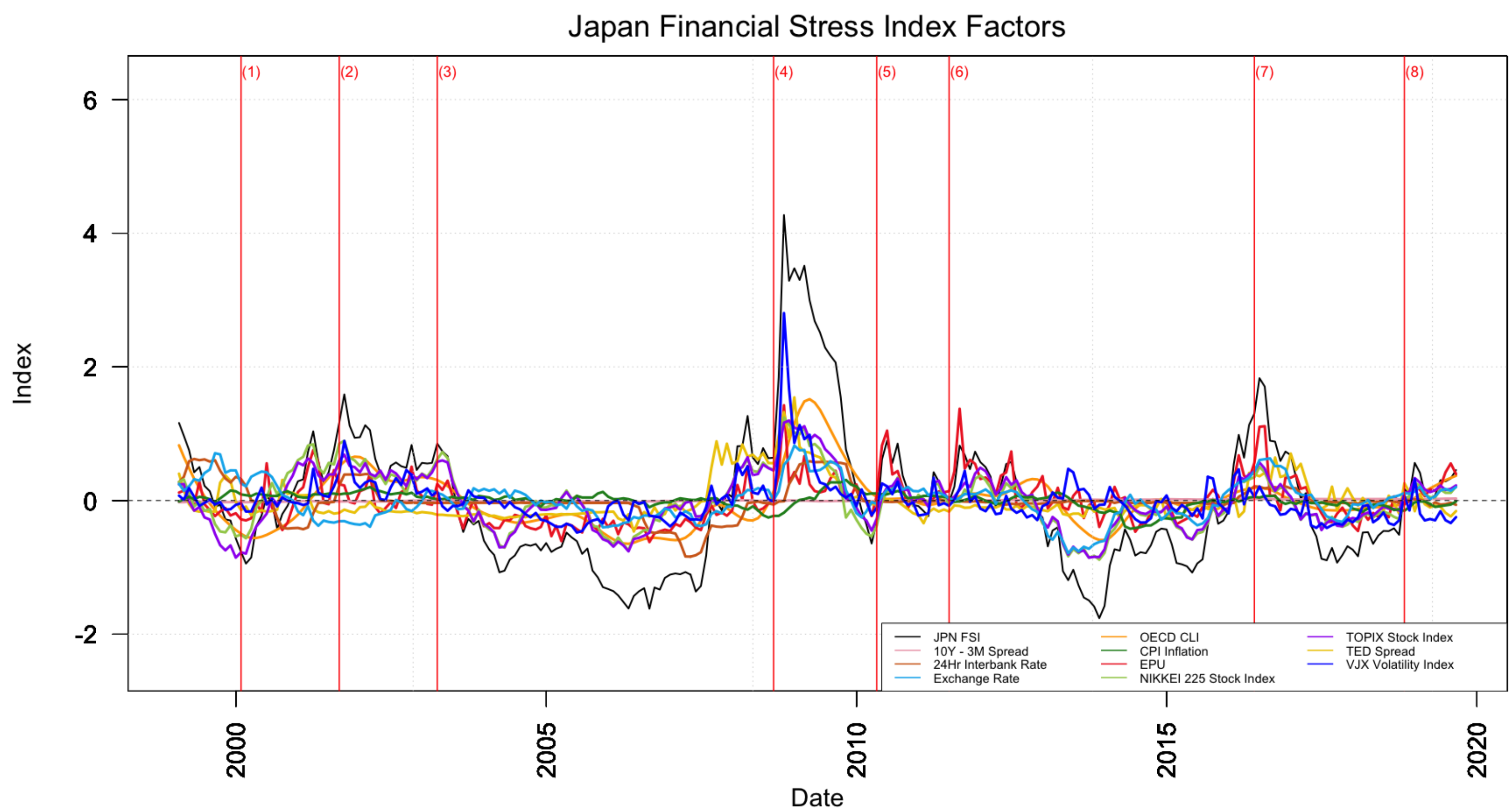


Figure 10: Japan Financial Stress Index



Note: The JPN FSI and the individual factors used to construct the JPN FSI are of the same unit. Thus, the JPN FSI in this figure is not the direct sum of the individual plotted factors, but stands to represent the trend of the JPN FSI in comparison to the trend of the individual factors. This is for the purpose to create a visual that compares the trends of the individual factors to the overall trend and deviations of the JPN FSI. The plot covers the period from January 1998 through August 2019.

Figure 11: Plotting the JPN FSI and Individual Factors

3.4 United Kingdom Financial Stress Index

The United Kingdom is currently the sixth largest economy in the world in terms of nominal GDP. They have one of the world's largest stock exchanges, and they are one of our largest trade partners, just behind Japan and Germany. Thus, I construct a financial stress index for the United Kingdom, for the same reasons as the other large economies that I have researched prior. After applying PCA and constructing the UK FSI, I find that the UK's first principal component explains approximately 39% of the co-movements within the dataset, and that UK FSI trends very closely with the USA FSI after 2003. Figure 12 provides a comparison of the two indexes, and they rarely deviate from one another on a large scale.

Figure 13 provides insight into the individual factors of the model. Before 2005, increases in financial stress are mainly captured by the FTSE 100 and FTSE All Share stock indexes. In the time surrounding the fall of Lehman Brothers, the TED spread captures increased stress before other factors. Only during the period after the second bailout of Greek debt does the TED spread greatly deviate from zero. After the fall of Lehman, stress is also captured the UK's composite leading indicator, both stock indexes, UK's broad effective exchange rate, and the percent change in the UK's 24 hour interbank lending rate. Lastly, a large increase in financial stress after the initial Brexit vote is captured by economic policy uncertainty and the broad effective exchange rate.

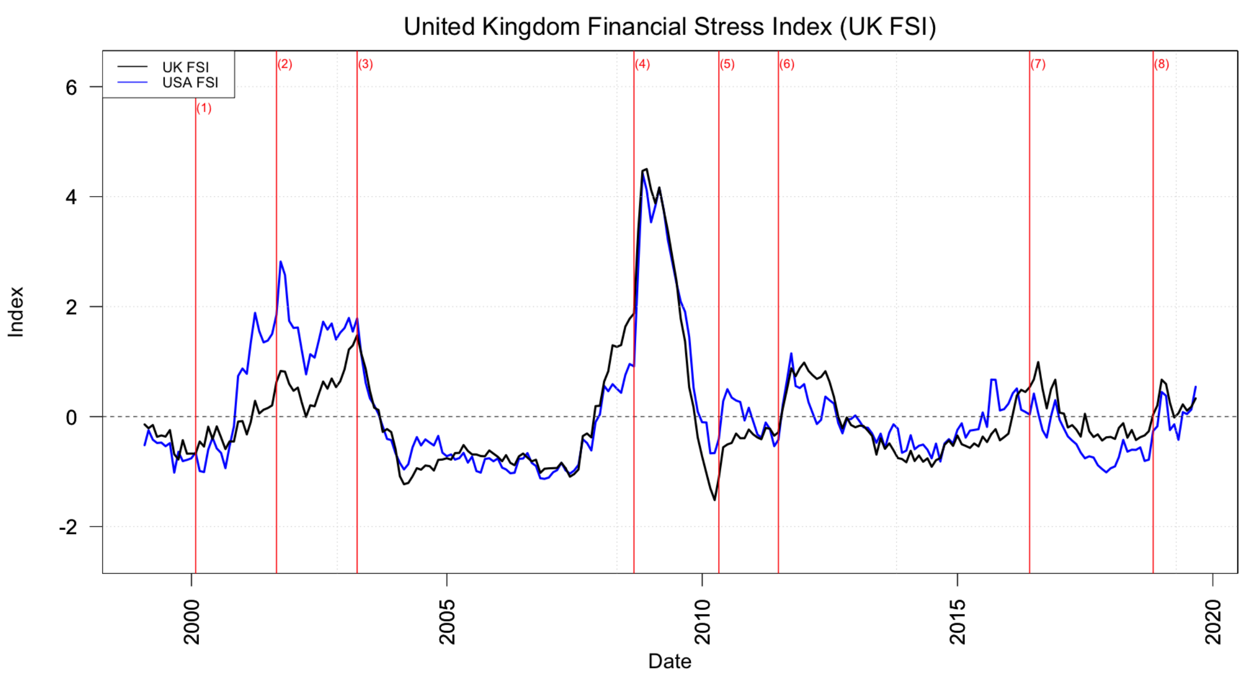
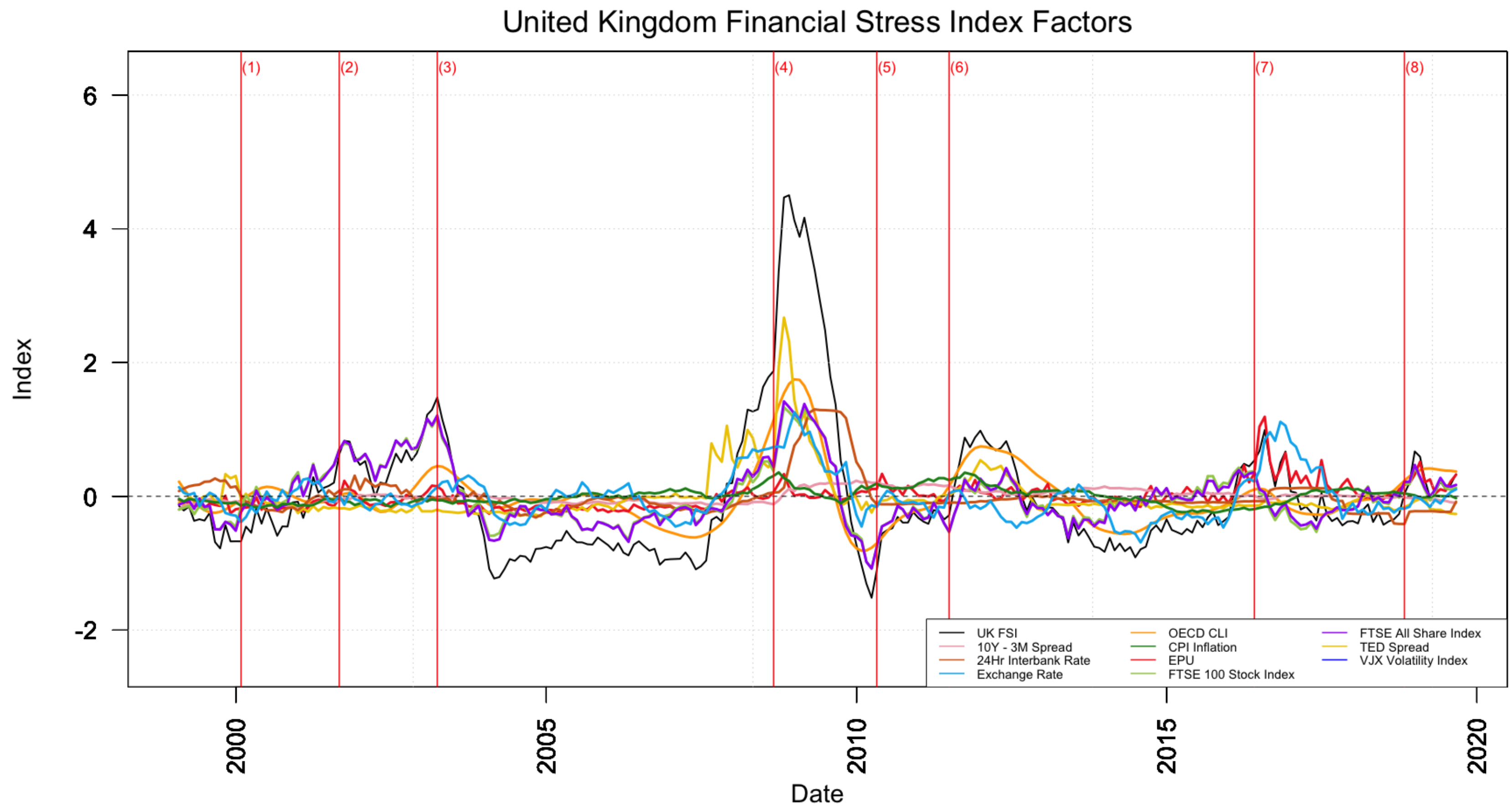


Figure 12: United Kingdom Financial Stress Index

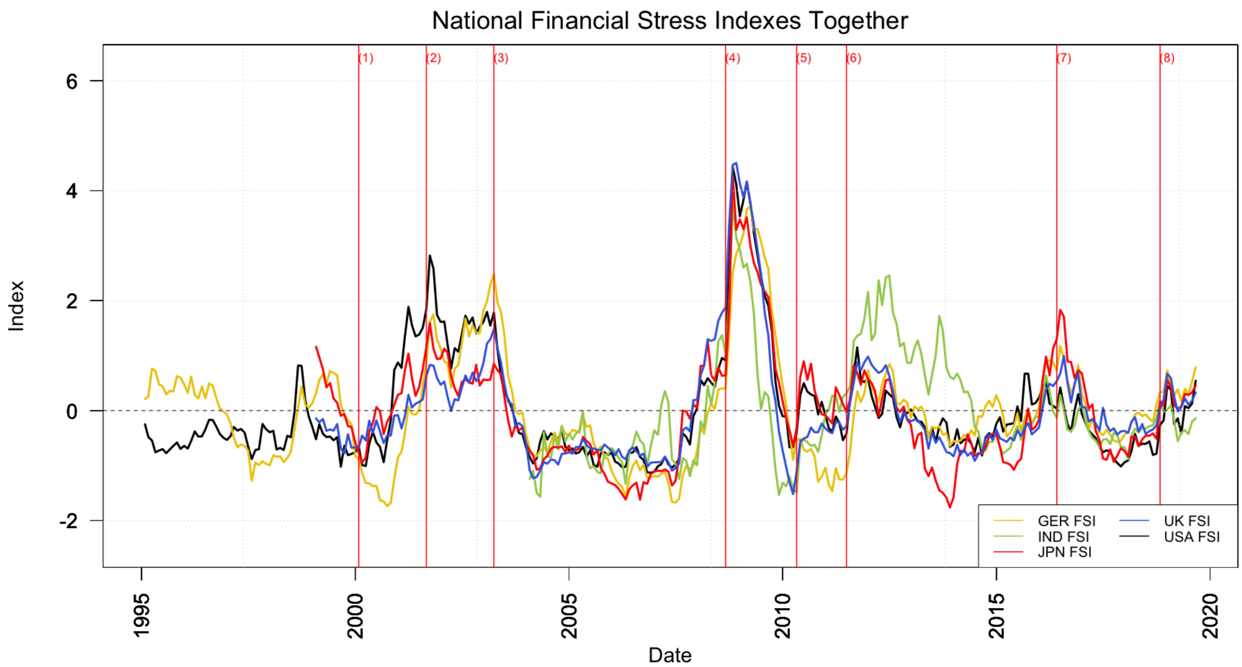


Note: The UK FSI and the individual factors used to construct the UK FSI are of the same unit. Thus, the UK FSI in this figure is not the direct sum of the individual plotted factors, but stands to represent the trend of the UK FSI in comparison to the trend of the individual factors. This is for the purpose to create a visual that compares the trends of the individual factors to the overall trend and deviations of the UK FSI. The plot covers the period from January 1998 through August 2019.

Figure 13: Plotting the UK FSI and Individual Factors

3.5 Global Financial Stress Comparison

After creating five indexes, I now plot their fluctuations in measured stress over time together. All five follow the same general trends over time: an increase in stress in from approximately 2001 to 2003; a large increase in stress in response to the Global Financial Crisis in 2007 through 2009; slightly elevated stress levels in 2012/13 and 2016; rising stress levels most recently in August 2019. Major deviations occur between 2012 and 2016. The IND FSI captures more elevated financial stress levels than the other indexes, while the JPN FSI captures two periods where financial conditions are much healthier. Here the JPN FSI produces larger negative measures of stress. Just as the five indexes converged between 2003 leading up through the events in 2007, the five indexes have converged most recently around 2016. After all five captured brief measures of healthy financial conditions prior to 2018, they are beginning to capture slightly elevated levels of stress at an increasing rate.



Note: This graph contains financial stress index plots for the United States (black) and Germany (purple) from January 1995 to August 2019, Japan (red) and the United Kingdom (light blue) from January 1999 to August 2019, and India (light green) from January 2004 to August 2019.

Figure 14: Plotting the Financial Stress Indexes Together

4 Measuring Spillover Between Countries

As seen in Figure 14, financial stress is rising, measured by the five constructed FSIs. Below, in Table 4, we have our correlation matrix. All five FSIs have positive relationships with one another. Of these relationships, the strongest appear to be amongst the United States, Germany, Japan, and the United Kingdom. Given the strong, positive correlations between these indexes, the objective of this section is to analyze how stress level in one nation's financial markets affects stress levels in those of other nations. If there is an elevated level of spillover between FSIs, a shock to one nation's economy may cause ripple effects that increase financial stress levels in others. I capture these affects by creating a spillover index (SOI) model, apply the methodology from Diebold & Yilmaz (2008), adapted by Klößner & Sekkel (2014), to measure the spillover effects between these five indexes.

Table 4: FSI Correlation Matrix

	GER FSI	IND FSI	JPN FSI	UK FSI	USA FSI
GER FSI	1				
IND FSI	0.668	1			
JPN FSI	0.820	0.513	1		
UK FSI	0.896	0.715	0.880	1	
USA FSI	0.849	0.633	0.849	0.845	1

Note: This table shows the correlation matrix among all financial stress indexes between January 2004 and August 2019.

4.1 Constructing a Spillover Model

The methodology that I utilize to measure spillover between my five country indexes is adapted from Diebold & Yilmaz (2008). First, I normalize my data so that my indexes are now free of units and are on the same scale. Then, I use an N-dimensional vector auto-regression (VAR) of the order p, VAR(p). I adapt a VAR(2) to analyze relationships between my indexes with a two month lag. This VAR regresses the data series on the entire dataset, both with a lag of one period as well as a lag of two periods. Then, by using coefficient matrices, dynamic relationships among the variables are summarized. Furthermore, to summarize information contained within the coefficient matrices, I utilize H-step ahead forecast error variance decompositions (FEVD) (Klößner & Sekkel, 2014). For my analysis, I set H equal to 3 to forecast relationship three months ahead. During this decomposition process, the lower-triangle Cholesky factor as applied, as explained by Klößner & Sekkel (2014), and this decomposition produces the forecast error variance for each index in the dataset. In other words, the forecast error variance of the USA FSI can be considered as the contribution of shocks to other indexes from the USA FSI. Lastly, as Klößner & Sekkel (2014) discuss, the Diebold and Yilmaz method may be affected by the ordering of the covariance matrix used in the decomposition process. Thus, applying a similar algorithm utilized by Klößner & Sekkel (2014), I run the spillover model, with the process of the VAR(2) and FEVD with the H-step ahead of 3, for all possible permutations of my data-set and average the results to calculate my robust spillover measures, which are shown in Table 5.

4.2 Financial Stress Spillover Results

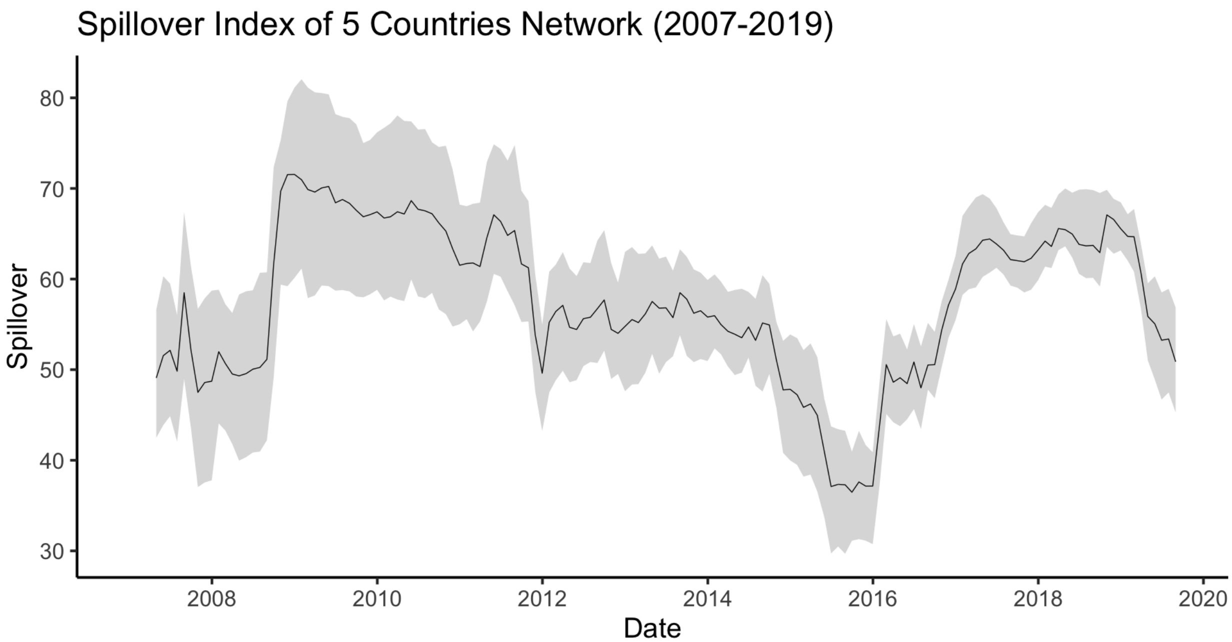
Due to limitations in the data for the constructed indexes, I run the spillover model on the five national FSIs from January 2004 through August 2019. I provide estimates of the overall SOI as well as further breakdown of forecast error variance components for each index. Table 5 summarizes my results. This table shows the averages of variance forecast error produced from running the spillover model on all possible permutations of the normalized FSI dataset. This table also shows total variance forecast errors that each FSI sends to all other FSIs ("*To* Others"), as well as the sum of the percentages of the forecast errors each FSI receives from all other FSIs ("*From* Others"). Lastly, Table 5 includes the total estimated SOI, which is also the representation of the average of all the non-diagonal, percentage forecast error variances.

Table 5: FSI Spillover Table

	GER FSI	IND FSI	JPN FSI	UK FSI	USA FSI	*Frome* Others
GER FSI	47.46	5.56	9.82	21.40	15.78	52.56
IND FSI	7.37	64.35	5.54	14.41	8.33	35.65
JPN FSI	9.76	5.01	52.57	17.86	15.10	47.73
UK FSI	13.22	5.55	10.91	54.97	15.34	45.03
USA FSI	12.96	4.87	11.48	20.06	50.62	49.38
To Others	43.30	20.99	37.76	73.74	54.56	
Net	−9.25	−14.67	−9.97	28.71	5.18	SOI = 11.52

Note: This table shows the Robust Spillover Table for the period of January 2004 to August 2019. It is based on the average across all N! = 120 permutations of the system. The columns show the percentage of the forecast error variance that the headline country exports to all countries. The rows indicate the percentage of the forecast error variance that the headline country imports from all countries. The row Net displays the difference between To Others and From Others. The SOI, the average of all non-diagonal entries, equals 11.52.

Similar to the correlation matrix in Table 4, the most spillover measured is between Germany, Japan, the United Kingdom, and the United States. While FSIs of the United Kingdom and United States have slightly larger affects to other indexes, they are also the only two indexes that yield a positive net value for variance affects. This means that the UK FSI and USA FSI give larger effects than they receive from other indexes. Conversely, the GER FSI, IND FSI, and JPN FSI all yield negative net values for variance effects. Thus, they receive larger effects than they give to other indexes. Overall, these net effects are minimal. If we focus on the diagonal values of the table, where each FSI explains their own variance levels, each index explains approximately 50% of their own variance, with the exception to Germany at 47%. This result paired with the total SOI of 11.5% shows that these national FSIs are more self-explanatory and resilient to shocks from other indexes.



Note: This figure shows the spillover index (SOI) from January 2007 to August 2019 estimated with a 40 months moving average estimate. The dashed line shows the average SOI, whereas the gray bands display the maximum and minimum range of estimates obtained for all possible Cholesky factorizations (Klößner & Sekkel, 2014).

Figure 15: Spillover Over Time

After constructing my spillover table, I construct a spillover plot with a rolling window to observe how spillover varies over time. Figure 15 plots spillover from January 2007 through August 2019 with a 40 months rolling window. This rolling SOI captures higher levels of spillover as smaller windows are analyzed due to limitations imposed by smaller datasets. The most dramatic changes in spillover occur towards the end of the Global Financial Crisis. Spillover measures drop back to pre-Crisis levels between 2014 and 2015. In 2016, the index falls to its lowest measures. Most recently, spillover has been decreasing once again from late 2018 through 2019, which indicates national financial markets are currently more resilient to shocks in other financial markets.

5 Conclusion

This paper successfully replicates the St. Louis Financial Stress Index and constructs financial stress indexes for five major economies and estimates spillover effects of financial stress between indexes. Although some FSIs are highly correlated, I find that spillovers between FSIs only explain approximately 11% of variance in financial stress between 2004 and 2019. The UK FSI and USA FSI are responsible for larger percentages of spillover, while all others are net receivers of spillover effects. Over time, spillover is not found to increase during all periods of elevated financial stress. The rolling SOI is high in the periods towards the end of the Global Financial Crisis, but measures are relatively low during periods where financial stress is elevated in early 2016. Thus, it is important to continuously observe financial stress along with updated spillover levels to properly gauge the health of the global financial system. These two measures respectively indicate stress in national financial markets as well as the vulnerability of the transmission of stress across markets.

Since late 2017, all five FSIs have been increasing. This is a negative sign for financial current conditions if FSIs continue to trend upward. Conversely, since approximately 2018, indexed spillover between FSIs is declining. With these two findings, I conclude that individual financial markets appear more resilient, and that if a shock were to occur to one of these nations' financial stress levels at this moment, that the effects of this shock would not be as widespread due to relatively lower measures of spillover at this time.

There is much work that may expand upon the findings of this paper. The construction of FSIs, while maintaining datasets that cover financial markets consistently, for other important global economies will provide a greater understanding of spillover connections across global markets. This paper only focuses on five nations. Furthermore, incorporating new data that maintains consistency across countries may increase the accuracy of financial stress measurements. New data may provide better measures of uncertainty as well as capture stress in the corporate sector, since my model excluded all corporate data. Another improvement upon this research is the extension of datasets further back in time. This will capture more events where financial stress was elevated and provide more observations to estimate spillover effects. Lastly, as the FSIs are constructed using consistent datasets, measuring spillover between individual factors may help researchers understand the paths through which financial stress is transmitted.

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Appendix: Data Sources:

St. Louis Financial Stress Index Replication

Data Series	Source	Reference Code
Effective Federal Funds Rate	St. Louis FRED Database	DFF
Government 3-Month T-Bills Constant Maturity Yield	Global Financial Database	ITUSA3CMD
3-year Note Constant Maturity Yield	Global Financial Database	IGUSA3D
10-year Bond Constant Maturity Yield	Global Financial Database	IGUSA10D
30-Year Constant Maturity Government Bond Yield	Global Financial Database	IGUSA30D
Moodys Seasoned BAA Corporate Bond Yield	St. Louis FRED Database	BAA
ICE BofAML US High Yield Master II Effective Yield	St. Louis FRED Database	BAMLH0A0HYM2EY
ICE BofAML US Corporate BBB (Effective Yield)	St. Louis FRED Database	BAMLC0A4CBBBEY
Three Month Treasury Euro-dollar (TED) Spread	St. Louis FRED Database	TED Spread
3-Month AA Financial Commercial Paper Rate	St. Louis FRED Database	DCPF3M
CBOE Volatility Index: VIX	St. Louis FRED Database	VIXCLS

Country Financial Stress Indexes

Country	Data Series	Source	Reference Code
United States	Effective Federal Funds Rate	St. Louis FRED Database	DFF
	Government 3 Month T-Bills Constant Maturity Yield	Global Financial Database	ITUSA3CMD
	10 Year Bond Constant Maturity Yield	Global Financial Database	IGUSA10D
	Three Month Treasury Euro-dollar (TED) Spread	St. Louis FRED Database	TED Spread
	Real Broad Effective Exchange Rate	St. Louis FRED Database	RBUSBIS
	Consumer Price Index Inflation Rate	Global Financial Database	CPXUSAM
	S&P 500 Total Return Index	Global Financial Database	_SPXTRD
	NASDAQ Composite Index	St. Louis FRED Database	NASDAQCOM
	CBOE Volatility Index: VIX	St. Louis FRED Database	VIXCLS
	US Economic Polixy Uncertainty Index	PolicyUncertainty.com	
	OECD Composite Leading Indicator for the United States	Data.OECD.org	
Germany	Immediate Rates: Less than 24 Hours: Call Money/Interbank Rate	St. Louis FRED Database	IRSTCI01DEM156N
	3 Month Treasury Bill Yield	Global Financial Database	ITDEU3D
	10 Year Benchmark Bond	Global Financial Database	IGDEU10D
	3 Month Euribor	Global Financial Database	IBEUR3D
	Real Broad Effective Exchange Rate	St. Louis FRED Database	RBDEBIS
	Consumer Price Index Inflation Rate	Global Financial Database	CPDEUM
	DAX Price Index	Global Financial Database	_GDAXIPD
	MDAX Price Index	Global Financial Database	_MDAXIPD
	Germany Economic Polixy Uncertainty Index	PolicyUncertainty.com	
	OECD Composite Leading Indicator for the Germany	Data.OECD.org	
India	Immediate Rates: Less than 24 Hours: Call Money/Interbank Rate	St. Louis FRED Database	IRSTCI01INM156N
	3 Month Treasury Bill Yield	Global Financial Database	ITIND3D
	10 Year Government Bond Yield	Global Financial Database	IGIND10D
	3 Month MIBOR	Global Financial Database	IBIND3D
	Real Broad Effective Exchange Rate	St. Louis FRED Database	RBINBIS
	Consumer Price Index Inflation Rate	Global Financial Database	CPINDM
	Bombay Stock Exchange Sensitive Index	Global Financial Database	_BSESND
	India NSE 50 Index	Global Financial Database	_NSEID
	India Economic Polixy Uncertainty Index	PolicyUncertainty.com	
	OECD Composite Leading Indicator for the India	Data.OECD.org	
Japan	Immediate Rates: Less than 24 Hours: Call Money/Interbank Rate	St. Louis FRED Database	IRSTCI01JPM156N
	3 Month Treasury Bill Yield	Global Financial Database	ITJPN3D
	10 Year Government Bond Yield	Global Financial Database	IGJPN10D
	3 Month LIBOR based on Japanese Yen	St. Louis FRED Database	JPY3MTD156N
	Real Broad Effective Exchange Rate	St. Louis FRED Database	RBJPBIS
	Consumer Price Index Inflation Rate	Global Financial Database	CPJPNM
	Nikkei 225	St. Louis FRED Database	NIKKEI225
	Japan TOPIX Large Capitalization Stocks	Global Financial Database	_TSILD
	VOLATILITY INDEX JAPAN (VXJ)	Center for Mathematical Modeling and Data Science	
	Japan Economic Polixy Uncertainty Index	PolicyUncertainty.com	
	OECD Composite Leading Indicator for the Japan	Data.OECD.org	
United Kingdom	Immediate Rates: Less than 24 Hours: Call Money/Interbank Rate	St. Louis FRED Database	IRSTCI01GBM156N
	3 Month Treasury Bill Yield	Global Financial Database	ITGBR3D
	10 Year Government Bond Yield	Global Financial Database	IGGBR10D
	3 Month LIBOR based on British Pound	St. Louis FRED Database	GBP3MTD156N
	Real Broad Effective Exchange Rate	St. Louis FRED Database	RBGBBIS
	Consumer Price Index Inflation Rate	Global Financial Database	CPHGBRM
	FTSE 100 Index	SGlobal Financial Database	_FTSED
	FTSE All-Share Index	Global Financial Database	_FTASD
	UK Economic Polixy Uncertainty Index	PolicyUncertainty.com	
	OECD Composite Leading Indicator for the United Kingdom	Data.OECD.org	

Note: Volatility Index Japan (VXJ) can be found at www-mmds.sigmath.es.osaka-u.ac.jp/en/activity/vxj.php