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What are the best indicators of systemic risk?

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Abstract

After the financial crisis of 2007-2008, the need of reliable indicators of financial stability became increasingly important. In a first stage, we review the current literature about ten systemic risk indicators (measures/early warnings). The second part is dedicated to an empirical study where we evaluate the performance of some indicators in order to know which is the best measure/early warning of systemic risk. We test only five indicators from the US and Europe that we consider as simple and easily available to everyone: market volatility (VIXX & VSTOXX), interbank rates (Ted spread), Yield curve slope, Return of the bank equity indices and CDS indices (CDX IG, Itraxx & Itraxx Financials). These monthly data are the independent variables for the US and Europe by means of which we try to see whether we can predict systemic risk. We test the performance of each of these indicators from 0 to 6 lags (in months). When the indicators are tested with 0 lags, we are testing the performance of the indicator as measure of systemic risk. When the indicators are tested from 1 to 6 lags, we are testing the performance of the indicator as early warning of systemic risk. We also choose two systemic stress indicators: the Composite Indicator of Systemic Stress (CISS) for Europe and the Cleveland Financial Stress Index (CFSI) for the US. They act as dependent variables which will tell us whether there is or there is no systemic risk. We use three methods to test the performance of the indicators. The first one is the Logit regression and we take the highest McFadden R^2 and Count R^2 as criteria of selection of the best performing indicator of systemic risk. The second one is the KLR signal approach and we take the smallest noise-to-signal ratio as criterion of selection of the best performing indicator of systemic risk. The third and last one is the Granger causality test and we take the Akaike Information Criterion as criterion of selection. After having computed the results for all these three methods, the purpose is to see if their results are consistent.

Key words: Systemic risk; Measure; Early Warning; Systemic stress event; Logit regression; KLR signal approach; Granger causality test.

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List of abbreviations

AIC :	Akaike Information Criterion
AIG :	American International Group
BEC :	Bayesian Estimation Criterion
BIC :	Bayesian Information Criterion
CBOE :	Chicago Board Options Exchange
CDS :	Credit Default Swaps
CDX :	Credit Default Swap Index
CDX HY:	Credit Default Swap Index High Yield
CDX IG:	Credit Default Swap Index Investment Grade
CDOs:	Collateralized Debt Obligations
CFSI :	Cleveland Financial Stress Index
CISS :	Composite Indicator of Systemic Stress
CMOs:	Collateralized Mortgage Obligations
CoVaR :	Conditional Value-at-Risk
CV:	Conditional Variance
DIP :	Distress Insurance Premium
DJIA :	Dow Jones Industrial Average
EL :	Expected loss
ES :	Expected Shortfall
EU :	Europe
EURIBOR-OIS:	European Interbank Offered Rate Overnight Indexed Swap
EW :	Early Warning
FDIC :	Federal Deposit Insurance Corporation
FPE :	Final Prediction Error
FSIs :	Financial Stress Indices
GFC :	Global Financial Crisis
IBM:	International Business Machines
JPoD:	Joint Probability of Distress/Default
KCFSI:	Kansas City Fed Financial Stress Index
KLR:	Kaminsky, Lizondo, Reinhart

LIBOR :	London Interbank Offered Rate
LTCM:	Long-Term Capital Management
LVG :	Leverage
MBSs:	Mortgage-Backed Securities
MES:	Marginal Expected Shortfall
NFCI:	Chicago Federal Reserve Bank's Financial Conditions Index
NSR :	Noise-to-Signal Ratio
OLS:	Ordinary Least Squares
P-H:	Pagana and Hartley
PODs:	Probabilities of Distress/Default
RMBS:	Residential Mortgage Backed Securities
SES:	Systemic Expected Shortfall
S&P:	Standard & Poor's
STLFSI:	St. Louis Fed Financial Stress Index
TBTF:	Too Big To Fail
T-CoVaR:	Time-varying Conditional Value-at-Risk
TED:	Treasury Euro Dollar
TITF:	Too Interconnected To Fail
UAL:	United Airlines
US:	United States
VaR :	Value-at-Risk
Vol:	Volatility
VP:	Variance Premium

Introduction: What is systemic risk?

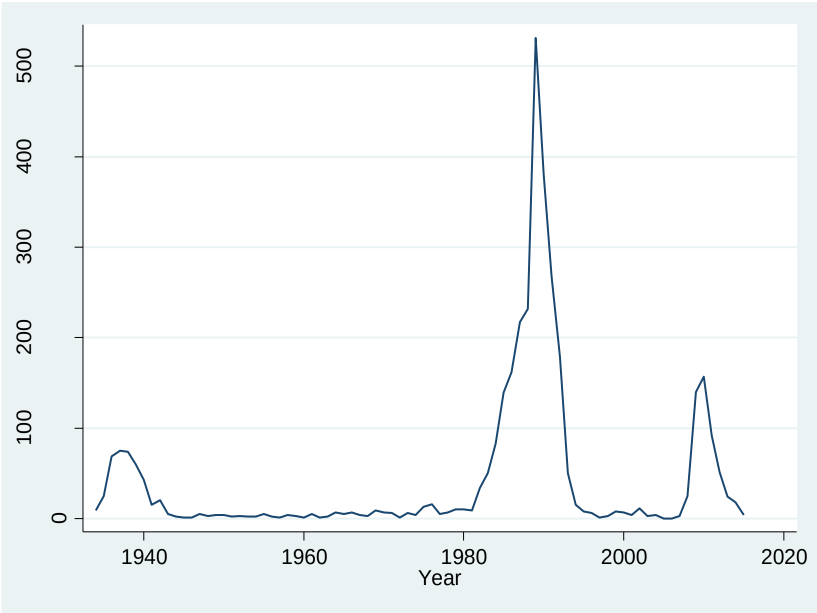
Systemic risk is a sudden, rapid and uncontrollable risk that a failure event, triggered by a single shock or bad news, expands to a large number of other financial institutions and that consequently this chain reaction destabilizes all the financial system at the end. In fact, the interconnectedness between the banks facilitates the propagation of systemic risk. As a reaction to a systemic crisis, investors become suspicious, paralyzing financial markets that become inefficient. Therefore, the real economy doesn't work properly anymore and goes into recession (Bijlsma, Klomp, & Duineveld, 2010, p. 19; Bugnon & Subtil, 2008, pp. 3, 5, 6; Bullard, Neely, & Wheelock, 2009, p. 403).

The problem is that because of the uncontrollable and unpredictable character of systemic risk, it is very difficult to find reliable systemic risk indicators (measures and early warnings). Therefore, the purpose of this paper is to have a more comprehensive analysis of systemic risk in order to find good systemic risk indicators. To do that, we will first review all the systemic risk indicators presented in the current literature. After that, we will use three different methods to know which is the best measure/early warning of systemic risk. What we will learn from that will help us to better manage systemic risk, which is very important in these times of crisis that are still ongoing at the time when we are writing.

The most striking example of a systemic crisis is the financial crisis of 2007-2008. In 2001, the Fed decreased interest rates in order to stimulate the economy. Consequently, there was an increase in the use of debt and therefore an increase of leverage. This resulted in a housing bubble. Besides, mortgage banks granted more and more loans to people with low or medium revenues. These loans were securitized through CDOs to transfer the default risk to other investors. Banks, insurance companies, hedge funds and pension funds decided massively to buy these types of CDOs, which were seen as safe and giving a higher return. However, during the mid 2004-2006 period, the Fed interest rates increased in order to deal with rising inflation. Therefore, a lot of lenders failed to reimburse the mortgages banks. Consequently, a lot of houses were sold, the housing prices decreased and that destabilized the US housing market. Besides, mortgage banks lost money and started going bankrupt. This US subprime crisis of 2007 was just the beginning. Afterwards, the crisis was intensified with the collapse of Lehman Brothers in September 2008.This crisis was aggravated even more because it spilled over into to markets outside the US, causing the European sovereign debt crisis in early 2010 (Knaepen, 2014, pp. 27-29).

Figure 1 below shows us other examples of systemic crises. Indeed, this graph shows the number of financial institutions failures per year from 1934 to 2015.

Figure 1: Number of Financial Institutions Failures per Year



Source: Federal Deposit Insurance Corporation, 2015, https://www2.fdic.gov/hsob/SelectRpt.asp?EntryTyp=30, own computations

We can clearly see three periods of extreme peaks. The first one appeared during the recession of 1937 during the Great Depression in the US in which 75 banks failed. The data that we collected from the Federal Deposit Insurance Corporation (FDIC) began in 1934 but if they had begun earlier, there would have been another peak in 1929 at the heart of the Great Depression. We can see that before 1937, in 1933 precisely, the impacts of the Great Depression were less severe thanks to President Franklin D. Roosevelt's New Deal that helped to overcome the crisis and to restore the confidence in the banking systems (Silber, 2009, p. 22). However, some economists asserted that this government action led to a weak recovery and not to a strong recovery (Cole & Ohanian, 2004, pp. 779-781). In other words, this government action accelerated the recession. Indeed, the economy went again into recession in 1937. The recession of 1937 was considered as America's third-worst recession of the twentieth century: real

GDP fell 10%, unemployment hit 20% and industrial production fell 32% (Waiwood, 2013, para. 2). Thus, the second phase of the Great Depression is the first peak that we see on the graph.

The second one appeared in 1989 in which 531 saving and loan associations failed. It was the time of the savings and loan crisis, producing the highest depression of US financial institutions since the Great Depression because of the increasing of inflation and interest rates. Indeed, these increases led the depositors to withdraw their funds and to a decrease of mortgages (Robinson, 2013, para. 1). Between 1986 and 1995, 1,043 thrifts with total assets of over $500 billion were unsuccessful (Curry & Shibut, 2000, p. 33).

The third and last peak occurred during the global financial crisis from 2007 to 2010. As we mentioned earlier, the crisis was aggravated in 2010 because it expanded to markets outside the US which led 157 banks to fail.

The aim of this thesis is to predict those peaks better in order to avoid them by finding the best indicators of systemic risk. Besides, all these systemic crises known until now highlight the need to measure and manage systemic risk. Furthermore, the term of systemic risk have got a prominent place in economic policy debates in recent years and this is for all these reasons that this issue is very interesting to study.

4.

Chapter 1

Literature review: common systemic risk indicators

1.1. Financial Stress Indices (FSIs)

The purpose of FSIs is to measure the financial instability in one piece by combining individual stress indicators into a single statistic (Kremer, Hollo, & Lo Duca, 2012, p. 3).

1.1.1. Composite Indicator of Systemic Stress (CISS)

The indicator's name and its abbreviation CISS was invented by Philipp Hartmann (2000). We outline below two main innovative features the CISS has vis-à-vis other FSIs.

The first innovative feature is in its economic foundation on the concept of systemic risk. For de Bandt and Hartmann (2000), the systemic risk can be defined as "*the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially*" (quoted in Kremer et al., 2012, p. 3).The higher the CISS, the higher the instability in the financial system, the higher uncertainty, the higher differences of opinions, the higher information asymmetry, the lower preferences for holding risky and illiquid assets and so the higher the systemic risk (Kremer et al., 2012, p. 10).

The second one is the application of the standard portfolio theory introduced by Hollo et al. (2012) and Louzis and Vouldis (2011). This portfolio theory is applied to the aggregation of sub-indices into the CISS. More precisely, the aggregation used to construct the CISS is a three-tier aggregation. It is only three-tier because it is impossible to cover all level of stress in the financial system because the real world is too complex and so the attention must be focused only on things that are systematically important (Kremer et al., 2012, p. 8).

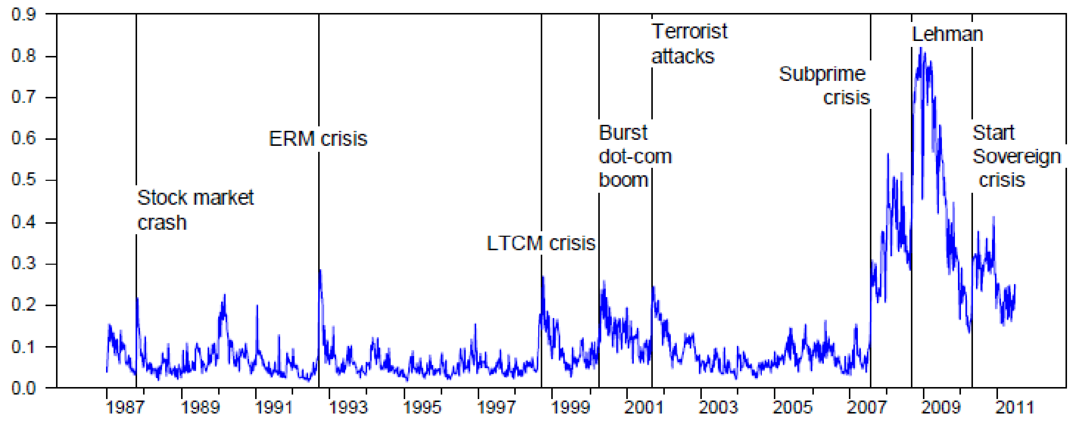
At the lower tier of this aggregation, fifteen individual indicators of financial stress are selected. These indicators are raw indicators and are presented in Appendix 1. According to Brunnermeier and Pedersen (2009) and Krishnamurthy (2010), it is more and more difficult to recognize individual stress features because of their interdependence. Therefore, the solution is to have market indicators catching diverse stress features simultaneously, called the raw indicators (Kremer et al., 2012, p. 10). Besides, these raw indicators have to meet some conditions: every five segments include at most three raw indicators, raw stress indicators have to cover market-wide developments, have to be accessible at daily/weekly frequency with a short publication lag, have to be computable for diverse countries and they have to contain sufficient long data histories that cover moments of financial stress (Kremer et al., 2012, p. 11).

At the intermediate tier of this aggregation, five segments are selected. Indeed, Hollo et al. (2012) measure systemic risk in Europe using a single composite measure (CISS) based on five market segments. The first one is the segment of financial intermediaries like banks, insurance companies, pension funds and other financial services providers. The second one is the bond market, including only sovereign and non-financial corporate issuers. The third one is the equity market, including only non-financial corporate issuers. The fourth one is the money (interbank and commercial paper) market. The fifth and the last one is the foreign exchange market, taking into account possible stresses having an impact on cross-border financing activities (Kremer et al., 2012, pp. 8-9).

At the top tier of this aggregation, we have all elements to compute the CISS. Fifteen stress indicators are now classified into five markets to form the CISS. After the transformation of the fifteen raw indicators, they are first aggregated by taking their simple arithmetic mean (Kremer et al., 2012, p. 13). Secondly, after having assembled the fifteen transformed raw indicators into the five sub-indices, each of the five sub-indices are now aggregated into the CISS, following the rules of the portfolio theory. To do that, we have to think about the weights we will give to the five sub-indices. The five sub-indices are combined by taking into account the cross-correlation between them. In consequence, the CISS puts relatively more weight on events in which stress is predominant in different market segments simultaneously, catching the perception that financial stress is more systemic and thus more dangerous for the economy as a whole. Besides, the weights can also be calibrated in proportion to their systemic importance as in Illing and Liu (2006) and Oet et al. (2011) (Kremer et al., 2012, pp. 17-18).

Finally, the CISS is an interesting indicator of systemic risk because it captures historical episodes of financial crises particularly well. For that matter, the narrative approach of Hakkio and Keeton (2009) find out whether peaks in the CISS can be related to well-known episodes of financial crises (Kremer et al., 2012, p. 29). The CISS appear to be a good indicator of systemic risk when we look at Figure 2 because all extreme peaks in the CISS can be associated with specific financial stress events (Kremer et al., 2012, pp. 29-31).

Figure 2: CISS and major financial stress events in the global and European financial markets



Source: Kremer et al., 2012, p. 30.

1.1.2. Cleveland Financial Stress Index (CFSI)

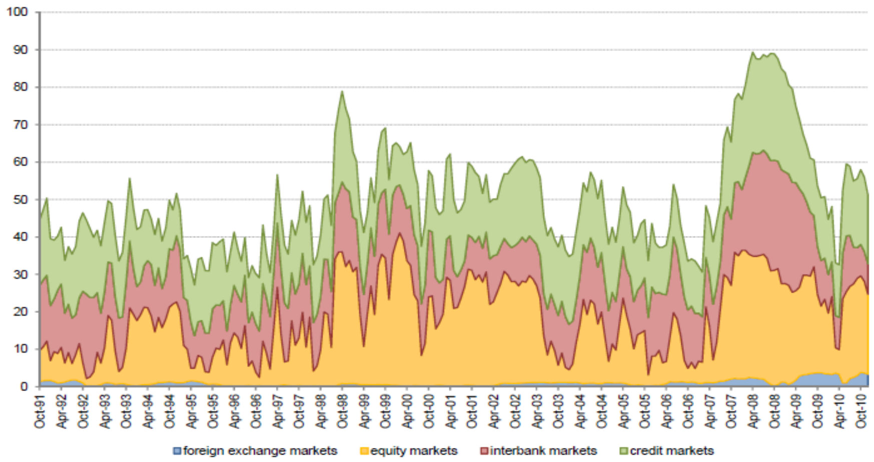
The CFSI measures the financial stress in the US and was originally constructed by Oet, Bianco, Gramlich, and Ong in early 2009.

The aggregation used to construct the CFSI is also a three-tier aggregation. At the lower tier, eleven individual indicators of financial stress are selected. At the intermediate tier, four segments are selected. At the top tier, the CFSI is computed by applying the portfolio theory to the aggregation of sub-indices composing the CFSI (for more information see Appendix 2).

Unlike other US financial stress indices like the Kansas City Fed Financial Stress Index (KCFSI) , the St. Louis Fed Financial Stress Index (STLFSI) and the Chicago Federal Reserve Bank's Financial Conditions Index (NFCI), the CFSI is the only one which can measure the financial stress in four different markets individually wherein interbank, foreign exchange, credit and equity markets. The decomposition of CFSI (see Figure 3) in these four markets allows representing the entire US financial market in order to produce more reliable signals on the financial stress in the US (Manamperi, 2013, pp. 18-21).

We can see on Figure 3 that the measure from the foreign exchange market contributes the least to overall financial stress whereas the measures from the credit, interbank and equity markets contribute the most to overall financial stress and rise and fall at the same time, which magnifies overall changes in financial stress. During times of crises, the stress increased in all four markets constituting the CFSI and consequently the Federal Reserve had to react in order to mitigate and reduce this stress. This decrease in overall stress was first apparent in equity markets followed by the interbank and credit markets (Oet et al., 2011, pp. 41-42).

Figure 3: Decomposition of CFSI in four markets



Source: Oet et al., 2011, p. 42.

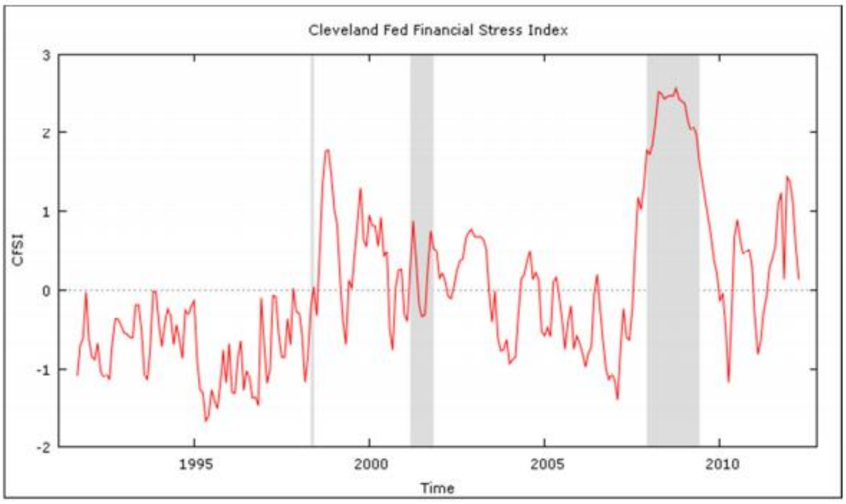
Besides, according to Manamperi (2013), the CFSI is a good indicator because it shows moderate stress (explained in Table 1) in 2001-2002 during the stock market crash and even significant stress in 1998 during the Long-Term Capital Management (LTCM) crisis and during the subprime crisis of 2007–2009. These significant periods of financial stress during the late 2000s recession are highlighted in Figure 4 in grey areas.

Table 1: Stress Episode and the corresponding CFSI values

Stress Episode	CFSI Range
Grade 1 (Below Normal Stress)	Less than or equal to -0.5
Grade 2 (Normal Stress)	Between -0.5 and 0.59
Grade 3 (Moderate Stress)	Between 0.59 and 1.68
Grade 4 (Significant Stress)	Greater than 1.68

Source: Manamperi, 2013, p. 21.

Figure 4: The Cleveland Financial Stress Index (CFSI)



Source: Manamperi, 2013, p. 21.

1.2. Volatility Indices

The volatility represents the unstable movements of financial assets over time. Assets that are more volatile are more risky than assets with lower volatility (iPath Exchange Traded Notes [iPath ETNs], n.d., p. 3).

There are two types of volatility (iPath ETNs, n.d., pp. 3-4). The first one is the realized/actual/historical volatility which is a backward-looking measure. This type of volatility evaluates the movements of stock prices based on the volatility that these stock prices had historically.

The second one is the implied volatility which is a forward-looking measure. The implied volatility is the market expectations/sentiments about future volatility, sometimes called “fear gauge”. It is why it is interesting to see how correct the market predictive powers are.

Most of the times, the predictions of the market are not correct because they are based on imperfect information and hypothesizes about the evolution of future returns. In consequence, Neely (2009) and a large number of other authors - Canina and Figlewski (1993), Day and Lewis (1992), Jorion (1995) - even say that the implied volatility is a biased predictor of realized volatility across asset markets. For example, if earning reports are worse than expectations, the uncertainty about future incomes increases, intensifying the implied volatility, meaning that the market is anxious about possible stock downside. This is the case when equity markets fall sharply. Indeed, the implied volatility has a strong negative correlation with equity markets.

However, earning reports can sometimes be in accordance or even better than expectations, meaning that the market is not worried and expects that the movements of stock prices will be stable in the future.

1.2.1. VIX (Implied volatility of S&P 500)

Whaley (1993) introduced the Chicago Board Options Exchange (CBOE) VIX index that measured the 30-day volatility of the S&P 100 Index (OEX Index) option prices in 1992. He chose the OEX Index because at this time, OEX options were the most actively-traded index options in the US (75%) whereas the SPX options were one-fifth less active (16,1%). A few years later, in 2003, two big changes were initiated by CBOE together with Goldman Sachs: the VIX measured the near-term volatility of the S&P 500 Index (SPX Index) option prices and out-of-money options were introduced in the index calculation (Chicago Board Options Exchange [CBOE], 2009, p. 2; Whaley, 2008, pp. 2-3). Therefore, the volatility of the S&P 500 over a space of 30 days is nowadays measured by the VIX index. Indeed, the VIX index is a forward-looking index of expected future price volatility by options contract prices. So, the VIX is an index, like other indices, but the difference is that this index measures the volatility and not the price.

The VIX shows the expectations of investors about the future volatility: the more the volatility index is advanced, the more the investors envisage the volatility of stock index to be bigger in the future and vice versa. It is often called a “fear index” or an “investor fear gauge" because the fear of investors increases when the VIX increases and vice versa. Indeed, the VIX increases when market declines and so investors are pessimistic and want to buy a lot of put options to hedge themselves. On the contrary, the VIX decreases when the market improves and so investors are blind optimistic and don't take any hedging action. It is why the VIX index represents the price of portfolio insurance (Andil Trader Inside, March 3, 2014, para. 4; Whaley, 2008, p. 4).

According to Bekaert and Hoerova (2014), the VIX index is subdivided into two different components: the conditional variance of the stock market (CV) measuring the economic uncertainty and the equity variance premium (VP) measuring the risk aversion.

The VIX index is a good indicator of systemic risk because it peaks in moments of stress events. For example, the level of VIX increased the most until a level of 100 during the October 19, 1987 market crash. The VIX had also known a rise in level during the "mini crash" in October 1989 resulting from the United Airlines (UAL) restructuring failure. The following dates namely 1990, 1991, 1997, 1998 and 2008 were related with stress events and this was exactly in these periods that VIX went up. High levels of VIX were concomitant with high degrees of market turmoil (Whaley, 2008, pp. 5-6).

1.2.2. VSTOXX (Implied volatility of EURO STOXX 50)

The VSTOXX Index is the European VIX i.e. the implied volatility on derivatives on the EURO STOXX 50, measuring the market expectations about the near-term volatility of the EURO STOXX 50 (STOXX, 2015a). However, his sample is smaller because VSTOXX futures were only introduced at the end of April 2009 (Stanescu & Tunaru, 2013, p. 16). The construction of this index is based on 50 blue-chip companies of dominant areas from 12 countries in Europe like Belgium, Finland, Australia, Ireland, Italy (STOXX, 2015b, p. 1).

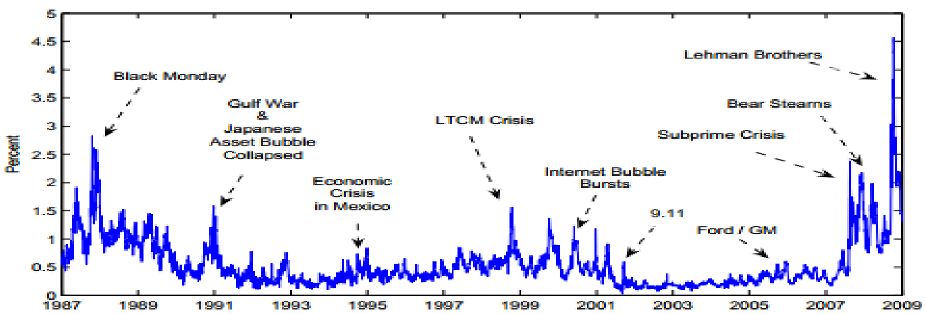
The VSTOXX index is a good indicator of systemic risk because it peaks in moments of stress events. For example, the level of VSTOXX spiked in 2001 with the terrorist attacks, followed by the Iraq crisis in 2002-2003. More recently, the VSTOXX also increased in 2007 because of the subprime crisis, in 2008 with the Lehman Brothers collapse, in 2010 during the Greek crisis and in 2011 during the European sovereign debt crisis (Stanescu & Tunaru, 2013, pp. 5-8). Besides, a clear advantage of the VSTOXX futures is that they are EUR- denominated volatility futures so they do not experience foreign and currency risk (Eurex Exchange [Eurex], June 27, 2013).

1.3. Ted Spread

The Ted spread is the difference between the interest rate at which bank lend each other and a risk free rate (Boudt, Paulus, & Rosenthal, 2014, p. 5; Gonzlez-Hermosillo & Hesse, 2009, p. 3). As a result, the more this spread is high, the fewer banks trust each other because there is more risk of default on interbank loans, forecasting a downturn in the stock market. In consequence, interbank lenders request a higher rate from their loans to compensate this risk. On the contrary, the more this spread is low, the more banks trust each other because there is less risk of default on interbank loans, predicting an expansion of the economy. As a result, interbank lenders request a lower rate from their loans (Boudt et al., 2014, p. 9; Learning Markets, 2008, para. 3). Consequently, according to Heider, Hoerova and Holthausen (2010); Acharya and Skeie (2011), the Ted spread is a good indicator of liquidity and counterparty risk in the interbank market (Hollo, et al., 2012, p. 13). Besides, it gives also a good idea about the well-being of the banking system (de la Torre, 2011, para. 1).

The Ted spread is a good indicator of systemic risk because an increase in Ted spread is related to an increase in systemic risk. Indeed, peaks in Ted spread correspond to stress events like we can see in Figure 5 (Giesecke & Kim, 2011, pp. 1393-1394; Wu & Hong, 2012, p. 7).

Figure 5: Ted spread during the sample period, along with significant events



Source: Giesecke & Kim, 2010, p. 1394.

Furthermore, the Ted spread has great capabilities to predict bank failures because a rise in the Ted spread always occurs before an increase in bank failure rates. For example, the Ted spread increased during the Black Monday crash of 1987, forecasting the bank failure of 1988. Besides, the Ted spread varies normally between 10 and 50 basis points. However, during the subprime mortgage crisis in 2007, the Ted spread skyrocketed until 150-200 basis points and increased even more in 2008, exceeding 300 basis points, respectively prognosticating bank catastrophes of 2008 and 2009 (Vincent, 2011, para. 6; Wu & Hong, 2012, p. 21).

1.4. Conditional Value-at-Risk (CoVaR)

The concept of Conditional Value-at-Risk is introduced by Adrian and Brunnermeier (2010). The Conditional Value-at-Risk is an extension of the Value-at-Risk (VaR) because the CoVaR determines the possibility that a specific loss exceeds the VaR. The VaR being the maximum loss in an asset value, if the specific loss exceeds the VaR, it will represent a real risk. In fact, the purpose of the CoVaR is to make a distinction between the Value-at-Risk of a system in normal times and the Value-at-Risk conditional on the stress under which the system is. Therefore, the idea is to observe how the Value-at-Risk is modified when an institution is under stress because it generates changes in the distribution of asset values of the system (Fullenkamp, 2013, pp. 3, 5).

According to Adrian and Brunnermeier (2010), the Conditional Value-at-Risk is a good indicator of systemic risk (Fouque & Langsam, 2013, pp. 165-170).

Sometimes, authors use slightly different Conditional Value-at-Risk indicators. For example, a study (Arsov, Canetti, Kodres, & Mitra, 2013, pp. 11-12) finds that time-varying CoVaR (T-CoVaR), as well in Europe and in the US, has a great power to predict systemic risk. Another example is the study (Rodríguez-Moreno & Peña, 2011, p. 33) from the Department of Business Administration, which finds that in the US, the worst reliable indicator of systemic risk is the equally weighted Delta-Co-Value-at-Risk.

1.5. Systemic Expected Shortfall (SES)

The concept of Systemic Expected Shortfall (SES) is introduced by Acharya, Pedersen, Philippon, and Richardson (2011). It evaluates the disposition of a firm to be undercapitalized when the system as a whole is undercapitalized (Fouque & Langsam, 2013, pp. 170-173).

The origin of the concept of Expected Shortfall (ES) comes from the weaknesses of the Value-at-Risk (VaR). These weaknesses are the following: assumption of the normality of the distribution, the fact that the risk is not taken into account beyond a certain threshold, the short memory of VaR related to periods of stress and the fact that the VaR does not respect the principle of sub-additivity. In this way, the ES is an additional measure to respond to these weaknesses. Therefore, the ES is more robust than VaR and has additional properties including the fact that the ES is more sensitive than VaR to extreme events (Henrard, 2014, pp. 30-32).

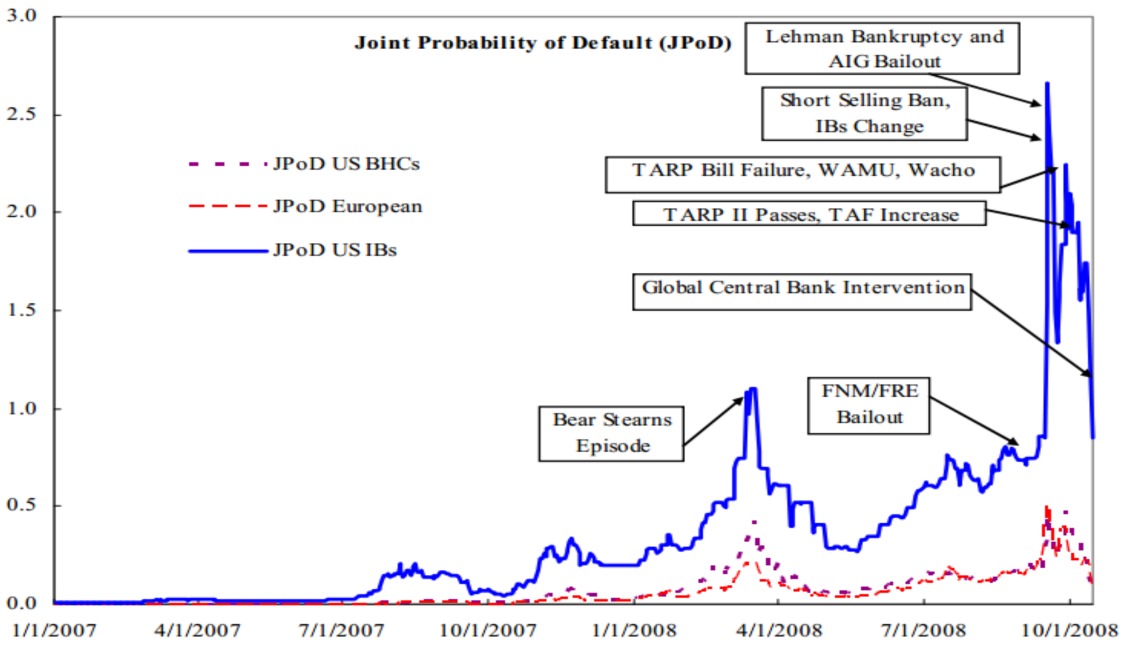
To measure systemic risk, some authors prefer using the Marginal Expected Shortfall (MES) which is closely related to the SES (Fouque & Langsam, 2013, p. 170). It was first estimated by Brownlees and Engle (2010). The MES is the predicted equity loss per dollar put in a firm if the system as a whole declines by a particular amount (Idier, Lamé, & Mésonnier, 2013, p. 5).

According to Acharya et al. (2010), the Systemic Expected Shortfall (SES) is the best indicator of systemic risk. Indeed, they found that there is a clear relation between MES (which is closely related to SES) and systemic risk: a higher MES is associated with a more negative return during the crisis. Besides, combining MES with leverage (LVG) explains the systemic risk even better. However, ES, expected loss (EL), volatility (Vol), the standard measure of covariance, and beta have a modest explanatory power of systemic risk (Acharya et al., 2010, pp. 6, 26-28).

1.6. Joint Probability of Distress/Default (JPoD)

The JPoD is the probability that every bank in the system experiences big losses at the same time. This indicator not only takes changes in the individual banks' probabilities of distress (PoDs) into account but also changes in the distress dependence among the banks (Segoviano & Goodhart, 2009, p. 17). The distress dependence is important to estimate in order to control the stability of the banking system. If banks suffer from large losses, it will threaten the stability of the whole system because of the interconnectedness between banks (Segoviano & Goodhart, 2011, p. 327). Besides, the distress dependence increased in times of distress, like we can see in Figure 6.

Figure 6: Joint Probability of Distress: January 2007-October 2008



Source: Segoviano & Goodhart, 2009, p. 23.

The European JPoD increased in the same way as JPoD US during relevant crisis periods. However, risks for European banks, measured by JPoD, tended to be lower than those for US banks. Besides, during the Bear Stearns Episode and the Lehman Brother's collapse, both European and US banks experienced highest risks. These risks were the same among European banks at these times whereas they appeared to be bigger during the Lehman's collapse for American banks (Segoviano & Goodhart, 2009, p. 27).

1.7. Credit Default Swap (CDS) Indices

A credit default swap is a contract similar to an insurance against default between two parties. Imagine that on the one hand, a party A, the CDS protection buyer, makes a loan to a certain company but is worried about the ability of the company to reimburse him. Therefore, the CDS protection buyer purchases a credit protection from party B, the CDS protection seller, meaning that he would pay quarterly premium, called the CDS spread, to the CDS protection seller over a certain period. The CDS protection buyer does that to protect himself against the possible company's default (late payments, bankruptcy, restructuring, repudiation, obligation acceleration). The company doesn't know anything about this agreement. In this way, the CDS protection seller is like an insurance company for the CDS protection buyer. In fact, Party A swaps the underlying credit default risk with Party B against a periodic fee. On the other hand, party B promises to pay an indemnity to party A only if a predefined default event occurs during this period. In this case, the contract is finished and the quarterly payments are interrupted but if there is no default, the contract ends at its maturity date (Cont, 2010, p. 36; Knaepen, 2014, p. 65).

Therefore, CDS were initially significant tools to decrease systemic risk. Indeed, CDS allowed the CDS protection buyer to beneficiate from a higher protection toward company's default thanks to the insurance of the CDS protection seller. Thanks to that, the corporate bond could be transformed into a risk-free bond. This resulted in lower systemic risk and in more stable financial system (Kiff, Elliott, Kazarian, Scarlata, & Spackman, 2009, p. 3). Consequently, credit default swaps were a way to hedge and securitize against credit risks and credit exposure (European Central Bank [ECB], 2009, pp. 10-11).

However, the positive aspect of the CDS has been debatable in recent years. Indeed, CDS were blamed for being at the origin of the financial crisis of 2007-2008 because they encouraged banks and other financial institutions to own mortgage securities on which they experienced big unexpected losses (Stulz, 2009, p. 80). The CDS market was also blamed for making the financial crisis worse because when failures, generated by CDS, occured in institutions, it was highly probable that these failures would expand in other institutions, destabilizing the financial system (Stulz, 2009, p. 81). Therefore, CDS increase systemic risk because a systemic risk is the risk that failures can expand to a large number of financial institutions and that consequently this chain reaction destabilizes all the financial system in the end.

Moreover, CDS become more and more complex so that it is sometimes even difficult to assess the related risks mostly because of the lack of disclosure/transparency of CDS. This is due to the amount of unavailable information about credit exposure and the inaccessible data on credit derivatives transactions, causing more systemic risk and more instability in the financial system because it creates opportunity for market abuses (Kiff et al., 2009, p. 16).

In addition to the lack of disclosure, the lack of regulatory surveillance also generates an increase in the systemic risk and compromises the market integrity. In fact, the CDS market is under regulated. Indeed, the CDS protection buyer can speculate on the evolution of the credit risk of the underlying party by buying CDS without having any credit exposure to the underlying party (Kiff et al., 2009, p. 16).

We also have to stress the importance of the possible counterparty risk, it is to say, the fact that the CDS protection seller may fail to comply with commitments suggested in the original contract, lowering the value of the default insurance and increasing the systemic risk. We can illustrate that with the case of American International Group (AIG) that was a seller of CDS. When AIG was rated AA- in September 2008, it had no problem but once it was rated A, they were obliged to post additional collaterals on their mortgage-backed CDS positions but they could not (Kiff et al., 2009, p. 15-16). Therefore, AIG defaulted but the problem got larger due to the concentration of market participants in the CDS market. Indeed, when a seller (in this case AIG) failed to repay his obligations, it impacted other dealers and even other markets. Indeed, the default of protection sellers increases the default contagion and therefore the systemic risk (Cont, 2010, p. 38). Giglio (2011) develops this point by saying that it is true that CDS transform corporate bond into risk-free bond, but just until the CDS protection seller is not solvent anymore. In extreme cases, we can even speak about joint default risk (systemic default risk) of both the reference entity and the CDS protection seller at the same time. It was the case for example on September 15, 2008 when Lehman Brothers defaulted on its bonds. Indeed, AIG sold many CDS with Lehman Brothers as reference entity. In reality, it is possible that these two defaults do not occur at the same time but they are still connected. To resolve the problem of counterparty risk associated to double default, collateral agreements are implemented but they are not very powerful (Giglio, 2011, pp. 6-10).

To sum up, we can see that even if CDS were instruments hedging and managing the systemic risk many years ago, the academics agree to say that CDS have created systemic risk since the financial crisis of 2007-2008.

1.8. Distress Insurance Premium (DIP)

The distress insurance premium is a systemic risk indicator introduced by Huang, Zhou, and Zhu (2009, 2010) that is described as the probable insurance premium to cover distressed losses in a banking system (Schwaab & Koopman, 2011, pp. 9-10).

Besides, the DIP is a composite indicator of individual banks probabilities of default measured from CDS spreads and correlated defaults measured from correlations in equity prices (Huang et al., 2010a, p. 5). Indeed, there is a link between equity prices and probabilities of default. The intuition behind is that when the counterparty has more chance to default, the CDS seller requires a greater CDS spread from the CDS buyer to protect him and that will lead to a decrease in equity prices. This negative relation between probability of default (measured by CDS spreads) and equity prices can be seen in Figure 7 and 8. For example, between 2011 and 2012, CDS spreads of KBC reached their maximum while equity prices of the bank were at their minimum.

Figure 7: KBC BB CDS EUR

Source: Bloomberg, given by Jérôme Bollue, Senior Fixed Income & Derivatives Dealer of CBC Banque & Assurance, where I made my internship from 02/02/2015 to 24/04/2015

Figure 8: KBC BB Equity

Source: Bloomberg, given by Jérôme Bollue, Senior Fixed Income & Derivatives Dealer of CBC Banque & Assurance, where I made my internship from 02/02/2015 to 24/04/2015

The concept of DIP is very close to these of MES of Acharya et al. (2010) and of CoVaR of Adrian and Brunnermeier (2009). However, a major advantage of the DIP, unlike the CoVaR, is that the DIP can determine the contribution of each particular bank or bank group to the overall distress of the banking system. The MES is in accordance with the DIP concerning this point and it is also a coherent risk indicator, just as the DIP. However, a first distinction between these two indicators is that the percentile distribution determines the extreme condition in the MES whereas a given threshold loss of the underlying portfolio does it in the case of the DIP. Besides, the probabilities in the tail event are normalized in the case of the MES whereas they are not normalized in the case of the DIP. Furthermore, the fact that the MES is computed depending on equity return data while the calculation of the DIP is based on CDS data is the most relevant difference between the DIP and the MES (Huang et al., 2010b, pp. 10-11).

1.9. Yield Curve Slope

The yield curve is a graphical representation of different bond yields with the same level of risk, but at different maturities (Fabozzi, 2007, pp. 3, 23).

The yield curve slope, which is the spread between long-term and short-term yields, is considered as an accurate predictor of future economic activity for three reasons. Firstly, the slope of the yield curve is linked to modifications in GDP, consumption, industrial production and investment (Estrella & Turbin, 2006, p. 1). Secondly, the yield curve slope is affected by the monetary policy because when the monetary policy is tightened (resp. eased), short (resp. long) -term interest rates rise above long (resp.short) -term interest rates which is a sign of an upcoming recession (resp. economic properity) (Estrella & Turbin, 2006, p. 2). Thirdly, when the expectations of investors about the average future path of short-term interest rates change, so does the slope of the yield curve: it is the so-called “expectations hypothesis” (EH) (Dewachter, Iania, & Lyrio, 2014, p. 1; Estrella & Turbin, 2006, p. 2; Fabozzi, 2007, pp. 79-80).

Besides, the future economic activity can take three ways depending on the slope of the yield curve: economic prosperity, economic transition and upcoming recession. Firstly, if the yield curve is rising, long-term bonds will have a higher yield compared to short-term bonds, which means that we are in a period of economic prosperity. Secondly, if the yield curve is flat, short-term and long-term yields will be very close to each other, forecasting an economic transition. Thirdly, if it the yield curve is declining (also called inverted yield curve), the short-term yields will be higher than the long-term yields, which would be a sign of an upcoming recession (Fabozzi, 2007, p. 77; Reilly & Brown, 2011, p. 753). Consequently, if a yield curve is inverted, it will be a sign of an upcoming recession, and therefore a sign of an increase in systemic risk. In addition to that, as the yield curve slope can predict recession signals earlier than other near coincident indicators, it is considered as a better forward-looking indicator of systemic stress (Arsov, Canetti, Kodres, & Mitra, 2013, p. 11).

1.10. Financial sector equity indices

Surprisingly, bank equity indices haven't been used yet in the systemic risk literature. In our opinion, it could be a good predictor of systemic risk because the stock market is often seen as a leading indicator of the economy. Many believe that large decreases in stock prices reflect future recession, whereas large increases in stock prices suggest future economic growth (Comincioli & Wesleyan, 1996, p. 1). In other words, the risk of a recession is incorporated in stock prices. Thus, systemic risk could also be incorporated in bank's stock prices. For this reason, we will analyze bank equity indices in the empirical part of this thesis.

22.

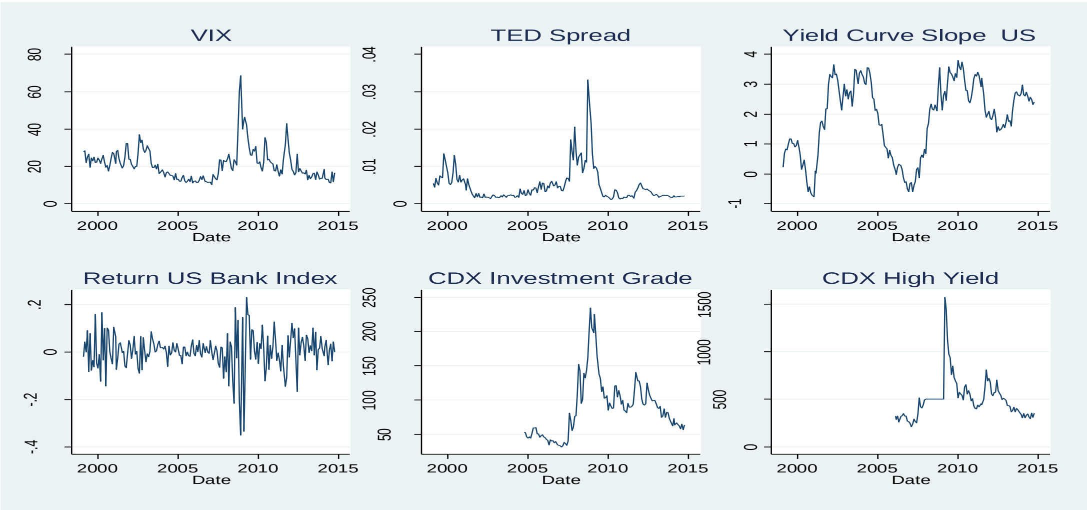
Chapter 2

Empirical study

2.1. Data

After testing different systemic risk measures for the US and Europe, Rodríguez - Moreno and Peña (2011) come to the conclusion that the best performing indicators of systemic risk are simple and robust indicators got from credit derivatives and market interest rates. On the contrary, the worst performing indicators of systemic risk are based on complex models (Rodríguez-Moreno & Peña, 2011, p. 29). This is why, like Rodríguez-Moreno and Peña, we concentrated on simple indicators of systemic risk that are easily available for everyone. Consequently, we will not cover indicators like CoVaR, SES, DIP, etc as indicators of systemic risk because they are the most complex indicators developed in the literature review. Indeed, we would rather focus our attention, for the US and Europe, on five simple indicators (measures/early warnings) of systemic risk: market volatility (VIXX & VSTOXX), interbank rates (Ted spread), Yield curve slope, Return of the bank equity indices and CDS indices (CDX IG, Itraxx & Itraxx Financials). These monthly data are the independent variables for the US and Europe by means of which we will try to see whether we can predict systemic risk (see Figure 9 and 10).

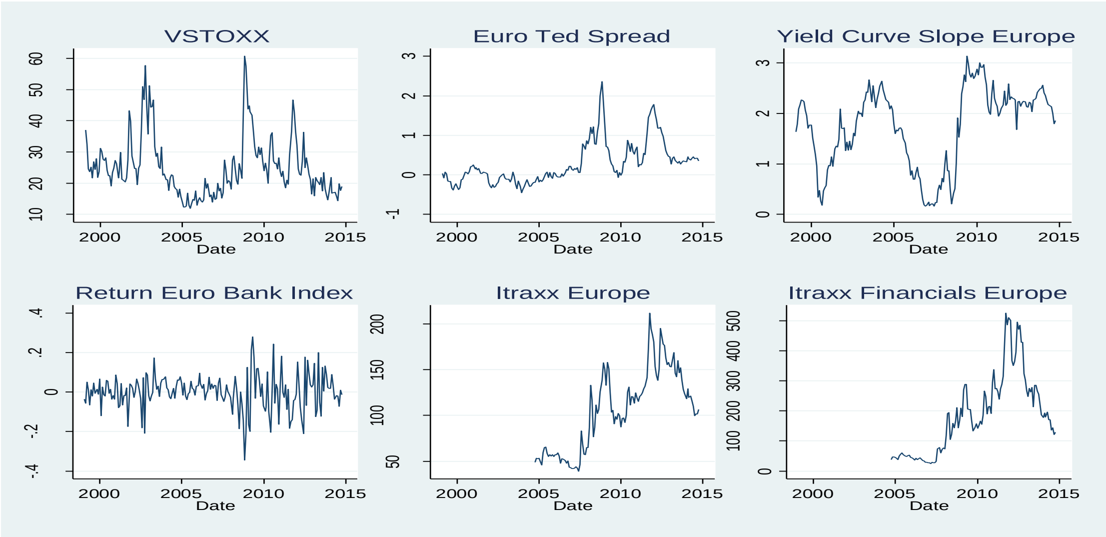
Figure 9: Potential measures/early warnings US



Source: Datastream & Bloomberg, own computations by Stata

Note: at the beginning, we also wanted to use the Credit Default Swap Index High Yield (CDX HY) but even when searching these data from two different sources (Datastream and Bloomberg), we always had missing data. Indeed, the curve is flat for the period of 2008. Therefore, we decided to drop off CDX HY from our data.

Figure 10: Potential measures/early warnings EU

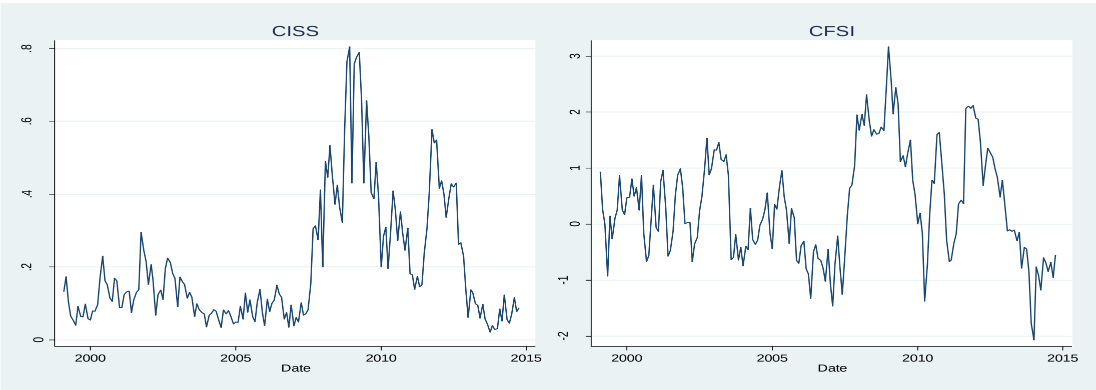


Source: Datastream, own computations by Stata

Since the CDS indices begin much later than the rest of the data, it raises questions about the comparability of their empirical results with the rest of the variables.

We also chose two systemic stress indicators, represented in Figure 11: the Composite Indicator of Systemic Stress (CISS) for Europe and the Cleveland Financial Stress Index (CFSI) for the US. They act as dependent variables which will tell us whether there is or there is no systemic risk.

Figure 11: Systemic Stress Indicators



Source: Datastream, own computations by Stata

We provided a table with the sources and symbols of the different series in Appendix 3.

The Ted spreads and Yield curve slopes are obtained by the following formulas:

(i) US Ted spread= US 3 months LIBOR – 3 months Treasury Bill
(ii) EU Ted spread= EU LIBOR 12 months – German Government Bond 2 years
(iii) US Yield curve slope= 10 years Treasury Yield – 3 months Treasury Yield
(iv) EU Yield curve slope= 30 years German Government Bond Yield – 2 years German Government Bond Yield

We followed the literature to find the formulas we used for the Yield curve slopes (Fabozzi, 2007, p. 187). In the formula for the EU Ted spread, we didn't use the same maturity for the LIBOR and the German Government Bond because the lowest maturity we found for the German Government Bond is two years whereas the highest maturity we found for EU LIBOR is one year.

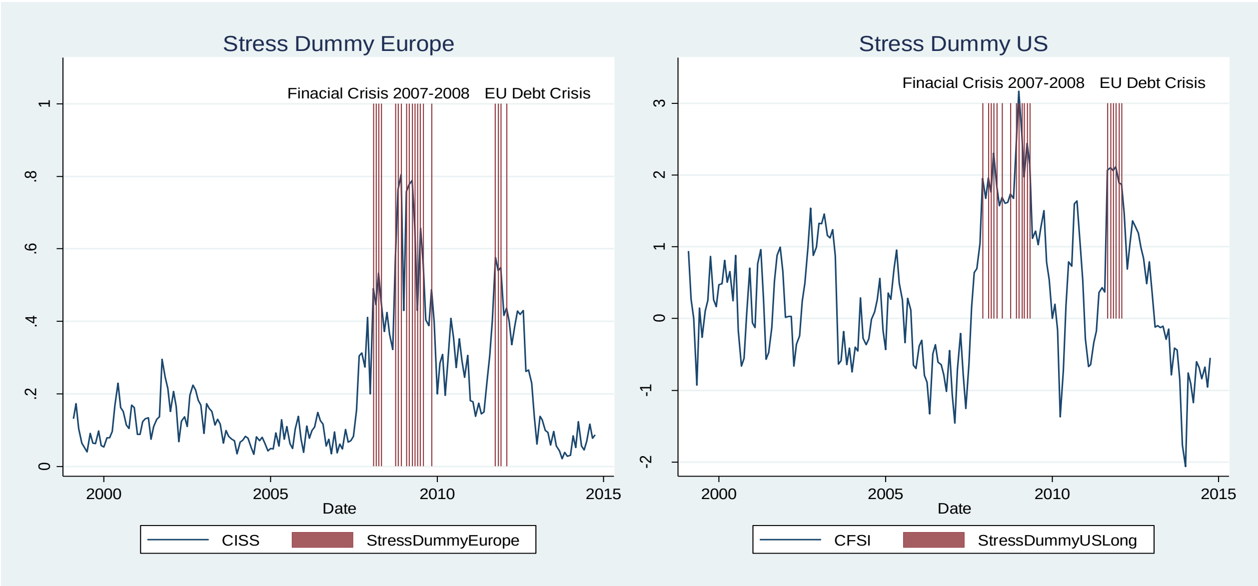
Please find also in Appendix 4 the summary statistics of our data.

2.2. Systemic stress events

The first step was to create a stress dummy variable for the US and Europe that took the value 1 when there was a systemic stress event and the value 0 otherwise, as it is represented by the red bars in Figure 12. The first issue was to find the systemic stress events. To solve this issue, we decided to follow this methodology: we identify an episode of extreme financial stress when the CISS (EU) or CFSI (US) crosses its 90th percentile (Lo Duca & Peltonen, 2011, p. 6). This means we make the assumption that the CISS and the CFSI are good systemic risk indicators.

In Figure 12, we can see the different periods of systemic stress events, when the value of the CISS (EU) or CFSI (US) is higher than the 90th percentile of the CISS (EU) or CFSI (US). Thanks to that, we can compare the peaks of each variable with theses systemic stress events: if the variable peaks during periods of systemic stress events, this would mean that this variable is a good measure/early warning of systemic risk.

Figure 12: Systemic Stress Dummies



Source: Datastream, own computations by Stata

Firstly, looking at these figures, we can notice that periods of systemic stress events are the same for Europe and the US. According to Forbes and Rigobon (2002), the contagion mechanism of systemic risk is such that, when a shock happens to one country, this shock will be propagated to other countries, making the systemic risk global (Kalotychou, Remolona, & Wu, 2014, p. 1).

Indeed, shocks are expanded around the world because of strong financial linkages during the recent US subprime crisis and the subsequent European sovereign debt crisis (Kalotychou et al., 2014, p. 1). During the US subprime crisis, mortgage banks granted more and more loans to people with low or medium revenues. These loans were securitized through Residential Mortgage Backed Securities (RMBS), Collateralized Mortgage/Debt Obligations (CM/DOs) and Credit Default Swaps (CDS) to transfer the default risk to worldwide investors (Markose, Giansante, Gatkowski, & Shaghaghi, 2009, p. 2).

Besides, during the European sovereign debt crisis, Fong and Wong (2012) found that shocks were extended to different countries in Europe, not only Greece but also Portugal, Ireland, Italy and Spain (Kalotychou et al., 2014, p. 1). However, the European sovereign debt crisis did not only impact Europe. It also had serious indirect repercussions in the US because for the Council on Foreign Relations (2012), "*the U.S.*

is tied into the global economy through interest rates, through trade, through exchange rates, through credit spreads, through bank borrowing costs, and so if Europe spirals downward, it will certainly impact us" (R. Clarida, interview, May 25, 2012, para. 7). It was also due to the fact that US banks had operations in many countries in Europe. Therefore, we can see that there are channels of exposure between US and Europe institutions (R. Clarida, interview, May 25, 2012, para. 2). Indeed for R. Clarida (interview, May 25, 2012, para. 7), "*We're all in this together*".

Secondly, we can see that three important events are not considered as systemic stress events in our methodology. The first one is the September 11, 2001 terrorist attacks where two airplanes flew into the North and South towers of the World Trade Center in New York City. This attack had huge consequences on the economy because it led to the fall of the Dow Jones index by more than 600 points, to the aggravation of the 2001 recession and to the War on Terror, which was one of the biggest government spending programs in the US history (Amadeo, 2015, para. 1). The second one is the Dot-com Crash or the Dot-com Bubble from 1990 to 2002 where computers and other technology-related stocks were traded on the new electronic Nasdaq stock exchange. At the beginning, banks saw internet as a way to boost their productivity and invested a lot in the shares of the early internet companies "Dot-coms". Unfortunately, investors realized by the early 2000 that this Dot-com Bubble was a speculative bubble (Colombo, 2012, para. 4). Indeed, within months, the Nasdaq Composite lost 78% of its value, sinking from 5046.86 down to 1114.1, and even down to 1108.49 in October 2002 (DeGrace, 2011, para. 1; The Equity Desk, March 29, 2015, para. 1). Besides, the increase in the internet trading led to the 2000 stock market crash (DeGrace, 2011, para. 2). The third one is the May 6, 2010 Flash Crash. Indeed, this crash was very fast: S&P 500, Nasdaq 100 and Rusell 2000 broke down and then recovered within only 36 minutes. Worse than that, the Dow Jones Industrial Average (DJIA) experienced this biggest fall ever, plunging about 1,000 points within also 36 minutes. This crash was due to the high frequency trading of the electronic market (Kirilenko, Kyle, Samadi, & Tuzun, 2014, pp. 1, 38). Therefore, in order to avoid this to happen again, the price of a stock has now a maximum range until it could go in a short period of time (Egan, 2014, para. 1). To sum up, we can see that all these three events had big impacts on the economy and certainly on the systemic stress but that these impacts were not big enough to consider these events as systemic stress events.

On the contrary, the financial crisis of 2007-2008 and the European sovereign debt crisis are considered as systemic stress events in our methodology. The financial crisis of 2007-2008 was caused by the combination of high leverage and by the securitization of low quality mortgages. Before the financial crisis of 2007-2008, pooling different mortgages assets was seen as a way to diminish the risk. Unfortunately, the major part of mortgages being securitized was actually of poor quality. However, many of the MBSs and CDOs were rated AAA by the rating agencies such as Moody's and Standard & Poor's only because they were paid by banks that created MBSs. In the mid 2000s, it became clear that these pooled loans weren't worth an AAA rating. Indeed, at that time, interest rates sharply increased, making impossible for borrowers to repay their mortgages loans (The Economist, 2013, para. 1). It was the worst financial crisis after the Great Depression of the 1930s and this is why the impacts of this crisis were big enough to consider this global crisis as a systemic stress event.

The European sovereign debt crisis was caused by an increase in sovereign risk that was due to high levels of debt that were already important in some countries before 2007. The countries with the highest levels of debt to GDP in 2007 were Greece, with a debt to GDP ratio of 105.4%, and Italy, with a debt to GDP ratio of 103.6%. Belgium, Portugal and Hungary were the next to have high levels of debt to GDP, at 84.2%, 68.3% and 66.1% respectively (Fouque & Langsam, 2013, p. 271). These countries continued to borrow much more between 2007 and 2010. In the case of Greece, it was the government that borrowed too much. For Ireland, Spain and Portugal, it was the households that borrowed heavily because of a consumption and housing boom (Murphy, 2011, p. 1). Ireland, Greece, Portugal, Spain, Germany and Italy increased their debt to GDP ratio by 71.2, 37.4, 24.7, 24, 18.3 and 15.4 % points respectively between 2007 and 2010 (Fouque & Langsam, 2013, p. 271). Before 2007, it was not a problem for European banks to lend because they received money easily from external credit markets. However, when the Global Financial Crisis (GFC) hit, the European banks met huge funding problems because credit markets dried. Consequently, European banks stopped lending money, interbank interest rates increased and households and businesses stopped borrowing (Murphy, 2011, p. 1).

It was the beginning of the European sovereign debt crisis, also called the Greek debt crisis because the first country that needed support in 2009 was Greece (Fouque &

Langsam, 2013, p. 270). Indeed, Greece had higher public deficits than expected and had a bad country economic outlook. Consequently, rating agencies downgraded Greek debt into high yield grade for the first time in April 2010. Furthermore, after a succession of strikes and austerity plans, their long term interests knew their highest peak ever at 33.84 in December 2011 (Audige, 2013, p. 2). This crisis became even worse in July 2011 when credit markets froze again inducing the highest increase of the EURIBOR-OIS spreads since the Lehman default (Fouque & Langsam, 2013, pp. 270-271). Therefore, debt problems expanded to the rest of the Euro area and firstly to Portugal and Ireland (Audige, 2013, p. 2). It went further when the European banks didn't even want to lend to each other anymore. This was the beginning of the credit crunch and the end of intermediation (Fouque & Langsam, 2013, pp. 270-271). Therefore, we can also see that the impacts of this crisis were big enough to consider this crisis as a systemic stress event.

2.3. Methodology

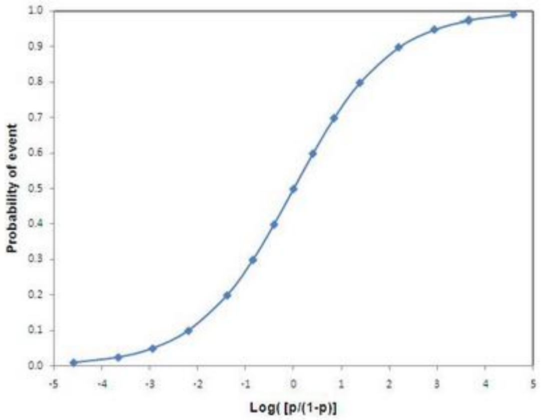
We chose three methods to evaluate the performance of the indicators as measures or early warnings of systemic risk: the Logit regression, the KLR signal approach and the Granger causality test.

A. Logit regression

The Logit approach is a parametric approach to determine currency crises. This method is well known, widely used and easy to run in statistical software packages (Powell & Barker, 2008, pp. 117-122). This approach involves the creation of a stress dummy variable. In a study, the dependent variable, dep_{it}, is the stress dummy variable and is equal to 1 in the h quarters preceding systemic event for a country i at time t, and to 0 otherwise (Lo Duca & Peltonen, 2011, p. 18).

In our study, we also used this approach because our dependent variable, y_t, is a stress dummy variable for the US or Europe that takes the value of 1 if the value of the CFSI (US) or CISS (EU) is higher than the 90^{th} percentile of the CFSI (US) or CISS (EU) and that takes the value of 0 otherwise. Besides, we considered predicted values ($\hat{y}$) as probabilities of having a '1' outcome (a systemic stress event in this case). For example: $\hat{y}_t = \hat{\beta}_0 + \hat{\beta}_1 X_t + \epsilon_t$, with $\hat{\beta}_0 = 0{,}1$; $\hat{\beta}_1 = 0{,}05; X = 10$. Therefore: $\hat{y}_t$= 0,1 +0,05*10 =0,6 which is the probability of having a systemic stress event when X equals to 10. Consequently, because $\hat{y}$ is a probability, $\hat{y}$ has to stay between 0 and 1 and cannot go above 1 or below 0. It is also what we can observe from the shape of the Logit function presented in Figure 13.

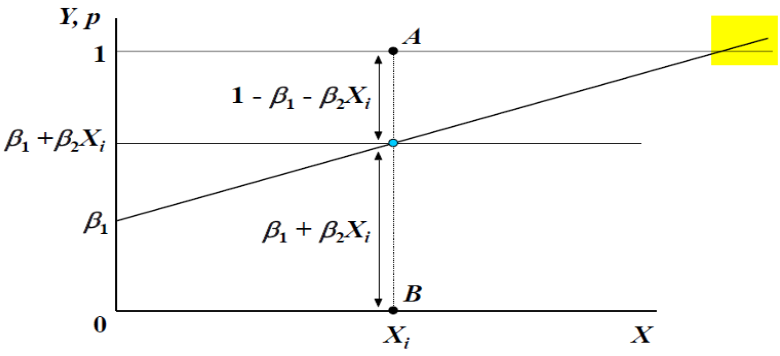
Figure 13: Shape of Logit function



Source: Srivastava, 2013, http://www.analyticsvidhya.com/blog/2013/10/trick-enhance-power-regression-model-2/

Therefore, the Ordinary Least Squares (OLS) is not applicable because, as Figure 14 shows us, OLS can predict probabilities above 1 and below 0. There are also additional technical problems with OLS such as heteroskedasticity and non-normality of errors (Verardi, 2013, p. 5).

Figure 14: Predicted probability are not restricted to be between zero and one



Source: Verardi, 2013, p. 8.

Lo Duca and Peltonen (2011) used a multivariate logit model to jointly estimate the effect of various vulnerability indicators to the probability of a systemic event (Lo Duca & Peltonen, 2011, p. 17). There were three groups of explanatory indicators of vulnerabilities: the domestic one, the global one and the one with interactions between domestic and global indicators (Lo Duca & Peltonen, 2011, pp. 18-19). They came to the conclusion that domestic indicators such as credit cycle and macro-overheating and global indicators such as equity valuations and macro-overheating were significant indicators of systemic risk (Lo Duca & Peltonen, 2011, p. 24). After evaluating the significant joint indicators, Lo Duca and Peltonen evaluated the best standalone indicators of systemic events. Global indicators performed better than domestic indicators. Besides, interactions between domestic and global indicators (and vice versa) were also one of the best standalone indicators (Lo Duca & Peltonen, 2011, p. 24). In addition to that, Abino, Adrias, Damot, and Virtucio (2014) also examined the systemic risk in their study by using the same type of logit model for determining the best indicator of systemic events (Abino, Adrias, Damot, & Virtucio, 2014, p. 1). Their model was an extension of the study done by Lo Duca and Peltonen, applied to one country in particular, the Philippines (Abino et al., 2014, p. 2). They came to two different types of conclusions. Firstly, they concluded from their study that domestic indicators such as ratio of debt to GDP, market returns, average bank lending rates, ratio of real estate loans to total loans and ratio of level of money to GDP were significant indicators in signalling future financial stresses. Secondly, they concluded that global indicators were significant indicators in predicting future systemic events (Abino et al., 2014, p. 5). Then, they also wanted to know what the best standalone indicators of systemic event were and they found that it was a domestic indicator and more precisely the average bank lending rate (Abino et al., 2014, p. 7).

In any cases, the results computed by these authors highlight that it is easier to analyze multiples indicators from various sources of vulnerabilities in the logit model than using standalone indicators to predict systemic events; mostly because the third set of explanatory variables is composed by the interactions between global and domestic indicators of vulnerabilities (Abino et al., 2014, p. 7; Lo Duca & Peltonen, 2011, p. 21). Indeed, using a multivariate logit model allows them to put all informations together in an understandable number. It also gives the marginal contributions of each indicator (Castillo IV, 2006, p. 22).

To follow the literature, we decided to run the following multivariate logit regressions (in Stata), using a six months signalling horizon (also called a crisis window), as the period before a crisis. The reason why we chose this crisis window length will be explained when we will run univariate logit regressions.

(v) $0\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t}X_{1,t} + \beta_{2,t}X_{2,t} + \beta_{3,t}X_{3,t} + \beta_{4,t}X_{4,t} + \epsilon_t$

(vi) $1\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t-1}X_{1,t-1} + \beta_{2,t-1}X_{2,t-1} + \beta_{3,t-1}X_{3,t-1} + \beta_{4,t-1}X_{4,t-1} + \epsilon_t$

(vii) $2\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t-2}X_{1,t-2} + \beta_{2,t-2}X_{2,t-2} + \beta_{3,t-2}X_{3,t-2} + \beta_{4,t-2}X_{4,t-2} + \epsilon_t$

(viii) $3\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t-3}X_{1,t-3} + \beta_{2,t-3}X_{2,t-3} + \beta_{3,t-3}X_{3,t-3} + \beta_{4,t-3}X_{4,t-3} + \epsilon_t$

(ix) $4\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t-4}X_{1,t-4} + \beta_{2,t-4}X_{2,t-4} + \beta_{3,t-4}X_{3,t-4} + \beta_{4,t-4}X_{4,t-4} + \epsilon_t$

(x) $5\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t-5}X_{1,t-5} + \beta_{2,t-5}X_{2,t-5} + \beta_{3,t-5}X_{3,t-5} + \beta_{4,t-5}X_{4,t-5} + \epsilon_t$

(xi) $6\ lags: Stress\_Dummy_t = \beta_0 + \beta_{1,t-6}X_{1,t-6} + \beta_{2,t-6}X_{2,t-6} + \beta_{3,t-6}X_{3,t-6} + \beta_{4,t-6}X_{4,t-6} + \epsilon_t$

Where X_1= Volatility index (VIX for the US, VSTOXX for EU), X_2 = Ted spread, X_3= Yield curve slope and X_4 = Return of the bank equity index.

We didn't add the CDS when we tested variables jointly because as we have said before, CDS begin much later and therefore they are not comparable with the other indicators.

Besides, as it is done in the literature, we also wanted to run another innovative set of univariate logit regressions (in Stata):

(xii) $0\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_t + \epsilon_t$

(xiii) $1\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_{t-1} + \epsilon_t$

(xiv) $2\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_{t-2} + \epsilon_t$

(xv) $3\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_{t-3} + \epsilon_t$

(xvi) $4\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_{t-4} + \epsilon_t$

(xvii) $5\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_{t-5} + \epsilon_t$

(xviii) $6\ lags: Stress\_Dummy_t = \beta_0 + \beta_1 X_{t-6} + \epsilon_t$

Where X is the Volatility index (VIX for US, VSTOXX for EU) or the Ted spread or the Yield curve slope or the Return of the bank equity index or the CDS (CDS IG for US, Itraxx and Itraxx Financials for EU).

By contrast with the literature, we considered here that it was more appropriate to use a univariate logit model because the purpose of this thesis is to rank the different indicators to know which one is the best indicator of systemic risk, which could be impossible to do when considering all indicators together. Our point of view is supported by Powell and Barker (2008) because they think that pooling many indicators together could be a weakness. Indeed, if there are too many predictor values, it could be a problem because it means that they have to be reduced to the most important one through pre-processing, inferential statistics or best subset selection (Powell & Barker, 2008, pp. 177-122). Besides, it could also induce problems of multicolinearity that can impair the results (Abino et al., 2014, p. 5). Consequently, we decided here to test each indicator separately.

We tested the performance of each of these indicators from 0 to 6 lags (in months). When the indicators are tested with 0 lags, we are testing the performance of the indicator as measure of systemic risk. When the indicators are tested from 1 or 6 lags, we are testing the performance of the indicator as early warning of systemic risk. We chose six months as the crisis window regarding the results of the univariate logit regressions. Indeed, we looked at the coefficients of the eleven indicators (VIXX, VSTOXX, US (EU) Ted spread, US (EU) Yield curve slope, US (EU) Return of the bank equity index, CDX IG, Itraxx and Itraxx Financials) and we checked until which lag the coefficient of each indicator is significant. For each indicator, we present in Table 2 and Table 3 the number of lags until the coefficient loses its significance.

Table 2: Number of lags before that coefficients of indicators are not anymore significant (US)

	US				
	VIX	***Ted spread***	***Return of the bank equity index***	***Yield curve slope***	***CDX IG***
lag	5	16	6	0	5

Source: Datastream & Bloomberg, own computations by Stata

Table 3: Number of lags before that coefficients of indicators are not anymore significant (EU)

	Europe					
	VSTOXX	***Ted spread***	***Return of the bank equity index***	***Yield curve slope***	***Itraxx***	***Itraxx Financials***
lag	7	18	6	0	3	2

Source: Datastream, own computations by Stata

Afterwards, we made an average of all these different lags and we obtained 6.18 lags. Mathematically, if we rounded 6.18 lags, we would take 6 lags as a signalling horizon. Besides, we rounded down lags to 6 because eight of the elven variables have a lag equal or below 6 while only three have a lag higher than 6.

In order to know what the best indicators of systemic risk are, we cannot use the classical R-squared because it does not exist in logistic regressions. However, some pseudo R-squareds have been introduced to assess the goodness-of-fit of logistic models. They have this name because they are on a similar scale as R-squareds, ranging from 0 to 1 with higher values indicating better model fit (Institute for Digital Research and Education, 2011). Therefore, to compare the performance of the different indicators, we use two pseudo R-squareds: the McFadden R-squared and the Count R-squared.

The McFadden R-squared approaches goodness of fit in a way comparable to the R-squared as a proportion of the total variability explained by the model. The more variability explained, the better the model.

$$McFadden\ R^2 = 1 - \frac{\ln \hat{L}(M_{Full})}{\ln \hat{L}(M_{Intercept})} = \frac{sum\ of\ squares}{sum\ of\ squared\ erros}$$

$M_{Full} = Model\ with\ predictors$

$M_{Intercept} = Model\ without\ \ predictors$

$\hat{L} = Estimated\ likelihood$

On the contrary, the Count R-Squared has nothing to do with any OLS approach. It transforms predicted probability into binary variables. For example, if the predicted probability is higher than 0,5, the binary variable takes the value of 1 and 0 otherwise. Then, if we predict that the probability of having a stress event is higher than 0,5 (binary variable=1) or that the probability of having a stress event is lower than 0,5 (binary variable =0), we have to check if it will really be the case or not. The Count R-squared is the number of records that we have correctly predicted divided by the total count. Therefore, the higher this Count R^2, the higher records correctly predicted.

$$Count\ R^2 = \frac{\#\ Correct}{Total\ Count}$$

Consequently, the higher these R-squareds, the better the performance of the indicators of systemic risk.

B. KLR signal approach

KLR signal approach of Kaminsky, Lizondo, and Reinhart (1998) is used to help for predicting financial crises of any kind. This method was first used to detect currency crises (Reinhart, Goldstein, & Kaminsky, 2000, p. 1). Using this method in the case of systemic crises can be a real contribution to the literature because in addition to find the best indicators of systemic risk (measures/early warnings), this method allows us to find per indicator a threshold above which a crisis is signaled.

This method aims to find for each indicator (which is a potential measure/early warning), the threshold value that maximizes the correctly signalled crises while minimizing the false alarms. To find this threshold, we have to minimize the so-called "noise-to-signal ratio" (NSR).

In order to do that, we have first to compute the NSR thanks to four steps (Kaminsky, Lizondo, & Reinhart, 1998, pp. 16-21):

1. Complete this table to have all the numbers

	Crisis (within 24 months)	No crisis (within 24 months)
Signal was issued	A= good signal	B= bad/false signal
No signal was issued	C= bad/false signal	D= good signal

A: number of months in which the indicator issued a good signal

B: number of months in which the indicator issued a false signal

C: number of months in which the indicator was unsuccessful to issue a signal

D: number of months in which the indicator renounced from issuing a signal

The perfect situation would be that A>0, B=0, C=0 and D>0. So the purpose of this method is to find one indicator that fits the profile of this perfect indicator most.

Consequently, the KLR method has two main objectives. The first one is to maximize good signals: a crisis signalled by threshold and a crisis occurred or a crisis not signalled by threshold and a crisis didn't occur. The second one is to minimize the fact that a crisis signalled by the threshold is not followed by a crisis or the fact that a crisis not signalled by the threshold is followed by a crisis, therefore minimizing false alarms or noises.

2. Compute the ratio of well predicted crises issued by the indicator (with respect to all crises of the sample): A/ (A+C)

3. Compute the ratio of false alarms issued by the indicator: B/ (B+D)

4. Combine information about the indicators' ability to issue good signals and avoid bad ones in order to measure the noisiness of the indicator: (B/ (B+D))/ (A/ (A+C)).

When first used by Kaminsky et al. (1998), fifteen macroeconomic and financial variables were selected, ranging from the real exchange rate, reserves and trade variables to variables reflecting money supply, lending and the equity index (Beckmann & Menkhoff, 2004, p. 6).

In this study (Kaminsky et al., 1998, p. 19), the real exchange rate was the indicator which issued the highest percentage of possible good signals (25%) whereas imports issued the lowest percentage (9%). Regarding the bad signals, the real exchange rate was once again the best indicator because it issued the lowest percentage of bad signals (only 5%) whereas the ratio of lending to deposit interest rate was the poorest indicator, issuing the highest percentage of bad signals (22%).

The indicators which had the smallest noise- to-signal ratio were the real exchange rate (0.19) and banking crises (0.34). Furthermore, indicators for which the noise-to-signal-ratio was equal or higher than 1 produced more of false alarms than good signals. Therefore, they didn't help to predict crises and this is why they had to be removed from the list of potential indicators because they produced excessive noise. This was the case for four indicators in the study of KLR: the ratio of lending interest rates to deposit interest rates (1.69), bank deposits (1.20), imports (1.16) and the real interest rate differential (0.99) (Kaminsky et al., 1998, p. 21). Therefore, we can see that KLR found twelve informative indicators, which are indicators with a NSR below unity.

To sum up the results from the study of Kaminisky et al., we can say that the best indicators for anticipating currency crises include the behavior of national reserves, the real exchange rate, domestic credit, credit to the public sector and domestic inflation. Other indicators also find support like trade balance, export performance, money growth, real GDP growth and the fiscal deficit (Kaminsky et al., 1998, p. 24) while others have to be excluded like the ratio of lending interest rates to deposit interest rates, bank deposits, imports and the real interest rate differential. These results are presented in Table 4.

Table 4: Performance of Indicators Under the KLR Signal Approach (1998)

	Number of crises for which there are data	Percentage of crises called	Good signals as percentage of possible good signals	Bad signals as percentage of possible bad signals	Noise/ signal (adjusted)
In terms of the matrix in the text			A/(A+C)	B/(B+D)	[B/(B+D)]/ [A/(A+C)]
Real exchange rate	72	57	25	5	0.19
Banking crises	26	37	19	6	0.34
Exports	72	85	17	7	0.42
Stock prices	53	64	17	8	0.47
M2/international reserves	70	80	21	10	0.48
Output	57	77	16	8	0.52
"Excess" M1 balances	66	61	16	8	0.52
International reserves	72	75	22	12	0.55
M2 multiplier	70	73	20	12	0.61
Domestic credit/GDP	62	56	14	9	0.62
Real interest rate	44	89	15	11	0.77
Terms of trade	58	79	19	15	0.77
Real interest differential	42	86	11	11	0.99
Imports	71	54	9	11	1.16
Bank deposits	69	49	16	19	1.20
Lending rate/deposit rate	33	67	13	22	1.69

Source: Kaminisky et al., 1998, p. 20.

In our study we analysed systemic risk in Europe and the US separately. For each continent, we selected five indicators that have potential predictive power of systemic risk: market volatility (VIXX & VSTOXX), interbank rates (Ted spread), Yield curve slope, Return of the bank equity indices and CDS indices (CDX IG, Itraxx & Itraxx Financials).

We tested the performance of each of these indicators from 0 to 6 lags (in months). When the indicators are tested with 0 lags, we are testing the performance of the indicator as measure of systemic risk. When the indicators are tested from 1 to 6 lags, we are testing the performance of the indicator as early warning of systemic risk. We know that most of the authors agree to say that the KLR leading indicator approach has 24 months as a signalling horizon (Beckmann & Menkhoff, 2004, p. 6; Berg & Pattillo, 1999, p. 110; Edison, 2000, p. 9, 14, 26, 29; Ito & Orii, 2009, pp. 5-6; Kaminsky et al., 1998, p. 17). Other authors choose a 6 months crisis window (EWS for Systemic Banking Crisis in India, n.d., p. 8; El-Shazly, 2002, p. 9) or a 12 months crisis window (Anh, 1997, p. 5). Unlike these previous methodologies, Rodríguez-Moreno and Peña (2010) do not test macroeconomic indicators but they test indicators that are very volatile wherein CDSs, interbank interest rates, co-risk measures etc. Logit regressions are run for each variable where the independent variables are lagged up to 2 weeks (Rodríguez-Moreno & Peña, 2010, p. 29). Therefore, because there are different window lengths ranging from 2 weeks to 6, 12 and 24 months, we can conclude that there is no specific criterion to select a “reasonable period of time”. The signalling horizon has to be chosen in function of the data sample and country-specific factors (El-Shazly, 2002, p. 7).

As a result, to select our crisis window, we got closer to the methodology of Rodríguez-Moreno & Peña (2010) because the indicators that we tested (VIX, Ted spread, CDS etc) are very volatile. It is why we cannot allow us to wait 24 months before a crisis happens. We must go faster but two weeks are not enough. Consequently, to find a balance, we selected a small signalling horizon of 6 months, as proposed in the analysis of El-Shazly (2002) and as we found thanks to the results of the univariate logit regressions.

Moreover, we differ from the traditional KLR signal approach in the way we define a signal. Indeed, in the KLR methodology, a signal is given when a variable exceeds its threshold within a time window (for example within 24 months before a crisis) whereas in our methodology, a signal is given when a variable exceeds its threshold in a fixed number of months before a crisis (for example 3 months before a crisis). This has the advantage of having a clear idea about how much time before a crisis the signal is given.

Finding the minimum noise-to-signal-ratio requires a great precision: we have to move the threshold by making small steps to find the optimal one with certainty. Besides, having the minimum noise-to-signal ratio and its corresponding optimal threshold for each indicator, allows us to compare the indicators: the one with the smallest ratio will be considered as the best measure/early warning of systemic risk.

According to Zhang (2001), this approach has some advantages such as an easy and wide understanding of problems by clearly showing the number of indicators that behave abnormally (Castillo IV, 2006, p. 20). Indeed, this method is more comprehensible than the logit model to the non-economically trained policy maker. Last but not least, this method focuses on a particular variable association with crisis (Davis & Karim, 2008, p. 100). However, this method has also some shortcomings. Indeed, it is difficult to compare this approach with another one because it is non-parametric. Furthermore, the stress dummy variables can be badly constructed which can lead to classification problems. Besides, it does not take into account the multicolinearity across indicators (Abiad, 2003, pp. 3-4). Therefore, one way to improve the univariate nature of the signal approach (thresholds decided indicators by indicators) is the introduction by Kaminsky (1999) and Goldstein, Kaminsky and Reinhart (2000) of a composite indicator of crisis using weighted average of many indicators (Ito & Orii, 2009, p. 6).

C. Granger causality test

The purpose of the Granger causality test is to assess if X Granger causes Y. In other words, it verifies if previous changes in X can explain the current changes of Y and bring more information than the one contained in past values of Y alone. If it is not the case, X does not Granger cause Y. Vice versa (Billio, Getmansky, Lo, & Pelizzon, 2010, p. 13; Rodríguez-Moreno & Peña, 2011, p. 32). Therefore, this test can help to better understand the direction of the true causation.

Billio, et al. (2010) used the Granger methodology to test the existence of systemic interconnections between firms to assess the systemic risk in the financial industry. In other words, it tested if there were Granger causal relationships in the direction of individual banks to the whole financial system (Balboa, López-Espinosa, & Rubia, 2013, pp. 3-4; Pagano & Sedunov, 2014, p. 13). According to Pagano and Sedunov (2014), Granger causality tests proved that there were spillover effects of financial systemic risk exposure on a country-by-country level. Indeed, countries that were close to each other (i.e. UK and Ireland) were interrelated. Besides, countries seriously touched by the European sovereign debt crisis Granger caused the systemic risk exposures of other countries (Greece, Italy, Portugal, Spain, and Ireland). However, the direction of the causation could also be inversed: large market shocks could cause individual shocks (Balboa, López-Espinosa, & Rubia, 2013, p. 3).

Therefore, because of the possibility of a two-way relation, two regressions are usually run in the literature (Sewell, 2001, p.3):

(xix) $Y_t = \beta_0 + \sum_{j=1}^{J} \beta_j Y_{t-j} + \sum_{k=1}^{K} \gamma_k X_{t-k} + \epsilon_t$: direction of causation

(xx) $X_t = \beta_0 + \sum_{j=1}^{J} \beta_j X_{t-j} + \sum_{k=1}^{K} \gamma_k Y_{t-k} + \epsilon_t$: reverse direction of causation

In our study, we just ran the first regression, which is the direct Granger method, where Y is the CISS (EU) or the CFSI (US) and X is the Volatility index (VIX for US and VSTOXX for EU) or the Ted spread or the Yield curve slope or the Return of the bank equity index or the CDS index (CDS IG for US, Itraxx and Itraxx Financials for EU). We did that because the purpose of this thesis is to know which variable Granger causes systemic stress indicators, the CISS (EU) and the CFSI (US). Our purpose is not to see if the systemic stress indicators Granger cause indicators of systemic risk even if it is highly probable that the CFSI (US) or the CISS (EU) has an impact on these indicators. However, it could be a great idea to run the second regression for further research.

The choice of lags J and K is tricky. On the one hand, insufficient lags lead to autocorrelated errors, incorrect test statistics and biased estimates but with a smaller variance. On the other hand, even if estimates are not biased, the power of the test is reduced when there are too many lags. Besides if J is too large and K too small or vice versa, estimates will be biased and inefficient (Sewell, 2001, p. 3; Thornton & Batten, 1984, p. 6). When we select arbitrarily the lags, such as 4-4 and 8-8, it can mislead results (Thornton & Batten, 1984, p. 1). If the chosen lags are 4-4, Y will not Granger cause X but with lags of 8-8, Y will Granger cause X. However, if we use longer lags, such 5-5 and 9-9, it will be the contrary (Thornton & Batten, 1984, p. 2). The lag length selection is therefore extremely important because when the lag of a variable changes, the Granger causality also changes, potentially leading to the structural un-stability of Granger causality (Sheng et al., 2008).

In our study, we first chose the optimal number of lags J of the dependent variable (CISS or CFSI) but it is not an easy task. To do that, we followed the advice of the literature. According to Hsiao (1981), the lag length should be selected on the basis of some statistical criterion (Thornton & Batten, 1984, p. 3). Indeed, there are different criteria that allow avoiding parsimonious parameterization and over parameterization. These criteria are the following: the C_p-statistic by Mallows (1973), the Final Prediction Error (FPE) by Akaike (1969), the Bayesian Information Criterion (BIC) by Schwartz (1978), the Bayesian Estimation Criterion (BEC) by Geweke and Meese (1981) and the P-H technique of Pagana and Hartley that is similar to using a standard F-test (Thornton & Batten, 1984, p. 6). The results computed by Thornton and Batten (1984) showed that the FPE criterion proposed by Akaike, also called the Akaike Information Criterion (AIC), was the best criterion to find a significant lag structure that will reject the null-hypothesis of non-independence between X and Y, giving evidence to the Granger causality (Thornton & Batten, 1984, pp. 9-10).

Therefore, in order to find the best lag length for Y (CISS or CFSI), we ran different autoregressive models on Y and we chose the model with the lowest Akaike Information Criterion (AIC). Indeed, the model with the smallest information criterion is preferred (Cameron & Trivedi, 2005, p. 278). For the CISS, the best lag length is 3 months while it is 1 month for the CFSI, as we can respectively see in bold in Table 5 and Table 6.

Table 5: Selection of the optimal number of lags for the CISS (EU)

	(1) CISS	(2) CISS	(3) CISS	(4) CISS	(5) CISS
_cons	0.192** (0.0788)	0.189** (0.0960)	0.187* (0.108)	0.185 (0.113)	0.189* (0.102)
L.CISS	0.891*** (0.0289)	0.710*** (0.0415)	0.685*** (0.0413)	0.678*** (0.0414)	0.684*** (0.0425)
L2.CISS		0.202*** (0.0364)	0.111* (0.0598)	0.105* (0.0603)	0.115* (0.0628)
L3.CISS			0.126** (0.0552)	0.0899 (0.0704)	0.101 (0.0749)
L4.CISS				0.0526 (0.0537)	0.124* (0.0704)
L5.CISS					-0.106* (0.0552)
AIC	-423.2	-429.1	**-430.1**	-428.7	-428.8

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 6: Selection of the optimal number of lags for the CFSI (US)

	(1) CFSI	(2) CFSI	(3) CFSI	(4) CFSI	(5) CFSI
_cons	0.322	0.326	0.320	0.323	0.331
	(0.259)	(0.244)	(0.268)	(0.262)	(0.236)
L.CFSI	0.869***	0.928***	0.935***	0.938***	0.933***
	(0.0361)	(0.0774)	(0.0778)	(0.0775)	(0.0764)
L2.CFSI		-0.0681	-0.163	-0.168	-0.149
		(0.0790)	(0.109)	(0.109)	(0.111)
L3.CFSI			0.103	0.126	0.103
			(0.0804)	(0.103)	(0.107)
L4.CFSI				-0.0256	0.0882
				(0.0763)	(0.119)
L5.CFSI					-0.119
					(0.0821)
AIC	**261.3**	262.4	262.4	264.3	263.7

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Thereafter, we augmented this regression with lags K of the independent variables. The choice of K lags is not difficult because we already know that it is 6 months (as we have computed earlier).

Finally, we did a Wald test, such as proposed by the program we used (Stata). The purpose of this chi-squared test is to examine if there is a Granger causality between X and Y. In other words, it tests if the coefficients of the lagged values of the independent variables and of the dependent variable are jointly 0 or different from 0.

H_0: β_j=0 and γ_k= 0

H_a: β_j≠0 and γ_k≠0

For both equations (xix) and (xx), we will reject the two null-hypothesis if the p-value is lower than 0.05. In this case, there is a dependency relation between X and Y. On the contrary, we will not reject the two null-hypothesis if the p-value is higher than 0.05. In this case, it would mean that X and Y are independent from each other. For the equation (xix), if the former null-hypothesis is not rejected and that the latter is, there is a unidirectional causality from X to Y while for the equation (xx); there is a unidirectional causality from Y to X (Thornton & Batten, 1984, p.4).

In order to know which is the best indicator of systemic risk in our study, we will just take the indicators which have a p-value lower than 0.05, meaning that the null-hypothesis is rejected, leading to a dependency relation between X and Y (X Granger causes Y). Wherein these indicators, the one with the smallest AIC will be the best performing early warning of systemic risk. Indeed, the Granger causality test only checks the early warning performance and not the measuring performance of indicators because we lag the independent variables in this test.

2.4. Empirical Results

2.4.1. Interpretations

As we already mentioned, it is difficult to compare the results of CDS indices with other indicators because of the lack of data coming from CDS. However, we will even compare the empirical results of the CDS indices with the empirical results of the rest of the indicators. Indeed, we think that it is important to include CDS indices in our comparisons to see if their presences change the results somehow and to see if they are better or worse than the other indicators.

A. Logit regression

Multivariate logit regressions ([1])

To follow the literature, we decided first to test the indicators of systemic risk jointly. We pooled the results that we obtained for the coefficients of the variables and their t-statistics at all different lags. We also add the marginal effects in Appendix 5 because the interpretation of the coefficients of a logit regression isn't straightforward otherwise. We can only interpret the sign and the significance of these coefficients but not their values. Indeed, the logit regression is not linear, in other words, the coefficient is not

([1]) Rember that the CDS indices are not added in these multivariate regressions because they don't take into account the same period of time as the other data.
([2]) If we introduced lags

constant for the values of the independent variables. Therefore, it is useful to measure this coefficient at a given point (called marginal effect at a given point). The 'given point' we chose is at the means of the independent variables. Therefore, we considered as necessary to add a second column in Appendix 5 where we found the marginal effects estimated at the means of the independent variables.

The tables below show the regression results of equations (v), (vi), (vii), (viii), (ix), (x) and (xi) for the US and Europe. We will first analyze the results from the *US*, coming from Table 7 and 8. When we test the indicators with 0 lags jointly, the coefficients of the VIX and the Ted spread are positive and significant at 1%. The coefficients of the other indicators (Return of the bank equity index & Yield curve slope) are also positive but are not significant at all.

When we test the indicators with 1 lags jointly, the coefficient of the Return of the bank equity index is the only one to be negative. The coefficient of the VIX is the most significant (at 1%), followed by the coefficient of the Ted spread (at 5%) and by the coefficient of the Return of the bank equity index (at 10%). However, the coefficient of the Yield curve slope is not significant at all.

When we test the indicators with 2 lags jointly, the coefficient of the Return of the bank equity index is again the only one to be negative. This time it is the coefficient of the Ted spread that is the most significant (at 1%) followed by the coefficient of the VIX (at 5%). Once again, the coefficient of the Yield curve slope is not significant at all. What is new here is that beyond the coefficient of the Yield curve slope, the coefficient of the Return of the bank equity index is also not at all significant either.

When we test the indicators with 3 lags jointly, the coefficient of the Return of the bank equity index is again the only one to be negative. It is again the coefficient of the Ted spread that is the most significant (at 1%). The coefficient of the Yield curve slope is still not significant at all. What is surprising is that the coefficient of the VIX is not significant anymore whereas the coefficient of the Return of the bank equity index starts being significant (at 10%).

Table 7: Coefficients and their corresponding t-statistics from 0 to 3 lags for US for multivariate logit regressions

	0 lags	1 lags	2 lags	3 lags
VIX	0.136***	0.150***	0.119**	0.0675
	(3.11)	(3.40)	(2.53)	(1.53)
TED_Spread	238.3***	155.1**	359.4***	336.3***
	(3.28)	(2.24)	(4.22)	(4.20)
US_Bank_Index_ Return	1.292	-6.184*	-4.533	-6.552*
	(0.41)	(-1.84)	(-1.33)	(-1.94)
Slope_US	0.321	0.0849	0.663	0.576
	(0.96)	(0.27)	(1.63)	(1.55)
_cons	-7.606***	-7.064***	-8.727***	-7.117***
	(-5.57)	(-5.31)	(-5.13)	(-4.94)
McFadden R^2	0.375	0.366	0.463	0.413
Count R^2	0.937	0.926	0.925	0.930

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

When we test the indicators with 4 lags jointly, we can make the same conclusions that we made for 3 lags except that beyond the coefficient of the Return of the bank equity index, the coefficient of the VIX becomes negative.

When we test the indicators with 5 lags jointly, the coefficients of the VIX and of the Return of the bank equity index are still negative. Besides, it is again the coefficient of the Ted spread that is the most significant (at 1%) and the coefficient of the Return of the bank equity index that is the less significant (at 10%). What is the most surprising is that the coefficient of the VIX becomes significant again at 5% while the coefficient of the Yield curve slope starts being significant and even the most significant with the coefficient of the Ted spread (at 1%).

When we test the indicators with 6 lags jointly, the strongest difference is that the coefficient of the VIX becomes one of the most significant coefficient (at 1%), wherein Ted spread and Yield curve slope. Besides, the coefficient of the Return of the bank equity index becomes even more significant (at 5%).

Table 8: Coefficients and their corresponding t-statistics from 4 to 6 lags for US for multivariate logit regressions

	4 lags	5 lags	6 lags
VIX	-0.00817	-0.121**	-0.183***
	(-0.19)	(-2.29)	(-3.21)
TED_Spread	310.1***	450.7***	395.1***
	(4.06)	(4.61)	(4.48)
US_Bank_Index_ Return	-5.622*	-6.550*	-9.325**
	(-1.74)	(-1.78)	(-2.14)
Slope_US	0.526	1.090***	0.938***
	(1.60)	(2.77)	(2.81)
_cons	-5.006***	-4.614***	-2.699***
	(-4.51)	(-3.91)	(-2.95)
McFadden R^2	0.317	0.378	0.310
Count R^2	0.903	0.924	0.918

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

We will now analyze the results from *Europe*, coming from Table 9 and 10. When we test the indicators with 0 lags jointly, the coefficients of these indicators are all positive. The coefficients of the VSTOXX and of the Ted spread are the most significant (at 1%) whereas the coefficient of the Return of the bank equity index is the less significant (at 10%). However, the coefficient of the Yield curve slope is not significant at all.

When we test the indicators with 1 lags jointly, we can make the same conclusions as we made for 0 lags except that beyond the coefficient of the Yield curve slope, the coefficient of the Return of the bank equity index is not significant at all either.

When we test the indicators with 2 lags jointly, we can make the same conclusions as we made for 1 lags except that the coefficient of the Yield curve slope is the only one to be negative.

When we test the indicators with 3 lags jointly, we can make the same conclusions as we made for 2 lags except that the coefficient of the VSTOXX loses in significance and becomes significant at only 5%.

Table 9: Coefficients and their corresponding t-statistics from 0 to 3 lags for EU for multivariate logit regressions

	0 lags	1 lags	2 lags	3 lags
VSTOXX	0.112***	0.0985***	0.0905***	0.0750**
	(3.26)	(2.86)	(2.66)	(2.22)
EUR_TED	2.376***	2.432***	2.288***	2.055***
	(4.27)	(4.42)	(4.38)	(4.11)
EURO_Bank_Index_Return	4.911*	4.559	4.465	1.387
	(1.77)	(1.63)	(1.56)	(0.47)
Slope_EU	0.502	0.0572	-0.372	-0.641
	(0.96)	(0.12)	(-0.88)	(-1.61)
_cons	-7.711***	-6.434***	-5.294***	-4.241***
	(-5.08)	(-5.13)	(-4.98)	(-4.48)
McFadden R^2	0.427	0.395	0.349	0.304
Count R^2	0.926	0.926	0.904	0.898

t statistics in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

When we test the indicators with 4 lags jointly, the coefficient of the VSTOXX has lost all this significance whereas the coefficient of the Yield curve slope gained a lot of significance (at 5%) and has become the second most significant coefficient after the coefficient of the Ted spread (at 1%). Besides, the coefficient of the Return of the bank equity index becomes negative as the coefficient of the Yield curve slope.

When we test the indicators with 5 lags jointly, we can make the same conclusions as we made for 4 lags.

When we test the indicators with 6 lags jointly, the coefficient of the Return of the bank equity index becomes positive again, meaning that the coefficient of the Yield curve slope is still again the only one to be negative. Besides, the coefficient of the Yield curve slope increases in significance to be the most significant coefficient (at 1%) with the Ted spread.

Table 10: Coefficients and their corresponding t-statistics from 4 to 6 lags for EU for multivariate logit regressions

	4 lags	5 lags	6 lags
VSTOXX	0.0508	0.0198	0.0417
	(1.41)	(0.50)	(1.02)
EUR_TED	2.056***	2.272***	2.426***
	(3.96)	(4.10)	(4.22)
EURO_Bank_Index_Return	-3.356	-2.968	2.279
	(-0.99)	(-0.85)	(0.66)
Slope_EU	-0.810**	-0.877**	-1.310***
	(-2.05)	(-2.26)	(-3.05)
_cons	-3.410***	-2.588***	-2.587***
	(-3.66)	(-2.81)	(-2.88)
McFadden R^2	0.322	0.317	0.334
Count R^2	0.892	0.897	0.929

t statistics in parentheses
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Source: Datastream, own computations by Stata

Logit univariate regressions

However, in our study, we considered that it was more appropriate to use a univariate logit model to rank the different indicators. The tables below show the regression results of equations (xii), (xiii), (xiv), (xv), (xvi), (xvii) and (xviii) for the US and Europe. We will test the measuring performance of each of these indicators at 0 lags and their early warning performance from 1 to 6 lags.

We will first analyse the results from the *US*, coming from Table 11. According to the McFadden R^2 criterion, the CDX IG is the best measure of systemic risk because it has the biggest McFadden R^2 at 0 lags. Besides, the Ted spread is the best early warning of systemic risk because it has the biggest McFadden R^2 from 2 to 6 lags. However, the worst performer as measure as well as early warning of systemic risk is the Yield curve slope because it has the smallest McFadden R^2 at all lags.

According to the Count R^2 criterion, the VIX is the best measure of systemic risk because it has the biggest Count R^2 at 0 lags. Besides, the best early warning of systemic risk is also the Ted spread because it has the highest Count R^2 from 2 to 6 lags. However, the worst measures of systemic risk are the Return of the bank equity index and the Yield curve slope because they have the same smallest Count R^2 at 0 lags while the worst early warning of systemic risk is the CDX IG because it has the smallest Count R² from 1 to 6 lags.

Table 11: Results of univariate logit regressions for US

	US													
	VIX		***Ted Spread***		***Return Bank Equity Index***		***Yield Curve Slope***		***CDX IG***		*Best variable*		*Worst variable*	
	Mc Fadden R²	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*
0lags	0,272	0,931	0,233	0,905	0,020	0,899	0,010	0,899	0,439	0,917	CDX IG	VIX	Yield	Bank & Yield
1lags	0,295	0,931	0,169	0,894	0,119	0,910	0,006	0,899	0,381	0,883	CDX IG	VIX	Yield	CDX IG
2lags	0,261	0,930	0,317	0,930	0,071	0,909	0,009	0,898	0,269	0,874	TED	VIX& TED	Yield	CDX IG
3lags	0,198	0,909	0,304	0,925	0,105	0,909	0,005	0,898	0,188	0,856	TED	TED	Yield	CDX IG
4lags	0,110	0,908	0,261	0,914	0,078	0,897	0,003	0,897	0,112	0,838	TED	TED	Yield	CDX IG
5lags	0,050	0,902	0,269	0,924	0,048	0,902	0,007	0,897	0,049	0,845	TED	TED	Yield	CDX IG
6lags	0,007	0,896	0,168	0,902	0,029	0,896	0,004	0,896	0,019	0,835	TED	TED	Yield	CDX IG

TED is the abbreviation of the Ted spread
Yield is the abbreviation of the Yield curve slope
Bank is the abbreviation of the Return of the bank equity index
CDX IG is the abbreviation of the CDX Investment Grade
&: When variables have the same values

Source: Datastream & Bloomberg, own computations by Stata

We will now analyse the results from *Europe*, coming from Table 12. According to the McFadden R² criterion, the best measure and early warning of systemic risk is the Ted spread because it has the biggest McFadden R² at all lags. However, the worst measure of systemic risk is the Return of the bank equity index because it has the smallest McFadden R² at 0 lags while the Yield curve slope or the Itraxx Financials is the worst early warning of systemic risk. Therefore, we cannot conclude that one variable is worse than another as an early warning of systemic risk because the worst early warning changes from one lag to another: it is the Yield curve slope from 1 to 3 lags and the Itraxx Financials from 4 to 6 lags.

According to the Count R² criterion, the Ted spread is the best measure of systemic risk because it has the highest Count R² at 0 lags. Besides, the VSTOXX and the Return of the bank equity index are the best early warning of systemic risk because they have the highest Count R² from 3 to 6 lags. However, the worst performer, as well as measure and early warning of systemic risk, is the Itraxx Financials because it has the smallest Count R² at all lags.

Table 12: Results of univariate logit regressions for EU

	Europe															
	VSTOXX		***Ted Spread***		***Return Bank Equity Index***		***Yield Curve Slope***		***Itraxx***		***Itraxx Financials***		*Best variable*		*Worst variable*	
	Mc Fadden R²	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*	*Mc Fadden R²*	*Count R²*
0lags	0,209	0,894	0,295	0,926	0,013	0,899	0,038	0,899	0,094	0,851	0,057	0,843	TED	TED	Bank	Itraxx Finan
1lags	0,177	0,883	0,311	0,910	0,018	0,899	0,016	0,899	0,095	0,850	0,057	0,842	TED	TED	Yield	Itraxx Finan
2lags	0,145	0,893	0,286	0,904	0,019	0,898	0,002	0,898	0,068	0,840	0,035	0,840	TED	TED	Yield	Itraxx Finan
3lags	0,118	0,903	0,256	0,887	0,053	0,903	0,002	0,898	0,034	0,839	0,011	0,839	TED	VSTOXX & Bank	Yield	Itraxx Finan
4lags	0,097	0,903	0,258	0,897	0,117	0,903	0,012	0,897	0,022	0,838	0,002	0,838	TED	VSTOXX & Bank	Itraxx Finan	Itraxx Finan
5lags	0,058	0,897	0,259	0,886	0,091	0,902	0,024	0,897	0,007	0,836	0,000	0,836	TED	Bank	Itraxx Finan	Itraxx Finan
6lags	0,043	0,896	0,240	0,885	0,038	0,896	0,050	0,896	0,003	0,835	0,002	0,835	TED	VSTOXX & Bank & Yield	Itraxx Finan	Itraxx Finan

TED is the abbreviation of the Ted spread
Yield is the abbreviation of the Yield curve slope
Bank is the abbreviation of the Return of the bank equity index
Itraxx Finan is the abbreviation of the Itraxx Financials
&: When variables have the same values

Source : Datastream, own computations by Stata

The tables of regression of equations (xii), (xiii), (xiv), (xv), (xvi), (xvii) and (xviii) for the US and Europe are available in the Appendix 6.

B. KLR signal approach

Below are the results of the KLR signal approach for the US and Europe. When the indicators are tested with 0 lags, we are testing the performance of the indicator as measure of systemic risk. When the variables are tested from 1 to 6 lags, we are testing the performance of the indicator as early warning of systemic risk.

We will first analyse the results from the *US*, coming from Table 13. We can see that the VIX is performing best at 0, 1 and 2 lags but the Ted spread is performing best for the remaining lags because they have the smallest noise-to-signal ratio at these lags. It means that the VIX is clearly performing best as measure of systemic risk while Ted spread is clearly performing best as early warning of systemic risk. The worst performer, as well as a measure and early warning, is clearly the Yield curve slope because it has the highest noise-to-signal ratio at all lags.

Table 13: Results of KLR signal approach for US

	US											
	VIX		***Ted Spread***		***Return Bank Equity Index***		***Yield Curve Slope***		***CDX IG***			
	MIN NTS	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*Best variable*	*Worst variable*
0lags	0,0160	36,9656	0,0373	0,0171	0,0279	-0,2070	0,7882	3,0513	0,0233	142,9407	VIX	Yield
1lags	0,0161	36,9656	0,0562	0,0205	0,0281	-0,2070	0,7370	2,7610	0,0314	162,0162	VIX	Yield
2lags	0,0162	36,9656	0,0162	0,0135	0,0283	-0,2070	0,8382	2,9206	0,0380	164,2405	VIX & TED	Yield
3lags	0,0284	42,2812	0,0190	0,0137	0,0284	-0,2070	0,8366	2,9206	0,0480	196,7968	TED	Yield
4lags	0,0572	44,8420	0,0191	0,0137	0,1145	-0,1073	0,8870	2,3110	0,0646	198,6167	TED	Yield
5lags	0,0576	44,8420	0,0165	0,0135	0,0576	-0,2163	0,9442	0,8214	0,1959	198,6167	TED	Yield
6lags	0,1159	46,3552	0,0463	0,0137	0,1738	-0,2070	0,6951	0,6801	0,2969	131,7516	TED	Yield

TED is the abbreviation of the Ted spread
Yield is the abbreviation of the Yield curve slope
&: When variables have the same values

Source: Datastream & Bloomberg, own computations by Matlab

We will now analyse the results from *Europe*, coming from Table 14. We can see that the Ted spread is clearly performing best as measure as well as early warning of systemic risk because it has the smallest noise-to-signal ratio at all lags. It is not so clear concerning the worst performer indicator of systemic risk. What we can say with certainty is that the Yield curve slope is the worst measure of systemic risk because it has the highest noise-to-signal ratio at 0 lags. However, the worst early warning can be the Yield curve slope, the Itraxx or the Itraxx Financials. Therefore, we cannot conclude that one variable is worse than another as an early warning of systemic risk because the worst early warning changes from one lag to another: it is the Yield curve slope for 1, 2 and 4 lags, it is the Itraxx Financials for 3 and 5 lags and it is the Itraxx for 6 lags.

Table 14: Results of KLR signal approach for EU

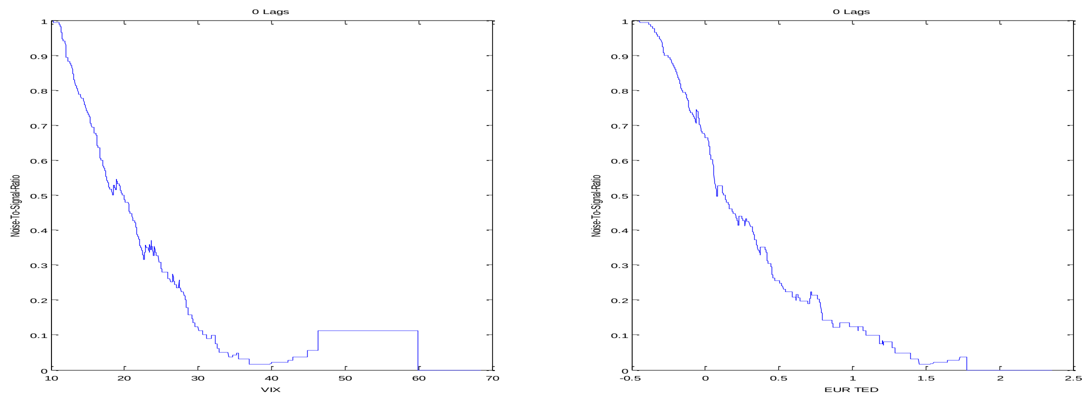
	Europe													
	VSTOXX		***Ted Spread***		***Return Bank Equity Index***		***Yield Curve Slope***		***Itraxx***		***Itraxx Financials***			
	MIN NTS	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*MIN NTS*	*Threshold*	*Best variable*	*Worst variable*
0lags	0,0559	51,2244	0,0160	1,4518	0,1118	-0,2110	1,0493	2,9817	0,0621	186,2336	0,0931	495,8343	TED	Yield
1lags	0,1124	57,5606	0,0375	1,7293	0,1124	-0,2110	0,8619	1,2674	0,0941	188,5953	0,0941	495,8343	TED	Yield
2lags	0,1583	36,3912	0,0565	1,7798	0,1293	-0,1412	0,7270	1,2674	0,1900	186,2336	0,0950	495,8343	TED	Yield
3lags	0,0569	51,2244	0,0569	1,7798	0,0683	-0,1826	0,4741	0,7117	0,3838	188,5930	0,5118	285,0354	VSTOXX &TED	Itraxx Finan
4lags	0,0572	51,2244	0,0382	1,7293	0,0687	-0,1826	0,3924	0,7117	0,1939	194,5861	0,1939	501,5090	TED	Yield
5lags	0,0576	51,2244	0,0384	1,7293	0,0864	-0,1861	0,3838	0,5822	0,6268	124,6552	0,6598	56,3778	TED	Itraxx Finan
6lags	0,0579	51,2244	0,0386	1,7293	0,1159	-0,2110	0,3145	0,5822	0,6979	57,3742	0,6563	56,3778	TED	Itraxx

TED is the abbreviation of the Ted spread
Yield is the abbreviation of the Yield curve slope
Itraxx Finan is the abbreviation of the Itraxx Financials
&: When variables have the same values

Source: Datastream, own computations by Matlab

According to our results, in the case of the US, the VIX is clearly performing best as measure of systemic risk while Ted spread is clearly performing best as early warning of systemic risk. In the case of Europe, the Ted spread is clearly the best performing as well as well as measure and early warning of systemic risk. We will give two examples of the procedure we followed to find the optimal thresholds, associated with their minimum noise-to-signal ratios. Figure 15 shows the noise-to-signal ratio associated to each value of threshold of these two selected examples coming from Appendix 7. The examples we chose are the best measure of systemic risk (i.e. with the minimum noise-to-signal ratio at 0 lags) for the US and Europe.

Figure 15: Optimal Thresholds of the Best Measures of Systemic Risk US & EU



Source: Datastream, own computations by Matlab

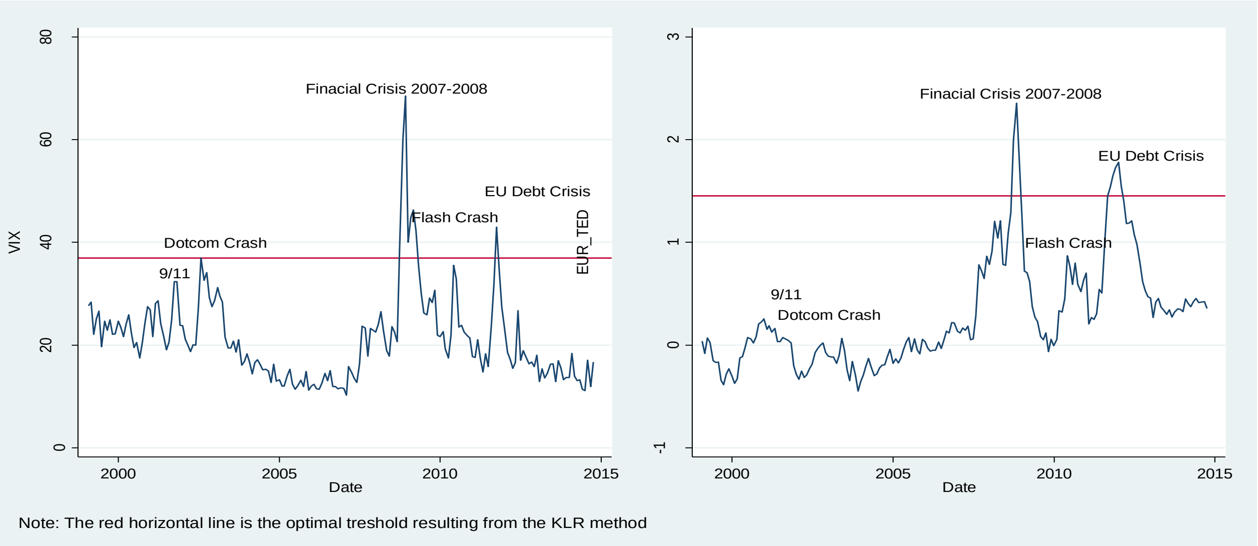
On these graphs, the value of threshold begins at the lowest value of the VIX (resp. Ted spread). In this case, the noise-to-signal ratio is extremely high because too many false alarms are given because all values except the minimum of the VIX (resp. Ted spread) are above the threshold. On the contrary, when the value of the threshold is too high, some real crisis signals will be missed because there will be not enough values of VIX (resp. Ted spread) above the threshold. The perfect equilibrium is therefore when we reach the lowest noise-to-signal ratio, having a value of 0.016 (resp. 0.016). At this point, we find the value of the optimal threshold: 36.9656 (resp. 1.4518). The optimal threshold we found for the VIX is really close to what is commonly used in the literature. Indeed, Malz (2011) used a value of 40 for the VIX as a crisis threshold.

In Figure 16, we will check for every period if the value of the variable (VIX or Ted Spread) is below or above this optimal threshold value. If it is above the threshold, there is a warning signal of an upcoming crisis in the following months ([2]) but if it is below, it means that there is no signal of a crisis. Then we will compare, for the best measure of systemic risk for the US and Europe, those warning signals with the stress dummies. If the CISS (EU) or CFSI (US) is greater than the 90th percentile of the CISS (EU) or CFSI (US) for one period (stress dummy variable=1) and if the value of the measure of systemic risk is above the threshold, we have well predicted crises (good signals) ([3]). On the contrary, if the CISS (EU) or CFSI (US) is lower than the 90th percentile of the

([2]) If we introduced lags
([3]) We used systemic stress events and crises as synonyms because the only two systemic stress events we detected are crises (financial crisis of 2007-2008 & European sovereign debt crisis of 2010).

CISS (EU) or CFSI (US) for one period (stress dummy variable =0) and if the value of the measure of systemic risk is above the threshold, this means that we do not have well predicted crises (false alarms).

Figure 16: Comparing signalled crises with episodes of systemic stress events for the best measure of systemic risk for US and EU according to the KLR signal approach



Source: Datastream, own computations by Stata

What we already know is that the financial crisis of 2007-2008 and the European sovereign debt crisis are considered as systemic stress events in our methodology. Therefore, we can see thanks to Figure 16 that we have well predicted crises because at these periods, the stress dummy variables took the value of 1 and the value of the VIX or TED spread was at the same time above the threshold (red horizontal line).

In our methodology, we did not consider the Dot-com Crash as a systemic stress event. We made good predictions in the case of Europe, because during the Dot-com Crash, the stress dummy variable took the value of 0 and the value of the Ted Spread was strongly below the threshold. In the case of the US, it is a little bit tricky: we also made good predictions because during the Dot-com Crash, the stress dummy variable took the value of 0 but the value of the VIX was just below the threshold, meaning that the Dot-com Crash was just at the limit to be considered as a systemic stress event in the US.

Therefore, we took care of that by seeing if the Dot-com Crash was considered as a systemic stress event by other authors. The 2007-2009 financial crisis was the period that induced the highest financial stress but it is not the only one: the Dot-com Crash was also a prominent example (Grimaldi, 2010, p. 5). Besides, a recent study (Doyran, 2013, p. 125) showed that problems of excessive liquidity were generated by the Dot-com Crash, producing systemic risks but it is true that the contagion effects were even worse during the subprime crisis. Woodard and Yan (2003) highlighted that financial bubbles and crashes like the S&P 500 Crash in 1987 and 1998, the International Business Machines (IBM) Crash of 1999, the Nasdaq Crash of 2000, the real estate bubble and the Mortgage-Backed Security (MBS) bubble were dangerous because they led to systemic failures. However, another study found that the Dot-com Crash was not an event of financial stress because the level of financial stress was not very high during this period (Pasricha, Roberts, Christensen, & Howell, 2013, pp. 15-16). Furthermore, according to Fatas (2009), it is debatable that the Dot-com Crash has systemic implications because all the bubbles (gold, dot-com and housing price bubble) are not the same and it is difficult to know which one generates systemic risks. Moreover, systemic risk can even emerge without bubbles. Therefore, as the opinions are not unanimous, we cannot conclude with certainty from the literature that the Dot-com Crash is a systemic stress event.

C. Granger causality test

The tables below show the regression results of the equation (xix) for the US and Europe ([4]). We will first analyze the results from the *US*, coming from Table 15. What results from the Wald test, testing the Granger causality between the dependent variable (CFSI) and the independent variables (VIX or Ted Spread…), is that only two on five of the independent variables Granger cause CFSI because they have a p-value lower than 0.05. These independent variables are the VIX and the Yield curve slope. We fail to reject the null-hypothesis for the other independent variables because they have a p-value greater than 0.05 (highlighted in bold), meaning that they do not Granger cause CFSI.

([4]) Remember that the Granger causality test only checks the early warning performance of the indicators (indicators tested from 1 to 6 lags).

Table 15: Results of Granger causality test for US

	VIX	TED Spread	US Bank Index Return	Slope US	CDX IG
1 lags	0.0297***	1.430	-0.888*	-0.198*	0.0104**
	(0.0101)	(25.29)	(0.466)	(0.108)	(0.00481)
2 lags	0.0159	29.07	-0.916	0.326***	0.00142
	(0.00973)	(17.82)	(0.670)	(0.114)	(0.00450)
3 lags	0.00514	32.05**	-0.239	-0.157	0.00346
	(0.00778)	(14.59)	(0.743)	(0.110)	(0.00346)
4 lags	0.0130	9.709	-0.372	-0.111	-0.000432
	(0.00871)	(15.27)	(0.711)	(0.121)	(0.00348)
5 lags	0.00728	14.43	-0.587	0.182	0.000604
	(0.00850)	(18.59)	(0.614)	(0.117)	(0.00462)
6 lags	-0.00446	28.44*	-0.00690	0.130	-0.000539
	(0.00850)	(16.43)	(0.487)	(0.122)	(0.00352)
_cons	-1.080**	-0.240	0.310	-0.0160	-0.932*
	(0.444)	(0.284)	(0.268)	(0.464)	(0.530)
L.CFSI	0.782***	0.833***	0.867***	0.885***	0.818***
	(0.0539)	(0.0426)	(0.0415)	(0.0370)	(0.0587)
P-value Wald	0.0148	**0.0924**	**0.3908**	0.0007	**0.1470**
AIC	236.7	247.3	251.7	240.8	162.3

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datasream & Bloomberg, own computations by Stata

Thereafter, we look only at the VIX and the Yield curve slope which have a p-value lower than 0.05, meaning that the null-hypothesis is rejected, leading to a dependency relation between these two independents variables and CFSI. Wherein these two independent variables, the one with the smallest AIC will be the best performing early warning of systemic risk. We can see from Table 16 that the VIX is the best performing early warning of systemic risk whereas the Yield curve slope is the worst one.

Table 16: AIC for independent variables of US with p-value <0.05

	US			
	VIX	***Yield Curve Slope***	***Best variable***	***Worst variable***
AIC	236,7	240,8	VIX	Yield

Yield is the abbreviation of the Yield curve slope

Source: Datastream, own computations by Stata

We will now analyze the results from *Europe*, coming from Table 17. What results from the Wald test, testing the Granger causality between the dependent variable (CISS) and the independent variables (VSTOXX or Ted Spread…), is that all independent variables, except the Itraxx Financials, Granger cause CISS because they have all a p-value lower than 0.05. Indeed, we only fail to reject the null-hypothesis for the Itraxx Financials because it has a p-value greater than 0.05 (highlighted in bold), meaning that it does not Granger cause CISS.

Table 17: Results of Granger causality test for EU

	VSTOXX	EUR TED	EURO Bank Index Return	Slope EU	Itraxx	Itraxx financials
1 lags	0.00484***	0.186***	-0.153**	0.0994***	0.00149*	0.000287
	(0.00140)	(0.0302)	(0.0757)	(0.0285)	(0.000877)	(0.000212)
2 lags	-0.000602	-0.0446	-0.107**	-0.0528*	0.000488	0.000413
	(0.00140)	(0.0430)	(0.0535)	(0.0296)	(0.00112)	(0.000284)
3 lags	-0.00146	-0.0174	-0.0875	-0.0219	-0.00107	-0.000447**
	(0.00143)	(0.0396)	(0.0558)	(0.0221)	(0.000831)	(0.000222)
4 lags	0.00280**	0.0435	-0.201***	-0.0210	0.00174**	0.000234
	(0.00125)	(0.0310)	(0.0746)	(0.0285)	(0.000821)	(0.000284)
5 lags	-0.000264	0.0454	-0.159***	0.0192	-0.00144**	-0.000471
	(0.00117)	(0.0313)	(0.0564)	(0.0304)	(0.000674)	(0.000330)
6 lags	-0.00107	0.00433	0.0236	-0.0332	-0.000217	0.000218
	(0.00100)	(0.0365)	(0.0573)	(0.0299)	(0.000607)	(0.000256)
_cons	0.0797	0.130**	0.182*	0.204*	0.113	0.174
	(0.112)	(0.0652)	(0.105)	(0.122)	(0.199)	(0.171)
L.CISS	0.507***	0.491***	0.577***	0.631***	0.580***	0.639***
	(0.0846)	(0.0512)	(0.0675)	(0.0651)	(0.0845)	(0.0648)
L2.CISS	0.209**	0.100*	0.200**	0.160**	0.134	0.0526
	(0.0876)	(0.0569)	(0.0791)	(0.0779)	(0.110)	(0.0932)
L3.CISS	0.208**	0.288***	0.147*	0.133*	0.205*	0.228***
	(0.0883)	(0.0623)	(0.0892)	(0.0727)	(0.123)	(0.0827)
P-value Wald	0.0028	0.0000	0.0029	0.0053	0.0071	**0.1068**
AIC	-421.4	-429.4	-417.7	-415.4	-218.5	-213.9

Standard errors in parentheses
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Thereafter, we look at the independent variables that have a p-value lower than 0.05 and the one with the smallest AIC will be the best performing early warning of systemic risk. We can see from the Table 18 that the Ted spread is the best performing early warning of systemic risk whereas the Itraxx is the worst.

Table 18: AIC for independent variables of EU with p-value <0.05

	Europe						
	VSTOXX	***Ted Spread***	***Return Bank Equity Index***	***Yield Curve Slope***	***Itraxx***	***Best variable***	***Worst variable***
AIC	-421,4	-429,4	-417,7	-415,4	-218,5	TED	Itraxx

TED is the abbreviation of the Ted spread

Source: Datastream, own computations by Stata

2.4.2. Robustness of the results

In Table 19 below, we can see all the results computed by the three methods. What we can observe is that in the *US*, the VIX is the best measure of systemic risk according to the Count R² criterion and the KLR signal approach but that the CDX IG is the best measure of systemic risk according to the McFadden R² criterion ([5]). Besides, we have to highlight that the Ted spread is the best early warning of systemic risk according to the univariate logit regression and the KLR signal approach but that the VIX is the best early warning according to the Granger causality test. Furthermore, the Yield curve slope is the worst measure of systemic risk according to the univariate logit regression and the KLR signal approach. It is also the worst early warning of systemic according to the McFadden R² criterion, the KLR signal approach and the Granger causality test. However, according to the Count R² criterion, the CDX IG is the one to be considered as the worst early warning of systemic risk.

In *Europe*, the best measure of systemic risk is the Ted spread according to the univariate logit regression and the KLR signal approach. The Ted spread is also the best early warning according to the McFadden R² criterion, the KLR signalling approach and the Granger causality test. However, according to the Count R² criterion, the VSTOXX and the Return of the bank equity index are considered as the best early warnings of systemic risk. What is surprising here is that the worst measures and early warnings of

([5]) Note that the Granger causality test only checks the early warning performance and not the measuring performance of variables because the independent variables are lagged in this test.

systemic risk are very different from one method to another. With regard to the worst measure, it is the Return of the bank equity index according to the McFadden R^2 criterion, it is the Itraxx Financials according to the Count R^2 criterion and it is the Yield curve slope according to the KLR signal approach. Concerning the worst early warning, it is the Yield curve slope or the Itraxx Financials according to the McFadden R^2 criterion, it is the Itraxx Financials according to the Count R^2 criterion, it is the Yield curve slope or the Itraxx or the Itraxx Financials according to the KLR signal approach and it is the Itraxx according to the Granger causality test.

Table 19: Combination of results of the three methods for the US and EU

			Univariate logit regression	**KLR signal approach**	**Granger causality test**
US	*Best variable*	Measure	***McFadden R^2: CDX IG Count R^2: VIX***	***VIX***	/[6]
		Early warning	***McFadden R^2: TED Count R^2: TED***	***TED***	***VIX***
	Worst variable	Measure	***McFadden R^2: Yield Count R^2: Bank & Yield***	***Yield***	/
		Early warning	***McFadden R^2: Yield Count R^2: CDX IG***	***Yield***	***Yield***
EU	*Best variable*	Measure	***McFadden R^2: TED Count R^2: TED***	***TED***	/
		Early warning	***McFadden R^2: TED Count R^2: VSTOXX & Bank***	***TED***	***TED***
	Worst variable	Measure	***McFadden R^2: Bank Count R^2: Itraxx Finan***	***Yield***	/
		Early warning	***McFadden R^2: Yield or Itraxx Finan Count R^2: Itraxx Finan***	***Yield or Itraxx or Itraxx Finan***	***Itraxx***

TED is the abbreviation of the Ted spread
Yield is the abbreviation of the Yield curve slope
Bank is the abbreviation of the Return of the bank equity index
Itraxx Finan is the abbreviation of the Itraxx Financials
&: When variables have the same values
Or: When it depends on the lag

Source: Datastream & Bloomberg, own computations by Matlab & Stata

[6] Remember that the Granger causality test doesn't assess the measuring performance of variables.

The main take-away from these results is that in the US, the VIX is the best measure of systemic risk according to all methods except according to the McFadden R^2 criterion where it is the CDX IG. Besides, the Ted spread is the best early warning of systemic risk according to all methods except according to the Granger causality test where it is the VIX. Furthermore, the Yield curve slope is the worst measure as well as early warning of systemic risk according to all methods except according to the Count R^2 criterion where it is the CDX IG which is the worst early warning of systemic risk. In Europe, the Ted spread is the best measure of systemic risk according to all methods. It is also the best early warning according to all methods except according the Count R^2 criterion where it is the VSTOXX and the Return of the bank equity index. As the worst measures and early warnings are different from one method to another, we cannot conclude what the worst measure and early warning of systemic risk is. Whit regard to the worst measure, it could the Return of the bank equity index or the Itraxx Financials or the Yield curve slope, depending on the method. Concerning the worst early warning, it could be the Yield curve slope or the Itraxx Financials or the Itraxx, depending on the method and on the lag.

To sum up, the three methods lead nearly to the same conclusions but they are some exceptions coming most of the time from the results based on the Count R^2 criterion. We can therefore conclude that the McFadden R^2 is clearly a better criterion than the Count R^2 in the Logit methodology to rank variables. Besides, as differences from one method to another occur most of the time when we look at the worst measures/early warnings, it means that they are insignificant because the fact that the best measures/early warnings are the same is the most important.

Conclusion

Before the financial crisis of 2007-2008, everybody thought that banks were “too big to fail” (TBTF) and “too interconnected to fail” (TITF). However, since the collapse of Lehman Brothers in 2008, everybody changed his mind. It was the beginning of the liquidity crisis and the systemic risk increased more and more.

The first chapter of this thesis provides a literature review about ten common systemic risk indicators (measures and early warnings) from the US and Europe: financial stress index (CISS for EU, CFSI for the US), volatility index (VSTOXX for EU, VIXX for the US), Ted spread, Conditional Value-at-Risk (CoVaR), Systemic Expected Shortfall (SES), Joint Probability of Distress/Default (JPoD), Credit Default Swap (CDS), Distress Insurance Premium (DIP), Yield curve slope and Return of the bank equity index.

The second chapter is dedicated to an empirical study where we keep only five indicators that are considered as simple and easily available to everyone: market volatility (VIXX & VSTOXX), interbank rates (Ted spread), Yield curve slope, Return of the bank equity indices and CDS indices (CDX IG, Itraxx & Itraxx Financials). As CDS indices begin much later than the rest of the data, it raises questions about their comparability with the other data. We also choose two systemic stress indicators: the Composite Indicator of Systemic Stress (CISS) for Europe and the Cleveland Financial Stress Index (CFSI) for the US.

The purpose of this thesis is to compare the measuring performance of each of these indicators at 0 lags and their early warning performance from 1 to 6 lags (in months). Even if there is a lack of data coming from CDS indices, we think it is important to include them in our comparisons to see if their presences change the results somehow. Three methods are used in order to corroborate the results obtained. The first method used is the Logit regression because the dependent variable is a stress dummy variable. We use multivariate logit regressions to follow the literature but we launch another innovative set of univariate logit regressions because the first one does not allow us to rank the indicators, which is the purpose of this thesis. To compare the performance of the different indicators, we use the McFadden R^2 and the Count R^2 criteria. The higher these R^2, the better the performance of the (lagged) indicators.

The second method is the KLR signal approach of Kaminsky, Lizondo and Reinhart (1998) and aims to find for each variable, the threshold value that maximizes the correctly signalled crises while minimizing the false alarms. To find this threshold, we have to minimize the so-called "noise-to-signal ratio". Having the minimum noise-to-signal ratio for each measure allows us to compare them: the one with the smallest ratio will be considered as the best measure/early warning of systemic risk.

The third and last method is the direct Granger causality test that finds which indicators Granger causes systemic stress indicators, the CISS (EU) and the CFSI (US) thanks to a Wald test, assessing if the lagged values of the independent variables and of the dependent variable are jointly 0 or different from 0. Only the indicators which have a p-value lower than 0.05 are taken into consideration, meaning that the null-hypothesis is rejected, leading to a dependency relation between the independent variables and the systemic stress indicators. Wherein these indicators, the one with the smallest Akaike Information Criterion (AIC) will be the best performing early warning of systemic risk. Indeed, the Granger causality test only assesses the early warning performance of variables because the independent variables are lagged in this test.

To summarize our results, we have to keep in mind that CDS indices begin much later than the other indicators and do not consider the same period of time as the other indicators. Therefore they will have less weight than the other indicators to be considered as the best or worst measure or early warning of systemic risk. Therefore, the main take-away from the results of all these three methods is that in the US, the VIX is the best measure of systemic risk. Besides, the Ted spread is the best early warning of systemic risk. Furthermore, the Yield curve slope is the worst measure as well as early warning of systemic risk. In Europe, the Ted spread is the best measure as well as early warning of systemic risk. As the worst measures and early warnings are different from one method to another, we cannot conclude what the worst measure and early warning of systemic risk is. With regard to the worst measure, it could be the Return of the bank equity index or the Itraxx Financials or the Yield curve slope, depending on the method. Concerning the worst early warning, it could be the Yield curve slope or the Itraxx Financials or the Itraxx, depending on the method and on the lag.

As our results about the best measures and early warnings of systemic risk are robust from one method to another, we consider as very important to share them in this thesis to allow our readers to have a more comprehensive view about systemic risk. More than that, the ultimate aim of this thesis is to catch the attention of the banks on the best indicators of systemic risk that we found to allow them to measure and predict this risk better. Indeed, this thesis could be a great asset for them mostly because they could not only avoid systemic risks in their bank but also avoid these risks to expand to other banks due to the effect of the interconnection between them. Besides, knowing the best indicators of systemic risk will also increase the ability to hedge against it, which can be very interesting to consider for further research.

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Appendices

Appendix 1: Individual financial stress indicators included in the CISS

Table 20: Individual financial stress indicators included in the CISS

Money market

1. Realised volatility of 3-month Euribor rate; weekly average of absolute daily rate changes; data start 8 Jan. 1999; source: Datastream.

2. Interest rate spread between 3-month Euribor and 3-month French T-bills; weekly average of daily data; data start 8 Jan. 1999; source: Datastream.

3. Monetary Financial Institution's (MFI) recourse to the marginal lending facility at Eurosystem central banks, divided by their total reserve requirements; MFIs can use the marginal lending facility to obtain overnight liquidity from the national central banks against eligible assets and, typically, at an interest rate which is higher than the prevailing overnight market interest rate; weekly average of daily data; data start 1 Jan. 1999; source: ECB.

Bond market

4. Realised volatility of German 10-year benchmark government bond index; weekly average of absolute daily yield changes; data start 5 Jan. 1990; source: Datastream.

5. Yield spread between A-rated non-financial corporations and government bonds (7-year maturity); weekly average of daily data; data start 3 Apr. 1998; source: Bloomberg.

6. 10-year interest rate swap spread; weekly average of daily data; data start 4 Mar. 1987; source: Datastream.

Equity market

7. Realised volatility of Datastream non-financial sector stock price index; weekly average of absolute daily log returns; data start 4 Jan. 1980; source: Datastream.

8. Maximum cumulated loss (CMAX) of Datastream non-financial sector stock price index (x_t) over a moving 2-year window: $CMAX_t = 1 - x_t / \max[x \in (x_{t-j} | j = 0, 1, \ldots, T)]$ with $T = 104$ for weekly data; data start 1 Jan. 1982; source: Datastream.

9. Stock-bond correlation; weekly average of the difference between the 4-year (1040 business days) and the 4-week (20 business days) correlation coefficients between daily log returns of Datastream total stock price index and the 10-year German government benchmark bond price index; final indicator is assigned a value of zero for negative differences; data start 8 Jan. 1982; source: Datastream.

Financial intermediaries

10. Realised volatility of idiosyncratic equity return of Datastream bank sector stock price index over the total market index; weekly average of absolute daily idiosyncratic returns; idiosyncratic return calculated as residual from OLS regression of daily log bank return on log market return over a moving 2-year window (522 business days); data start 1 Jan. 1982; source: Datastream.

11. Yield spread between A-rated financial and non-financial corporations (7-year maturity); weekly average of daily data; data start 3 Apr. 1998; source: Bloomberg.

12. CMAX of Datastream financial sector stock price index interacted with the sector's book-price ratio; both indicators transformed by their recursive sample CDF prior to multiplication; final indicator obtained by taking the square root of this product; data start 1 Jan. 1982; source: Datastream.

Foreign exchange market

13. Realised volatility of euro exchange rate vis-à-vis US dollar; weekly average of absolute daily log foreign exchange returns; data start 6 July 1990; source: Datastream.

14. Realised volatility of euro exchange rate vis-à-vis Japanese Yen; weekly average of absolute daily log foreign exchange returns; data start 6 July 1990; source: Datastream.

15. Realised volatility of euro exchange rate vis-à-vis British Pound; weekly average of absolute daily log foreign exchange returns; data start 6 July 1990; source: Datastream.

Source: Kremer et al., 2012, p. 14

Appendix 2: The Variable Composition of CFSI

Table 21: The Variable Composition of CFSI

Market	**Variables**
Interbank Market	Financial Beta
	Bank Bond Spread
	Interbank Liquidity Spread
	Interbank Cost of Borrowing
Stock Market	Stock Market Crashes
Foreign Exchange Market	Weighted Dollar Crashes
Credit Market	Covered Interest Spread
	Corporate Bond Spread
	Liquidity Spread
	90 Day Commercial Paper Treasury Bill Spread
	Treasury Yield Curve

Source: Manamperi, 2013, p. 20.

Appendix 3: Data descriptions

Table 22: Data descriptions of the independent variables

		Name	Source	Symbol
US	VIX	CBOE SPX VOLATILITY VIX (NEW) - PRICE INDEX	Datastream	CBOEVIX(PI)
	Ted spread	US T-BILL SEC MARKET 3 MONTH (D) - MIDDLE RATE	Datastream	FRTBS3M
		IBA USD IBK. LIBOR 3M DELAYED - OFFERED RATE	Datastream	BBUSD3M
	Yield curve slope	10-Year Treasury Constant Maturity Rate	Federal Reserve Bank of St. Louis	DGS10
		3-Month Treasury Constant Maturity Rate	Federal Reserve Bank of St. Louis	DGS3MO
	Return of the bank equity index	US-DS Banks - PRICE INDEX	Datastream	BANKSUS(PI)
	CDX Investment Grade	CDX IG	Bloomberg (CBC)	IBOXUMAE
	CDX High Yield	CDX HY	Bloomberg (CBC)	IBOXHYSE
EU	VSTOXX	VSTOXX VOLATILITY INDEX - PRICE INDEX	Datastream	VSTOXXI(PI)
	Ted spread	12-Month LIBOR based on Euro	Federal Reserve Bank of St. Louis	EUR12MD156N
		GERMANY GOVERNMENT BOND 2 YEAR - RED. YIELD	Datastream	BMBD02Y(IY)
	Yield curve slope	GERMANY GOVERNMENT BOND 30 YEAR - RED. YIELD	Datastream	BMBD30Y(IY)
		GERMANY GOVERNMENT BOND 2 YEAR - RED. YIELD	Datastream	BMBD02Y(IY)
	Return of the bank equity index	EMU-DS Banks - PRICE INDEX	Datastream	BANKSEM(PI)
	Itraxx	Itraxx Europe	Datastream	ITEEU10Y
	Itraxx Financials	Itraxx Sub Financials	Datastream	ITEFS10Y

Source: Bloomberg (CBC), Datastream, Federal Reserve Bank of St. Louis

Table 23: Data descriptions of the dependent variables

		Name	Source	Symbol
US	Cleveland Financial Stress Index	Cleveland Financial Stress Index	Federal Reserve Bank of Cleveland	/
EU	Composite Indicator of Systemic Stress	SYS STRESS COMPO SITE INDICATOR - ECONOMIC SERIES	Datastream	EMCISSI

Source: Datastream, Federal Reserve Bank of Cleveland

Appendix 4: Summary statistics

Table 24: Mean, standard deviation, min, max of the data

	mean	sd	min	max
CISS	.2697752	.2022756	.021	.8042
CFSI	.4205905	1.172159	-2.062	3.165
EURO_Bank_Index_Return	-.0023814	.1065102	-.3440837	.2795767
US_Bank_Index_Return	.0004405	.0926458	-.3502747	.2315298
VIX	21.14648	10.0816	10.31	68.51
VSTOXX	24.6081	9.118362	14	60.68
TED_Spread	.0053229	.0054128	.0012169	.0331
EUR_TED	.5864089	.5107486	-.063	2.35525
Slope_US	1.962	1.206915	-.6	3.79
Slope_EU	1.779514	.9040344	.164	3.13
Itraxx	113.1932	42.40986	39.229	212.04
Itraxxfinancials	204.056	128.7302	25	525.71
CDXIG	93.48974	42.85152	31.791	234.004
CDXHY	497.8398	215.6525	212.971	1574.715
N	105			

Source: Bloomberg (CBC), Datastream, Federal Reserve Bank of Cleveland, Federal Reserve Bank of St. Louis, own computations by Stata

Appendix 5: Results of multivariate logit regressions

US

For these first results, we will give an example of the way to interpret the marginal effects with the VIX: if at a given period the independent variables (VIXX, US Ted Spread, …) are at their means, an increase of one unit of VIX increases, ceteris paribus, the probability of a systemic stress event by 0.00624 (or 0.624%).

Table 25: Multivariate logit regression with US Stress Dummy as dependent variable (0lags)

	Coefficients	Marginal effects
VIX	0.136***	0.00624***
	(3.11)	(2.87)
US_TED	238.3***	10.93***
	(3.28)	(2.66)
US_Bank_Index_Return	1.292	0.0593
	(0.41)	(0.41)
Slope_US	0.321	0.0147
	(0.96)	(0.93)
McFadden R^2	0.375	
Count R^2	0.937	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 26: Multivariate logit regression with US Stress Dummy as dependent variable (1lags)

	Coefficients	Marginal effects
L.VIX	0.150***	0.00684***
	(3.40)	(3.17)
L.US_TED	155.1**	7.059**
	(2.24)	(1.99)
L.US_Bank_Index_Return	-6.184*	-0.281*
	(-1.84)	(-1.73)
L.Slope_US	0.0849	0.00386
	(0.27)	(0.26)
McFadden R^2	0.366	
Count R^2	0.926	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 27: Multivariate logit regression with US Stress Dummy as dependent variable (2lags)

	Coefficients	Marginal effects
L2.VIX	0.119**	0.00426**
	(2.53)	(2.28)
L2.US_TED	359.4***	12.92***
	(4.22)	(2.73)
L2.US_Bank_Index_Return	-4.533	-0.163
	(-1.33)	(-1.28)
L2.Slope_US	0.663	0.0238
	(1.63)	(1.57)
McFadden R^2	0.463	
Count R^2	0.925	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 28: Multivariate logit regression with US Stress Dummy as dependent variable (3lags)

	Coefficients	Marginal effects
L3.VIX	0.0675	0.00306
	(1.53)	(1.54)
L3.TED_Spread	336.3***	15.23***
	(4.20)	(3.03)
L3.US_Bank_Index_Return	-6.552*	-0.297*
	(-1.94)	(-1.78)
L3.Slope_US	0.576	0.0261
	(1.55)	(1.52)
McFadden R^2	0.413	
Count R^2	0.930	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 29: Multivariate logit regression with US Stress Dummy as dependent variable (4lags)

	Coefficients	Marginal effects
L4.VIX	-0.00817	-0.000478
	(-0.19)	(-0.19)
L4.TED_Spread	310.1***	18.14***
	(4.06)	(3.41)
L4.US_Bank_Index_Return	-5.622*	-0.329*
	(-1.74)	(-1.68)
L4.Slope_US	0.526	0.0307
	(1.60)	(1.61)
McFadden R^2	0.317	
Count R^2	0.903	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 30: Multivariate logit regression with US Stress Dummy as dependent variable (5lags)

	Coefficients	Marginal effects
L5.VIX	-0.121**	-0.00545**
	(-2.29)	(-2.37)
L5.TED_Spread	450.7***	20.21***
	(4.61)	(3.33)
L5.US_Bank_Index_Return	-6.550*	-0.294*
	(-1.78)	(-1.73)
L5.Slope_US	1.090***	0.0489***
	(2.77)	(2.89)
McFadden R^2	0.378	
Count R^2	0.924	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 31: Multivariate logit regression with US Stress Dummy as dependent variable (6lags)

	Coefficients	Marginal effects
L6.VIX	-0.183***	-0.00848***
	(-3.21)	(-3.36)
L6.TED_Spread	395.1***	18.33***
	(4.48)	(3.32)
L6.US_Bank_Index_Return	-9.325**	-0.433**
	(-2.14)	(-2.24)
L6.Slope_US	0.938***	0.0435***
	(2.81)	(2.76)
McFadden R^2	0.310	
Count R^2	0.918	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

EU

Table 32: Multivariate logit regression with EU Stress Dummy as dependent variable (0lags)

	Coefficients	Marginal effects
VSTOXX	0.112***	0.00359**
	(3.26)	(2.43)
EUR_TED	2.376***	0.0764**
	(4.27)	(2.57)
EURO_Bank_ Index_Return	4.911*	0.158
	(1.77)	(1.56)
Slope_EU	0.502	0.0161
	(0.96)	(1.01)
McFadden R^2	0.427	
Count R^2	0.926	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 33: Multivariate logit regression with EU Stress Dummy as dependent variable (1lags)

	Coefficients	Marginal effects
L.VSTOXX	0.0985***	0.00379**
	(2.86)	(2.46)
L.EUR_TED	2.432***	0.0936***
	(4.42)	(2.99)
L.EURO_Bank_Index_Return	4.559	0.175
	(1.63)	(1.54)
L.Slope_EU	0.0572	0.00220
	(0.12)	(0.12)
McFadden R^2	0.395	
Count R^2	0.926	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 34: Multivariate logit regression with EU Stress Dummy as dependent variable (2lags)

	Coefficients	Marginal effects
L2.VSTOXX	0.0905***	0.00403**
	(2.66)	(2.47)
L2.EUR_TED	2.288***	0.102***
	(4.38)	(3.24)
L2.EURO_Bank_Index_Return	4.465	0.199
	(1.56)	(1.54)
L2.Slope_EU	-0.372	-0.0166
	(-0.88)	(-0.89)
McFadden R^2	0.349	
Count R^2	0.904	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 35:Multivariate logit regression with EU Stress Dummy as dependent variable (3lags)

	Coefficients	Marginal effects
L3.VSTOXX	0.0750**	0.00375**
	(2.22)	(2.18)
L3.EUR_TED	2.055***	0.103***
	(4.11)	(3.32)
L3.EURO_Bank_Index_Return	1.387	0.0694
	(0.47)	(0.47)
L3.Slope_EU	-0.641	-0.0320*
	(-1.61)	(-1.67)
McFadden R^2	0.304	
Count R^2	0.898	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 36: Multivariate logit regression with EU Stress Dummy as dependent variable (4lags)

	Coefficients	Marginal effects
L4.VSTOXX	0.0508	0.00238
	(1.41)	(1.38)
L4.EUR_TED	2.056***	0.0964***
	(3.96)	(3.15)
L4.EURO_Bank_Index_Return	-3.356	-0.157
	(-0.99)	(-0.98)
L4.Slope_EU	-0.810**	-0.0380**
	(-2.05)	(-2.11)
McFadden R^2	0.322	
Count R^2	0.892	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 37: Multivariate logit regression with EU Stress Dummy as dependent variable (5lags)

	Coefficients	Marginal effects
L5.VSTOXX	0.0198	0.000913
	(0.50)	(0.49)
L5.EUR_TED	2.272***	0.105***
	(4.10)	(3.28)
L5.EURO_Bank_Index_Return	-2.968	-0.137
	(-0.85)	(-0.84)
L5.Slope_EU	-0.877**	-0.0405**
	(-2.26)	(-2.24)
McFadden R^2	0.317	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 38: Multivariate logit regression with EU Stress Dummy as dependent variable (6lags)

	Coefficients	Marginal effects
L6.VSTOXX	0.0417	0.00170
	(1.02)	(1.00)
L6.EUR_TED	2.426***	0.0990***
	(4.22)	(3.06)
L6.EURO_Bank_Index_Return	2.279	0.0930
	(0.66)	(0.66)
L6.Slope_EU	-1.310***	-0.0534***
	(-3.05)	(-2.90)
McFadden R^2	0.334	
Count R^2	0.929	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Appendix 6: Results of univariate logit regressions

US

VIX

Table 39: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (0lags)

	Coefficients	Marginal effects
VIX	0.159***	0.00874***
	(4.64)	(3.95)
McFadden R^2	0.272	
pseudo R^2	0.931	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 40: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (1lags)

	Coefficients	Marginal effects
L.VIX	0.169***	0.00886***
	(4.74)	(3.90)
McFadden R^2	0.295	
Count R^2	0.931	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 41: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (2lags)

	Coefficients	Marginal effects
L2.VIX	0.154***	0.00880***
	(4.58)	(3.97)
McFadden R^2	0.261	
Count R^2	0.93	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 42: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (3lags)

	Coefficients	Marginal effects
L3.VIX	0.126***	0.00827***
	(4.20)	(3.93)
McFadden R^2	0.198	
Count R^2	0.909	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 43: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (4lags)

	Coefficients	Marginal effects
L4.VIX	0.0877***	0.00676***
	(3.46)	(3.43)
McFadden R^2	0.110	
Count R^2	0.908	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 44: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (5lags)

	Coefficients	Marginal effects
L5.VIX	0.0585**	0.00498**
	(2.53)	(2.58)
McFadden R^2	0.050	
Count R^2	0.902	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 45: Univariate logit regression with US Stress Dummy as dependent variable and VIX as independent variable (6lags)

	Coefficients	Marginal effects
L6.VIX	0.0241	0.00221
	(0.98)	(0.99)
McFadden R^2	0.007	
Count R^2	0.896	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Ted spread

Table 46: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (0lags)

	Coefficients	Marginal effects
TED_Spread	252.0***	16.17***
	(4.47)	(3.84)
McFadden R^2	0.233	
Count R^2	0.905	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 47: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (1lags)

	Coefficients	Marginal effects
L.TED_Spread	202.3***	14.45***
	(4.03)	(3.68)
McFadden R^2	0.169	
Count R^2	0.894	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 48: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (2lags)

	Coefficients	Marginal effects
L2.TED_Spread	318.5***	17.69***
	(4.88)	(3.80)
McFadden R^2	0.317	
Count R^2	0.93	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 49: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (3lags)

	Coefficients	Marginal effects
L3.TED_Spread	307.7***	17.66***
	(4.82)	(3.82)
McFadden R^2	0.304	
Count R^2	0.925	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 50: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (4lags)

	Coefficients	Marginal effects
L4.TED_Spread	273.7***	17.12***
	(4.60)	(3.85)
McFadden R^2	0.261	
Count R^2	0.914	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 51: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (5lags)

	Coefficients	Marginal effects
L5.TED_Spread	280.3***	17.38***
	(4.64)	(3.85)
McFadden R^2	0.269	
Count R^2	0.924	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 52: Univariate logit regression with US Stress Dummy as dependent variable and Ted spread as independent variable (6lags)

	Coefficients	Marginal effects
L6.TED_Spread	201.6***	14.81***
	(3.99)	(3.67)
McFadden R^2	0.168	
Count R^2	0.902	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Return of the bank equity index

Table 53: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (0lags)

	Coefficients	Marginal effects
US_Bank_Index_Return	-4.462	-0.387*
	(-1.62)	(-1.66)
McFadden R^2	0.02	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 54: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (1lags)

	Coefficients	Marginal effects
L.US_Bank_Index_Return	-10.84***	-0.789***
	(-3.58)	(-3.63)
McFadden R^2	0.119	
Count R^2	0.91	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 55: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (2lags)

	Coefficients	Marginal effects
L2.US_Bank_Index_Return	-8.207***	-0.656***
	(-2.93)	(-3.04)
McFadden R^2	0.071	
Count R^2	0.909	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 56: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (3lags)

	Coefficients	Marginal effects
L3.US_Bank_ Index_Return	-10.04***	-0.759***
	(-3.41)	(-3.49)
McFadden R^2	0.105	
Count R^2	0.909	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 57: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (4lags)

	Coefficients	Marginal effects
L4.US_Bank_ Index_Return	-8.546***	-0.682***
	(-3.03)	(-3.14)
McFadden R^2	0.078	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 58: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (5lags)

	Coefficients	Marginal effects
L5.US_Bank_ Index_Return	-6.733**	-0.569**
	(-2.47)	(-2.57)
McFadden R^2	0.048	
Count R^2	0.902	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 59: Univariate logit regression with US Stress Dummy as dependent variable and Return of the bank equity index as independent variable (6lags)

	Coefficients	Marginal effects
L6.US_Bank_ Index_Return	-5.276*	-0.464**
	(-1.94)	(-2.01)
McFadden R^2	0.029	
Count R^2	0.896	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Yield curve slope

Table 60: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (0lags)

	Coefficients	Marginal effects
Slope_US	0.233	0.0205
	(1.10)	(1.13)
McFadden R^2	0.01	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 61: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (1lags)

	Coefficients	Marginal effects
L.Slope_US	0.176	0.0157
	(0.85)	(0.86)
McFadden R^2	0.006	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 62: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (2lags)

	Coefficients	Marginal effects
L2.Slope_US	0.215	0.0192
	(1.03)	(1.05)
McFadden R^2	0.009	
Count R^2	0.898	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 63: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (3lags)

	Coefficients	Marginal effects
L3.Slope_US	0.157	0.0142
	(0.77)	(0.78)
McFadden R^2	0.005	
Count R^2	0.898	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 64: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (4lags)

	Coefficients	Marginal effects
L4.Slope_US	0.117	0.0107
	(0.58)	(0.58)
McFadden R^2	0.003	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 65: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (5lags)

	Coefficients	Marginal effects
L5.Slope_US	0.188	0.0171
	(0.91)	(0.93)
McFadden R^2	0.007	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 66: Univariate logit regression with US Stress Dummy as dependent variable and Yield curve slope as independent variable (6lags)

	Coefficients	Marginal effects
L6.Slope_US	0.135	0.0125
	(0.67)	(0.68)
McFadden R^2	0.004	
Count R^2	0.896	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

CDX IG

Table 67: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (0lags)

	Coefficients	Marginal effects
CDXIG	0.0524***	0.00317***
	(4.37)	(3.35)
McFadden R^2	0.439	
pseudo R^2	0.917	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

Table 68: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (1lags)

	Coefficients	Marginal effects
L.CDXIG	0.0448***	0.00324***
	(4.39)	(3.66)
McFadden R^2	0.381	
Count R^2	0.883	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

Table 69: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (2lags)

	Coefficients	Marginal effects
L2.CDXIG	0.0328***	0.00304***
	(4.25)	(3.94)
McFadden R^2	0.269	
pseudo R^2	0.874	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

Table 70: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (3lags)

	Coefficients	Marginal effects
L3.CDXIG	0.0255***	0.00270***
	(3.90)	(3.84)
McFadden R^2	0.188	
Count R^2	0.856	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

Table 71: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (4lags)

	Coefficients	Marginal effects
L4.CDXIG	0.0188***	0.00222***
	(3.25)	(3.34)
McFadden R^2	0.112	
Count R^2	0.838	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

Table 72: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (5lags)

	Coefficients	Marginal effects
L5.CDXIG	0.0122**	0.00157**
	(2.26)	(2.33)
McFadden R^2	0.049	
Count R^2	0.845	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

Table 73: Univariate logit regression with US Stress Dummy as dependent variable and CDX IG as independent variable (6lags)

	Coefficients	Marginal effects
L6.CDXIG	0.00770	0.00104
	(1.43)	(1.45)
McFadden R^2	0.019	
Count R^2	0.835	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Bloomberg, own computations by Stata

EU

VSTOXX

Table 74: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (0lags)

	Coefficients	Marginal effects
VSTOXX	0.114***	0.00692***
	(4.71)	(4.14)
McFadden R^2	0.209	
Count R^2	0.894	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 75: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (1lags)

	Coefficients	Marginal effects
L.VSTOXX	0.104***	0.00676***
	(4.44)	(4.12)
McFadden R^2	0.177	
Count R^2	0.883	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 76: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (2lags)

	Coefficients	Marginal effects
L2.VSTOXX	0.0932***	0.00650***
	(4.12)	(4.01)
McFadden R^2	0.145	
Count R^2	0.893	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 77: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (3lags)

	Coefficients	Marginal effects
L3.VSTOXX	0.0836***	0.00617***
	(3.78)	(3.80)
McFadden R^2	0.118	
Count R^2	0.903	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 78: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (4lags)

	Coefficients	Marginal effects
L4.VSTOXX	0.0757***	0.00584***
	(3.47)	(3.56)
McFadden R^2	0.097	
Count R^2	0.903	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 79: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (5lags)

	Coefficients	Marginal effects
L5.VSTOXX	0.0591***	0.00491***
	(2.73)	(2.85)
McFadden R^2	0.058	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 80: Univariate logit regression with EU Stress Dummy as dependent variable and VSTOXX as independent variable (6lags)

	Coefficients	Marginal effects
L6.VSTOXX	0.0517**	0.00443**
	(2.38)	(2.48)
McFadden R^2	0.043	
Count R^2	0.896	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Ted spread

Table 81: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (0lags)

	Coefficients	Marginal effects
EUR_TED	2.561***	0.127***
	(5.18)	(3.89)
McFadden R^2	0.295	
Count R^2	0.926	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 82: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (1lags)

	Coefficients	Marginal effects
L.EUR_TED	2.647***	0.127***
	(5.24)	(3.81)
McFadden R^2	0.311	
Count R^2	0.91	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 83: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (2lags)

	Coefficients	Marginal effects
L2.EUR_TED	2.499***	0.128***
	(5.14)	(3.93)
McFadden R^2	0.286	
Count R^2	0.904	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 84: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (3lags)

	Coefficients	Marginal effects
L3.EUR_TED	2.319***	0.129***
	(4.98)	(4.06)
McFadden R^2	0.256	
Count R^2	0.887	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 85: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (4lags)

	Coefficients	Marginal effects
L4.EUR_TED	2.324***	0.129***
	(4.99)	(4.05)
McFadden R^2	0.258	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 86: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (5lags)

	Coefficients	Marginal effects
L5.EUR_TED	2.321***	0.130***
	(4.99)	(4.05)
McFadden R^2	0.259	
Count R^2	0.886	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 87: Univariate logit regression with EU Stress Dummy as dependent variable and Ted spread as independent variable (6lags)

	Coefficients	Marginal effects
L6.EUR_TED	2.210***	0.130***
	(4.88)	(4.11)
McFadden R^2	0.240	
Count R^2	0.885	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Return of the bank equity index

Table 88: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (0lags)

	Coefficients	Marginal effects
EURO_Bank_ Index_Return	-3.348	-0.294
	(-1.26)	(-1.30)
McFadden R^2	0.013	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 89: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (1lags)

	Coefficients	Marginal effects
L.EURO_Bank_Index_Return	-3.907	-0.342
	(-1.48)	(-1.53)
McFadden R^2	0.018	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 90: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (2lags)

	Coefficients	Marginal effects
L2.EURO_Bank_Index_Return	-4.087	-0.358
	(-1.56)	(-1.61)
McFadden R^2	0.019	
Count R^2	0.898	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 91: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (3lags)

	Coefficients	Marginal effects
L3.EURO_Bank_Index_Return	-6.740**	-0.552***
	(-2.55)	(-2.73)
McFadden R^2	0.053	
Count R^2	0.903	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 92: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (4lags)

	Coefficients	Marginal effects
L4.EURO_Bank_Index_Return	-10.11***	-0.726***
	(-3.61)	(-3.83)
McFadden R^2	0.117	
Count R^2	0.903	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 93: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (5lags)

	Coefficients	Marginal effects
L5.EURO_Bank_Index_Return	-8.834***	-0.674***
	(-3.25)	(-3.50)
McFadden R^2	0.091	
Count R^2	0.902	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 94: Univariate logit regression with EU Stress Dummy as dependent variable and Return of the bank equity index as independent variable (6lags)

	Coefficients	Marginal effects
L6.EURO_Bank_Index_Return	-5.601**	-0.481**
	(-2.15)	(-2.27)
McFadden R^2	0.038	
Count R^2	0.896	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Yield curve slope

Table 95: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (0lags)

	Coefficients	Marginal effects
Slope_EU	0.763**	0.0621**
	(2.00)	(2.24)
McFadden R^2	0.038	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 96: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (1lags)

	Coefficients	Marginal effects
L.Slope_EU	0.459	0.0401
	(1.33)	(1.39)
McFadden R^2	0.016	
Count R^2	0.899	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 97: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (2lags)

	Coefficients	Marginal effects
L2.Slope_EU	0.142	0.0129
	(0.45)	(0.45)
McFadden R^2	0.002	
Count R^2	0.898	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 98: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (3lags)

	Coefficients	Marginal effects
L3.Slope_EU	-0.155	-0.0142
	(-0.52)	(-0.52)
McFadden R^2	0.002	
Count R^2	0.898	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 99: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (4lags)

	Coefficients	Marginal effects
L4.Slope_EU	-0.358	-0.0321
	(-1.21)	(-1.24)
McFadden R^2	0.012	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 100: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (5lags)

	Coefficients	Marginal effects
L5.Slope_EU	-0.504*	-0.0443*
	(-1.71)	(-1.78)
McFadden R^2	0.024	
Count R^2	0.897	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 101: Univariate logit regression with EU Stress Dummy as dependent variable and Yield curve slope as independent variable (6lags)

	Coefficients	Marginal effects
L6.Slope_EU	-0.735**	-0.0612***
	(-2.45)	(-2.67)
McFadden R^2	0.050	
Count R^2	0.896	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Itraxx

Table 102: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (0lags)

	Coefficients	Marginal effects
Itraxx	0.0189***	0.00213***
	(2.93)	(3.30)
McFadden R^2	0.094	
Count R^2	0.851	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 103: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (1lags)

	Coefficients	Marginal effects
L.Itraxx	0.0189***	0.00214***
	(2.93)	(3.30)
McFadden R^2	0.095	
Count R^2	0.85	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 104: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (2lags)

	Coefficients	Marginal effects
L2.Itraxx	0.0157**	0.00188***
	(2.54)	(2.79)
McFadden R^2	0.068	
Count R^2	0.84	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 105: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (3lags)

	Coefficients	Marginal effects
L3.Itraxx	0.0107*	0.00137*
	(1.83)	(1.92)
McFadden R^2	0.034	
Count R^2	0.839	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 106: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (4lags)

	Coefficients	Marginal effects
L4.Itraxx	0.00860	0.00113
	(1.50)	(1.55)
McFadden R^2	0.022	
Count R^2	0.838	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 107: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (5lags)

	Coefficients	Marginal effects
L5.Itraxx	0.00460	0.000624
	(0.82)	(0.83)
McFadden R^2	0.007	
Count R^2	0.836	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 108: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx as independent variable (6lags)

	Coefficients	Marginal effects
L6.Itraxx	0.00301	0.000414
	(0.54)	(0.54)
McFadden R^2	0.003	
Count R^2	0.835	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Itraxx Financials

Table 109: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (0lags)

	Coefficients	Marginal effects
Itraxxfinancials	0.00449**	0.000547**
	(2.44)	(2.57)
McFadden R^2	0.057	
Count R^2	0.843	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 110: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (1lags)

	Coefficients	Marginal effects
L.Itraxxfinanc ials	0.00447**	0.000549**
	(2.43)	(2.56)
McFadden R^2	0.057	
Count R^2	0.842	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 111: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (2lags)

	Coefficients	Marginal effects
L2.Itraxxfinan cials	0.00347*	0.000444**
	(1.91)	(1.98)
McFadden R^2	0.035	
Count R^2	0.84	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 112: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (3lags)

	Coefficients	Marginal effects
L3.Itraxxfinan cials	0.00194	0.000258
	(1.06)	(1.08)
R^2	0.011	
pseudo R^2	0.839	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 113: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (4lags)

	Coefficients	Marginal effects
L4.Itraxxfinancials	0.000932	0.000126
	(0.50)	(0.51)
McFadden R^2	0.002	
Count R^2	0.838	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 114: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (5lags)

	Coefficients	Marginal effects
StressDummy Europe		
L5.Itraxxfinancials	-0.000249	-0.0000342
	(-0.13)	(-0.13)
McFadden R^2	0.000	
Count R^2	0.836	

t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Table 115: Univariate logit regression with EU Stress Dummy as dependent variable and Itraxx Financials as independent variable (6lags)

	Coefficients	Marginal effects
L6.Itraxxfinancials	-0.000775	-0.000107
	(-0.40)	(-0.40)
McFadden R^2	0.002	
Count R^2	0.835	

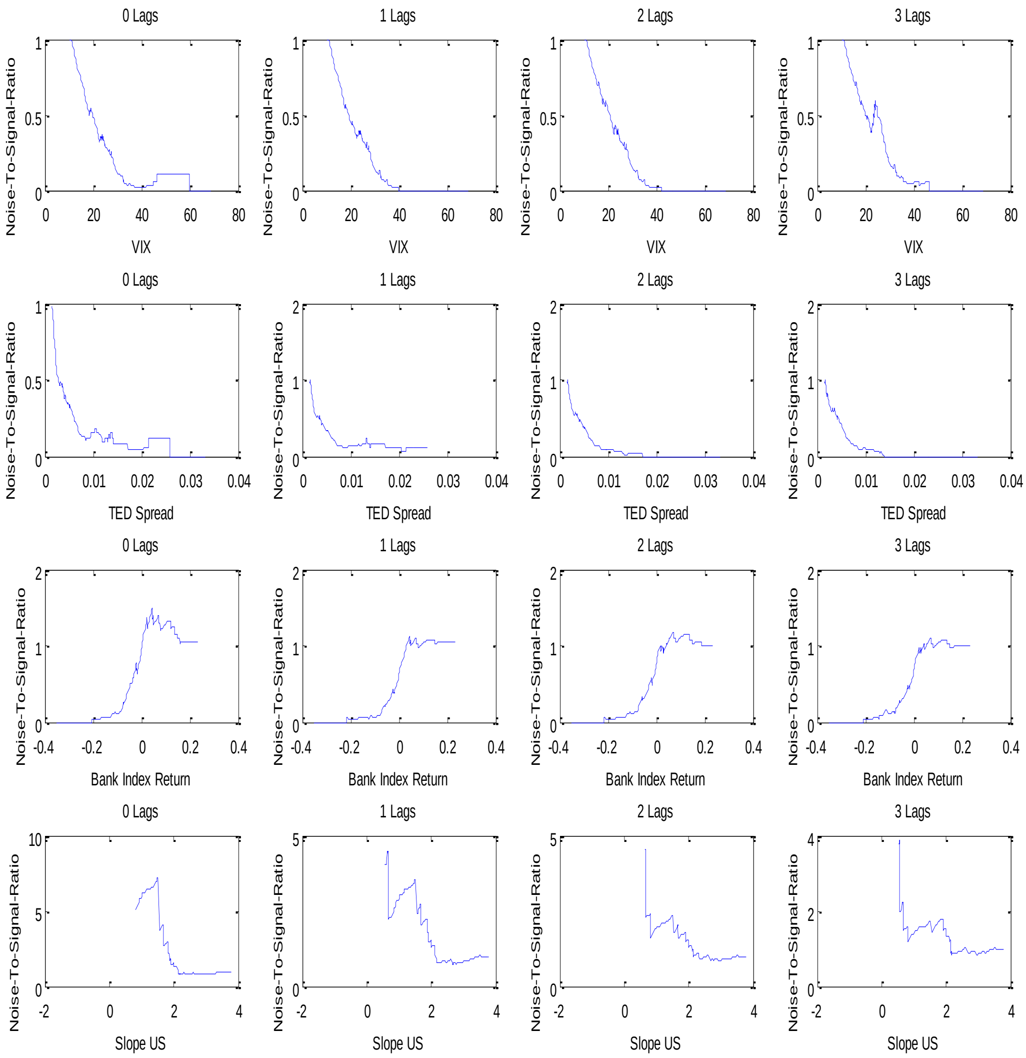
t statistics in parentheses; marginal effects estimated at means of independent variables
* p<0.1, ** p<0.05, *** p<0.01

Source: Datastream, own computations by Stata

Appendix 7: Noise-to-signal ratios and their corresponding thresholds from 0 to 6 lags according to the KLR signal approach

US

Figure 17: US NTS ratios and corresponding thresholds from 0 to 3 lags (except for CDS)

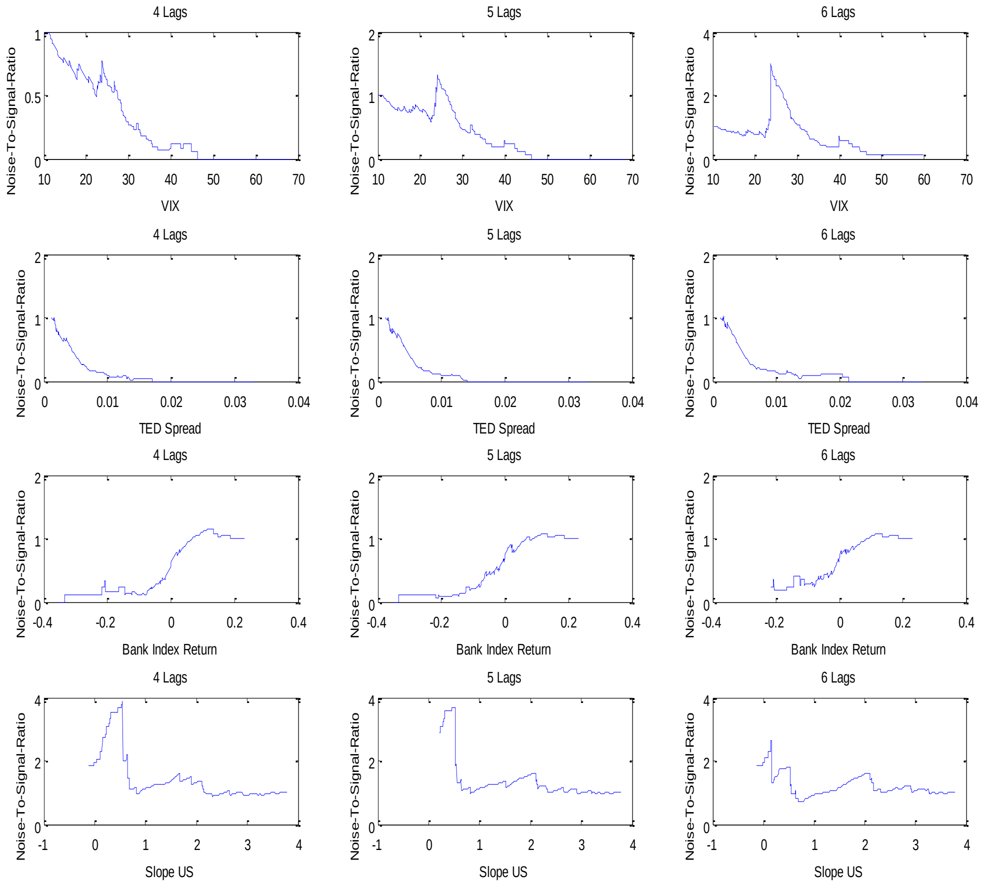


Source: Datastream, own computations by Matlab

Appendix 7 ([7])

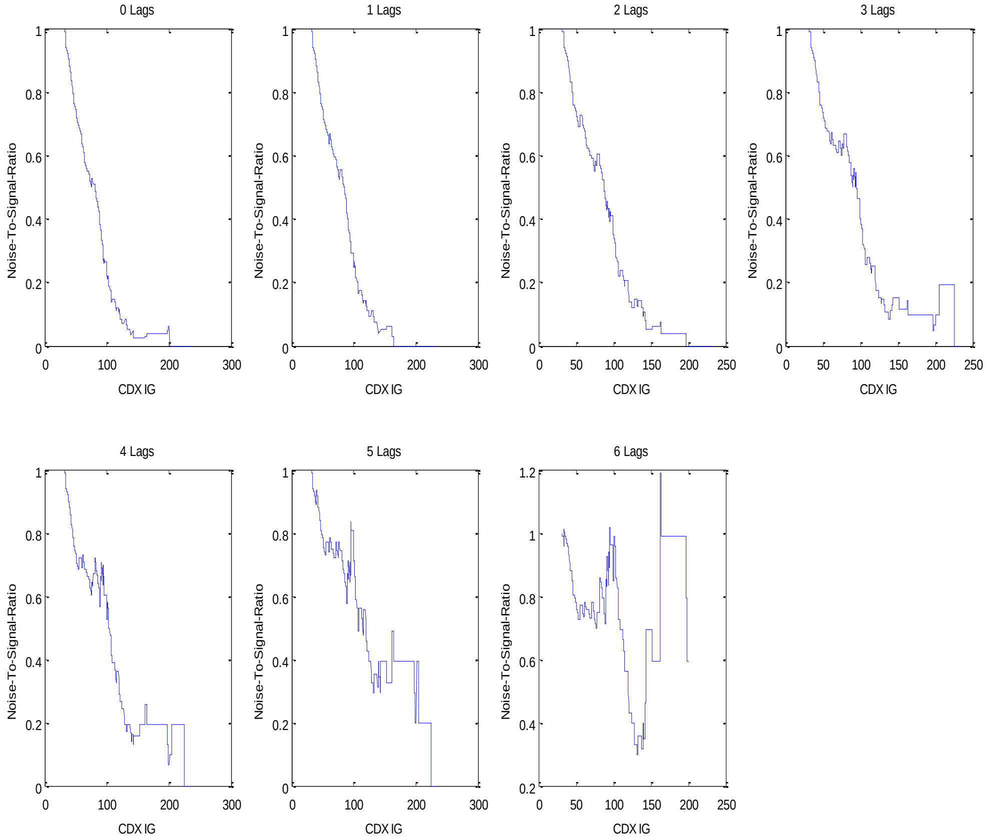
([7]) We will always present here the results of US and EU CDS indices separately from the other results because CDS indices begin much later than the rest of the data.

Figure 18: US NTS ratios and corresponding thresholds from 4 to 6 lags (except for CDS)



Source: Datastream, own computations by Matlab

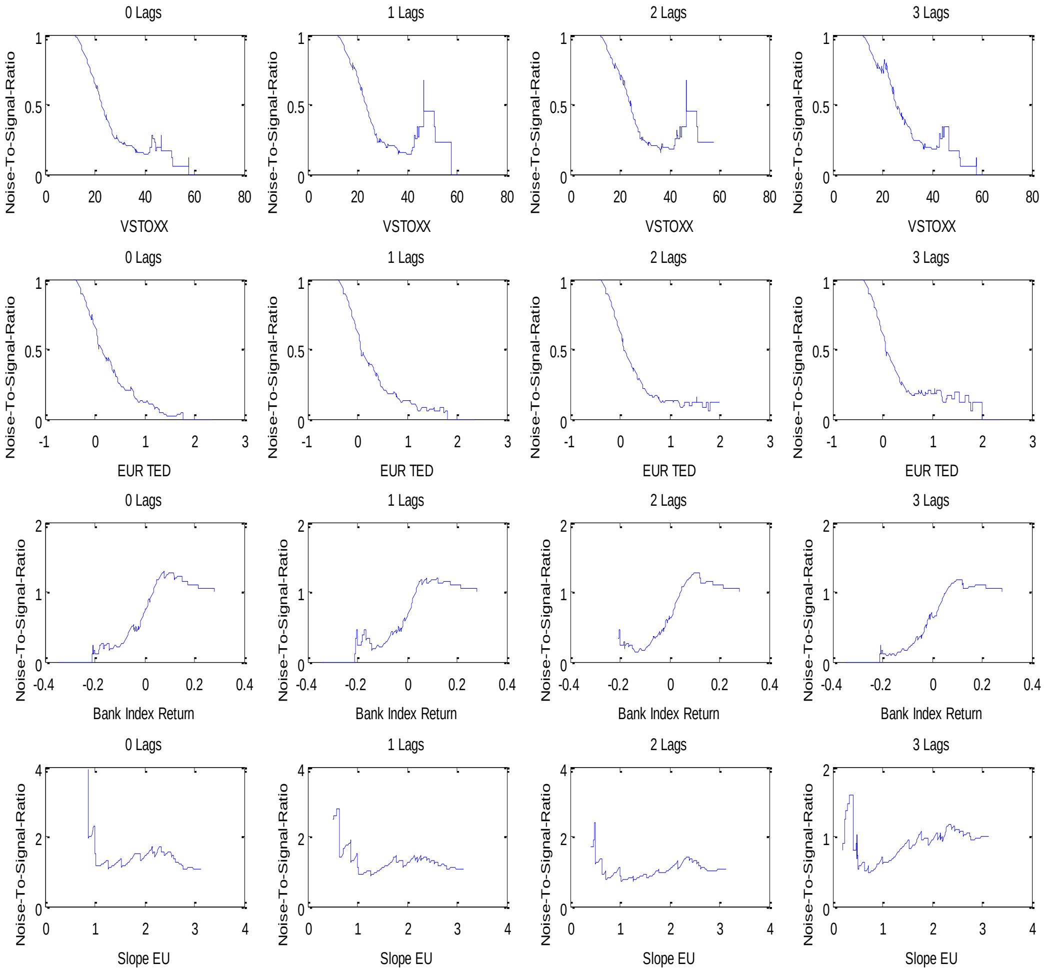
Figure 19: NTS ratios and corresponding thresholds from 0 to 6 lags for CDX IG



Source: Bloomberg, own computations by Matlab

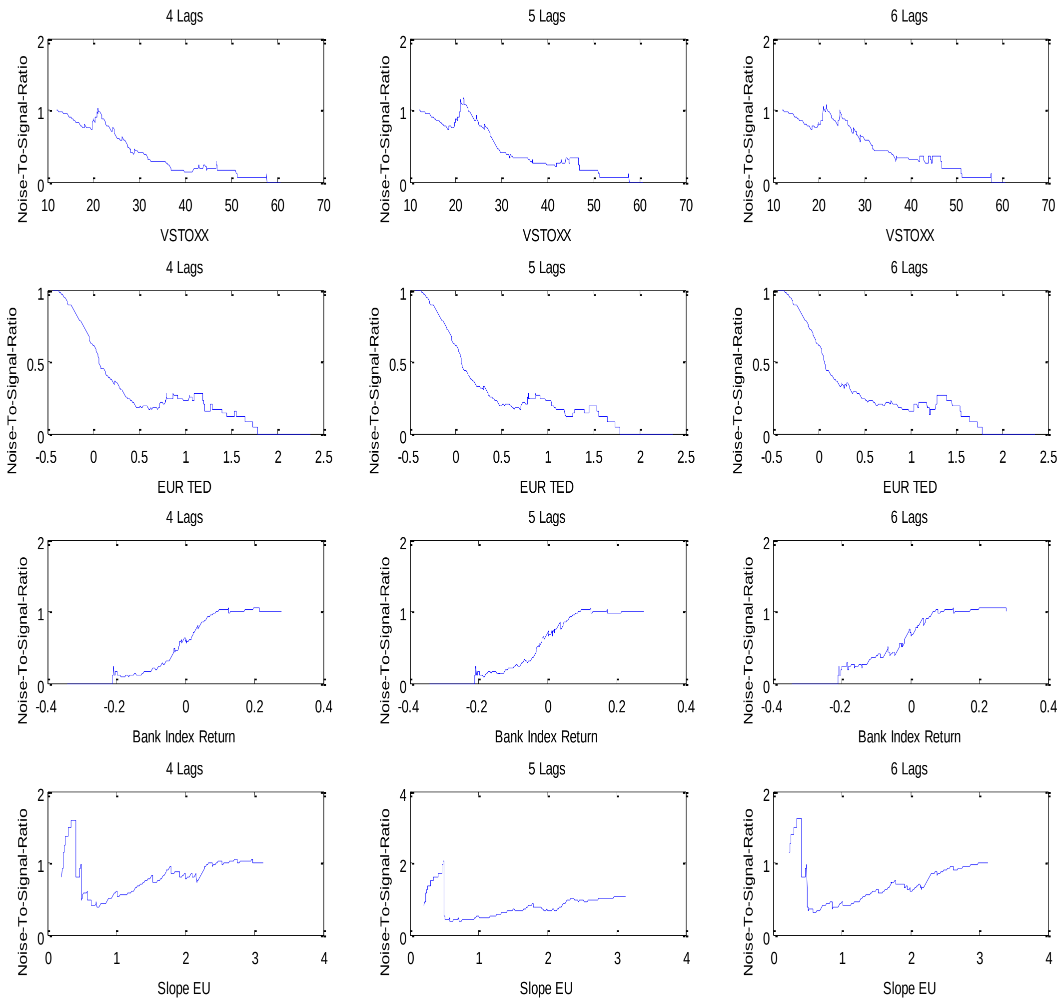
EU

Figure 20: EU NTS ratios and corresponding thresholds from 0 to 3 lags (except for CDS)



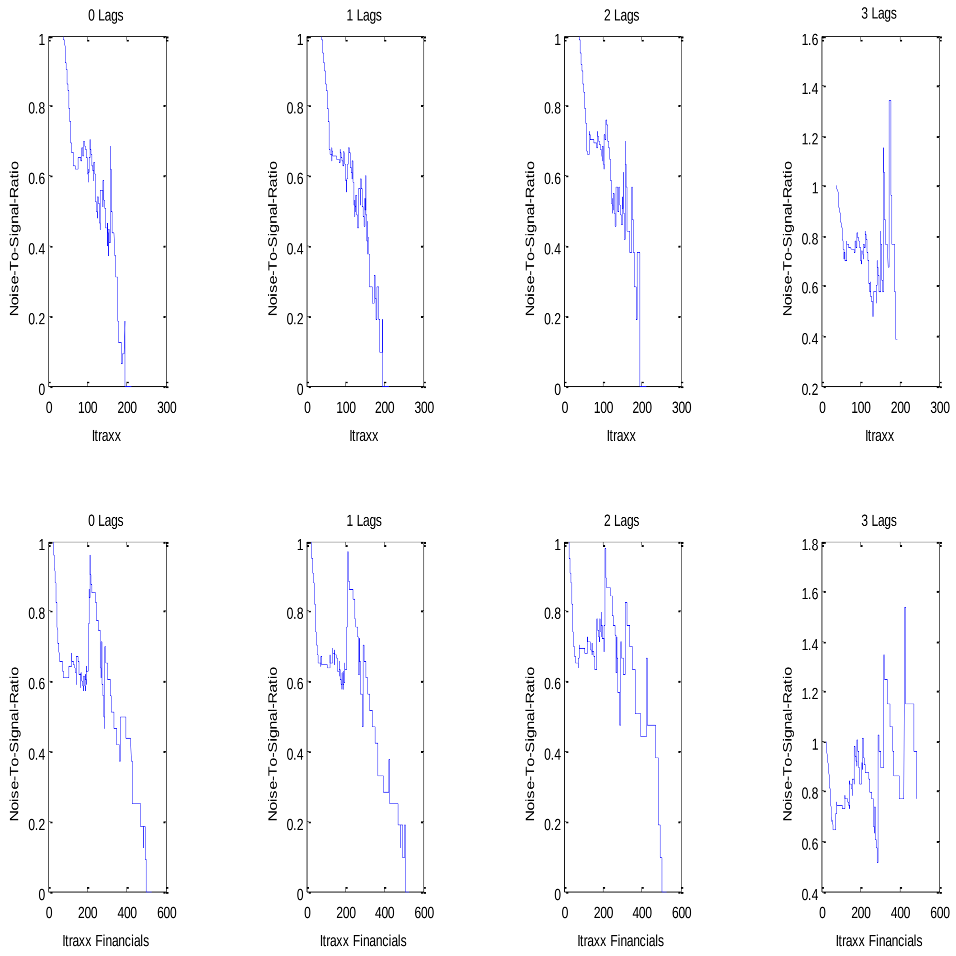
Source: Datastream, own computations by Matlab

Figure 21: EU NTS ratios and corresponding thresholds from 4 to 6 lags (except for CDS)



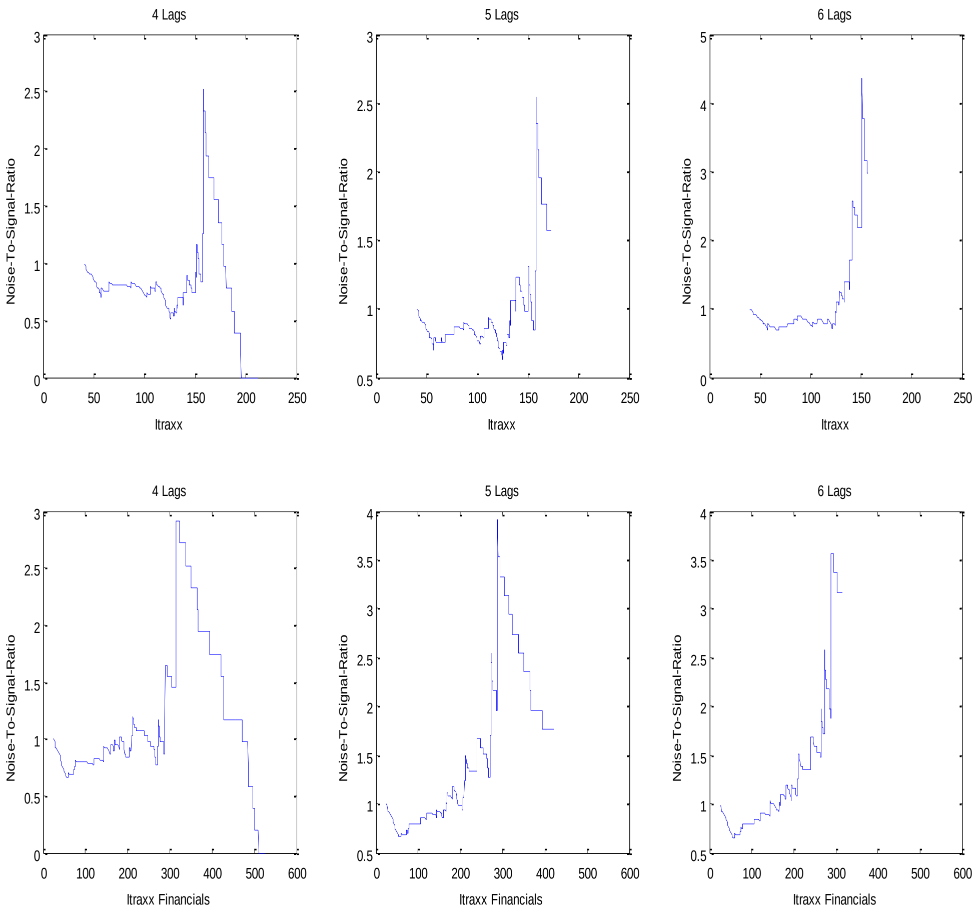
Source: Datastream, own computations by Matlab

Figure 22: NTS ratios and corresponding thresholds from 0 to 3 lags for EU CDS



Source: Datastream, own computations by Matlab

Figure 23: NTS ratios and corresponding thresholds from 4 to 6 lags for EU CDS



Source: Datastream, own computations by Matlab