BANK OF GREECE
EUROSYSTEM

Working Paper

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Dimitrios P. Louzis
Angelos T. Vouldis

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MARCH 2013

BANK OF GREECE
Economic Research Department – Special Studies Division
21, E. Venizelos Avenue
GR-102 50 Athens
Tel: +30210-320 3610
Fax: +30210-320 2432

www.bankofgreece.gr

Printed in Athens, Greece
at the Bank of Greece Printing Works.

ISSN 1109-6691

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Dimitrios P. Louzis
Bank of Greece

Angelos T. Vouldis
Bank of Greece

ABSTRACT

The paper develops a financial systemic stress index (FSSI) for Greece. We present a methodology for constructing and evaluating a systemic stress index which: i) adopts the suggestion of Hollo *et al.* (2012) [Hollo, Kremer, and Duca (2012) "CISS – A 'Composite Indicator of Systemic Stress' in the Financial System" ECB Working Paper 1426] to incorporate time-varying correlations between different market segments, and uses a multivariate GARCH approach which is able to capture abrupt changes in correlations; ii) utilizes both market and balance sheet data; and iii) evaluates the FSSI utilizing the results of a survey, conducted among financial experts, in order to construct a benchmark chronology of financial crises for Greece, which in turn is used to investigate whether changes in the FSSI are good indicators for financial crises. The results show that the FSSI is able to provide a precise periodization of crises.

Keywords: Financial crisis, systemic stress, stress index, multivariate GARCH.

JEL Classifications: G01, G10, G20, E44

Acknowledgements: We are grateful to Heather Gibson, Manfred Kremer, Stephen Hall, George Kaoudis, Vassilis Metaxas, Nick Tsaveas and Kostas Zavandis for their constructive comments. We would also like to thank participants at the ECB Macroprudential Research Network (MaRS) and 1st ECB MaRS conference for helpful discussions. The views expressed in this paper do not necessarily represent Bank of Greece.

Correspondence:
Angelos Vouldis
Bank of Greece
Financial Stability Department.
3 Amerikis Str.,
105 64, Athens, Greece,
e-mail: avouldis@bankofgreece.gr

1. Introduction

Empirical investigation on the nature and causes of financial crises rests on the development of tools that enable their precise dating and quantification. Dating of financial crises can be accomplished by binary indicators, usually defined on the basis of a simple criterion (for example, by events such as bank runs followed by state intervention). This, for example, is the approach adopted by Reinhart and Rogoff (2009) which is a natural choice given the breadth of their study. However, when one focuses on specific countries or crisis events, it would be desirable to have a measure of the 'stress' exercised on the financial system, finally culminating in a financial crisis, and not just a binary indicator defining the time boundaries of each crisis event.

The identification and prediction of the state of the financial system is also a crucial practical issue for policy purposes. In the first place, it is a necessary first step in developing early warning systems (EWS) with the aim of providing timely warnings for imminent systemic events. The development of stress indicators for particular segments of the market and their aggregation into a composite index of systemic stress provides insights into the propagation channels of specific events and the extent to which a financial crisis affected segments of the financial system.

This paper introduces a systemic stress indicator for the Greek financial system – the Financial Systemic Stress Index (FSSI). It builds upon the proposition of Hollo et al. (2012) to consider the systemic nature of stress by taking into account the time-varying cross-correlations between different stress components corresponding to different aspects of the financial system. Specifically, these authors apply insights from standard portfolio theory to the aggregation of specific subindices, each one reflecting financial stress in a specific market segment, by aggregating them in the same way as individual risks are aggregated in order to quantify portfolio risk i.e. by taking into account the cross-correlations between individual asset returns. The idea behind this approach is that systemic stress (for the definition of the systemic stress see Section 0) tends to be higher when the financial system is in a state of widespread instability, meaning that several elements of the financial system are simultaneously under stress. The time-varying cross-correlations used in the portfolio based approach try to capture this feature of systemic stress. It should be noted that we do not assign any causative role to increased correlations as regards crisis events. We simply consider it as a symptom of the systemic nature of an episode.

Here, we extend their approach by using a data-driven approach, namely multivariate GARCH, to model time-varying cross-correlations, which seems to be able to capture abrupt changes in the correlation structure and enables the index to identify systemic events precisely. Additionally, the set of variables used in the construction of the FSSI includes both market and balance sheet data which is still an uncommon feature for systemic stress indicators.[1]

Developing similar indices has been a concern for regulatory authorities all over the world and the financial crisis which started on 2007 has given a new impetus to such efforts. Table 1 provides a detailed review on the time period, aggregation methodologies, type of data, and validation methods that have been proposed in the extant financial stress index literature.

Previous attempts to develop stress indicators have emphasized the selection of variables which is driven primarily by the need to reflect stress conditions in all dimensions related to the functioning of the financial system (Hakkio and Keeton, 2009; Illing and Liu, 2006; Hanscel and Monnin, 2005). Most of the studies utilized market data (e.g. see Illing and Liu, 2006; Cardarelli et al., 2009; Hatzious et al., 2010) while Hanscel and Monnin (2005) and Hollo et al. (2012) utilized mixed market and balance sheet data and Morales and Estrada (2010) considered only balance sheet data. A methodological choice, which is also adopted here, is to construct composite indices for sets of variables and then aggregate them into a systemic stress indicator (Grinaldi, 2010; Hollo et al., 2012).

Aggregation schemes vary among authors; the usual choices can be broadly classified into variance-equal weight method i.e. taking the average of standardized variables (e.g. Bordo et al., 2001; Hanscel and Monnin, 2005; Garderelli et al, 2009), factor analysis using the principal

[1] Our index is able to track down crises that appear in at least one of the examined market segments. An episode impacting, for example, only a specific market infrastructure but remaining confined in this segment will not affect the FSSI.

components method (Illing and Liu, 2006; Hakkio and Keeton; 2009, Hatzius et al., 2009), logit models to construct a stress index that shows the probability of stress (Nelson and Perli, 2007; Grinaldi 2010) and, recently, portfolio theory based aggregation schemes that take into account the correlation structure of stress indicators in order to quantify the level of systemic stress (Hollo et al., 2012). Finally, Brave and Butters (2010) have proposed a state space representation of the level of financial stress.

In contrast to indices representing other economic concepts (such as 'economic activity'), an index of systemic stress has no natural observable counterpart in the real world[2] and, consequently, there is an issue of validating a constructed index of this kind. The approach to validation mostly followed in the extant literature has been to compare the derived index with known events of intensified financial stress (e.g. see Hakkio and Keeton, 2009; Hanscel and Monin, 2005; Cardarelli et al., 2009), with the exception of Illing and Liu (2006) who conducted an internal survey within the Bank of Canada to determine the most stressful events for the Canadian financial system and evaluated their index based on its ability to match the results of the survey. We also conducted a similar survey among experts on the Greek financial system in order to identify periods of financial crises and subsequently, using a probit model, tested whether escalation of the FSSI culminates in actual financial crises.

The remainder of the paper is structured as follows: Section 2 provides the conceptual framework on financial (systemic) stress. Section 3 presents the selection of variables classified into five distinct sets. Section 4 presents the methodology for constructing the FSSI while in Section 5 the empirical results are discussed. Section 6 concludes.

[Insert Table 1 about here]

2. Definitions and concepts

In selecting the variables used for constructing the FSSI, insights provided by economic theory with respect to what exactly constitutes a financially stressed situation and the phenomena

[2] For example, Hall and Zonzilos (2003) constructed an index of economic activity and used the growth rate of the real GDP to validate their results.

associated with it have to be considered. In the first place, a precise definition of financial stress is hard to pin down; however it is commonly thought that it is directly linked to a disruption in the normal functioning of financial markets. According to Illing and Liu (2006, p. 244) and (Grimaldi (2010, p. 8), it is 'the product of vulnerable markets and of shocks'.

Nonetheless, our aim here is to focus on systemic stress, which, according to Hollo et al. (2012), can be defined as the materialization of the systemic risk up until a given moment in time. Systemic risk, in turn, is the "risk of an extensive financial instability that causes the dysfunctioning of a financial system to the point where economic growth and welfare suffer materially" (ECB, 2009a p. 134). The common underlying feature of the main forms of systemic risk i.e. contagion risk, the risk of a macroeconomic shock and the unraveling of imbalances that have built over time, is that it induces simultaneous problems in most segments of the financial system, whilst at the same time increasing the interdependence among them. Moreover, the systemic nature of an event may be defined by the interaction between a number of factors and the existence of feedback mechanisms and second order effects which affect the stability of the overall financial architecture.

The majority of authors agree that the main underlying phenomenon of a stress situation is uncertainty and changing expectations. For example, Illing and Liu (2006) note that: "Financial Stress is defined as the force exerted on economic agents by uncertainty and changing expectations of loss in financial markets and institutions. Financial stress is a continuum […] where extreme values are called financial crises" (Illing and Liu 2006, p. 243). In a similar vein, Reinhart and Rogoff (2009) argue that the *lack of confidence* is the unifying underlying cause of financial crises in their various forms of appearance (as bank runs, government debt crises, exchange rate crashes etc). Uncertainty increases stress as it amplifies informational asymmetries in the financial markets (Mishkin 1992, p. 119). In a similar vein, Hakkio and Keeton (2009) associate the following phenomena with financial stress: i) increased uncertainty about the fundamental value of assets; ii) increased uncertainty about behaviour of other investors; iii) increased asymmetry of information; iv) decreased willingness to hold risky assets (flight to quality); and v) decreased willingness to hold illiquid assets (flight to liquidity).

Other authors have focused exclusively on financial crises. According to Mishkin (1992, pp. 117-8), a financial crisis is a disruption in the financial markets, during which, adverse selection and moral hazard phenomena are intensified and, as a consequence, financial intermediation malfanctions. In their quantitative and historical analysis of financial crises, Reinhart and Rogoff (2009) use a binary definition of financial crises. They suggest that the following variables can be used to date banking crises: i) the relative price of financial institutions relative to the market; ii) changes in bank deposits (reflecting bank runs and withdrawals), signifying the liability side of the crisis; iii) non-performing loans (reflecting increased bankruptcies in the nonfinancial sector or a collapse in real estate prices) implying asset side deterioration (Reinhart and Rogoff 2009, pp. 8-9).

Another important conceptual distinction is between *fragility* and *stress* and their relationship with *financial crises*. As Bell and Pain (2000) insightfully note, fragility may not be casually linked to a crisis: "We might view 'fragility' as relating to the structure of the financial system, and 'crisis' as *the results of the interaction between that fragility and some exogenous shocks*" (Bell and Pain 2000, p. 124 emphasis added). In other words, only a shock can turn a fragile situation into a crisis. In this line of thinking, it makes sense to link logically financial stress and crises, the latter being a severe version of the former.

Our approach is to view financial stress as a situation in which one or more segments of the market show the signs associated with financial stress, namely increasing uncertainty and asymmetry of information. In addition, due to the emphasis we wish to place on the systemic nature of events, we take into account the time-varying correlation between different segments of the market, the rationale being that a systemic event tends to feature, although this is not a necessary condition, increasing correlations. Finally, we include both forward-looking and state variables when constructing the index, since both uncertainty (related to expectations) and market malfunctioning (reflected in the current state of the financial system) are components of a systemic event.

The primary motivation behind studying financial stress is, of course, its impact on the real economy and the social costs that it usually entails. Reinhart and Rogoff (2009, p. 233 ff.) document profound declines in output, increasing unemployment and worsening of fiscal balances as a consequence of financial crises. Monnin and Jokipii (2010) also find a link between banking sector stability and real output growth which is driven primarily by stress events (see also Bernanke and James (1991) for an international comparison).

3. Selection of variables

In this section we present the variables selected for the measurement of stress in the financial system. The choice of the variables or raw stress indicators is of crucial importance for the construction of financial stress indices as they should represent key features of financial stress (Hakkio and Keeton, 2009). We rely on the recent literature for financial stress indices (e.g. see Hancshel and Monnin, 2005; Illing and Liu, 2006; Hakkio and Keeton, 2009 and Table 1) and we select sets of variables that reflect developments in the following dimensions: (i) fundamentals of the Greek economy; (ii) banking sector – market data; (iii) banking sector – balance-sheet data; (iv) equity markets; and (v) money markets.

The frequency of the constructed financial stress index is another issue of concern. High frequency stress indices depict in a more precise way the level of stress in a given time period. This may be a desirable result for policy makers but data availability poses limitations on the frequency of a stress index. Generally, stress indices that rely only on market data (e.g. see Illing and Liu, 2006; Hakkio and Keeton, 2009) are of daily or monthly frequencies while those that use both market and balance-sheet data (e.g. see Hancshel and Monnin, 2005) are of a lower – usually quarterly - frequency. We strike a balance between high (daily) and low (quarterly) frequencies and we use both market and balance-sheet data of monthly frequency.[3] Nevertheless, in order to exploit all the information available in high frequency data, we rely on daily observations for the estimation of certain raw stress indicators such as the realized volatilities and correlations (see next subsections for details). In the remainder of this section, we provide an analytical description of the variables used and their economic interpretation.

[3] Balance sheet data are published with a lag of two months.

3.1. Fundamentals of the Greek economy

It is assumed that the economic environment has an effect on financial stress as it may amplify or damp existing tensions in the financial sector. In some cases it may act as the primary cause for a financial crisis, for example in the case of a public debt crisis. The raw stress indicators utilized are:

- ***10 year Greek Government Bond/German Bund spread***: Following Grimaldi (2010), it is assumed that the sovereign spread with the German Bund (usually chosen as the benchmark as it is characterized by the lowest risk premium within the EU) expresses market *fundamentals*, namely liquidity and risk premiums with respect to sovereign creditworthiness as well as market uncertainty.

- ***Yield Realized volatility***: The volatility of the yield of the 10-year Greek bond reflects uncertainty regarding fundamentals of the Greek economy.[4] We follow the strand of literature represented by Andersen and Bollerslev (1998), Andersen et al., (2001a, 2001b, 2003) and Bandorlof-Nielsen and Shepard (2002) where it is proposed that high frequency data can be utilized in order to consistently estimate lower frequency unobserved volatility in the financial markets, the so called *realized volatility*. Given the absence of intraday data, we used the sum of squared daily differenced yields to proxy the monthly volatility of the 10-year Greek bond yield. Increased volatility of asset prices is related to increased uncertainty about fundamental value of assets as well as increased uncertainty about the behaviour of other investors (Hakkio and Keeton, 2009).

- ***Correlation between returns on Greek stocks and the German Bund***: The empirical literature has shown that the correlation between stock market and sovereign bond returns is negative during periods of financial stress while having a modest positive value over the long run. Specifically, Connolly et al. (2005), working with daily data, find that uncertainty measures have a negative relation with contemporaneous and future correlation between stock and bond returns. The time-varying nature of correlation is an expression of the flight-to-quality phenomenon

[4] It should be noted that volatility is just one indicator of stress and that high volatility does not necessarily arise in stressful periods. For example, as Grimaldi (2010) notes "with high financial spreads signifying something amiss, for example that no trade is taking place, the volatility might be very low but stress very high" (Grimaldi 2010, p. 5).

during periods of financial stress (Andersson et al. 2008; Hakkio and Keeton 2009, p. 16). Here, we use daily returns of the General Index of Athens Stock Exchange (ASE) and the German Bund to calculate their monthly *realized correlation* (see Andersen et al., 2001a, 2001b, 2003 and Bandorlof-Nielsen and Shepard, 2002):

$$RCOR_t^{ASE-Bund} = \frac{\sum_{m=1}^{M} r_{m,t}^{ASE} r_{m,t}^{Bund}}{\sqrt{\sum_{m=1}^{M}\left(r_{m,t}^{ASE}\right)^2}\sqrt{\sum_{m=1}^{M}\left(r_{m,t}^{Bund}\right)^2}} \qquad (1)$$

where M is the number of trading days within the month t. We choose the German Bund as a representative safe bond among EU countries.

3.2. Banking sector – market data

Market data on the banking sector reflect expectations regarding the prospects of the banking sector. Since the banking sector is a primary component of the financial system, a financial stress index should also include a measure that captures banking stress or crisis.

- ***Stock market prices (Banking Index)***: The Stock Index for the Banking Sector presumably reflects the market expectations regarding the prospects of the banking sector. Grimaldi (2010) suggest including this index on the grounds that an increase may be indicative of a potential bubble (*impending* stress) while a prolonged downward direction is a symptom of stress. We use the CMAX transformation for the Greek banking stock index to identify periods of sharp declines in the banking stock market (Patel and Sarkar, 1998, Illing and Liu, 2006). The CMAX is defined as:

$$CMAX_t = \frac{P_t}{\max[P \in (P_{t-j} \mid j = 0,...,12)]}$$

where P_t is the price of banking stock index at month t.

- ***Idiosyncratic risk of bank stock prices***: The idiosyncratic risk of the banking sector, i.e. the risk that is attributed to bank specific events, is quantified by utilizing the residuals' variance of the market model. In order to account for the inherent heteroscedasticity of the residuals' variance, a GARCH(1,1) model is fitted to the market model

$$r_t^{Banks} = \alpha + \beta r_t^{ASE} + u_t \tag{2}$$

$$u_t = \varepsilon_t \sqrt{h_t}\ ,\ \varepsilon_t \sim \mathrm{N}(0,1) \tag{3}$$

$$h_t = \omega + a u_{t-1}^2 + b h_{t-1} \tag{4}$$

Thus the idiosyncratic risk for the banking sector at time t is defined as h_t.[5]

- ***Greek Banks CDS spreads:*** We use the average 5-year Credit Default Swap (CDS) spread of the four biggest Greek banks as a proxy of their credit risk (see also Brave and Butters, 2010).[6] The CDS spread can be defined the annual cost for protection against a default of a company or a sovereign (Hull et al., 2004) and thus it is regarded as an appropriate measure for a market-based price for credit risk. The alternative is to use banks' bonds spreads to quantify the credit risk. However, according to Hull et al. (2004) the data offered by the CDS markets have several advantages over the bonds spreads. First, the CDS spread corresponds to a price that the dealer is obliged to trade, at least, a minimum amount, whereas the data provided to researchers from the bond markets are often "indications from dealers". Second, the CDS spreads can be directly used as credit risk measures, while bond yields have to be converted to credit spreads by utilizing a proxy for the risk free rate.

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[5] We would like to thank an anonymous referee for suggesting the use of the market model for the estimation of the idiosyncratic risk.

[6] The "biggest" refers to the asset size. The four biggest Greek banks account for more than 65% of the Greek banking system. All CDS data were obtained from Markit™.

For the periods prior to 2001 M02 there is lack of data for the CDS and therefore we adjust the spread using the following method: we estimate the following regression

$$\Delta CDS\_Spread_t = c_0 + c_1 \Delta SovereignSpread_t + e_t$$

for the available data and we use the estimated equation to extrapolate the values of the CDS spreads for the period before 2001 M02.

3.3 Banking sector – balance sheet data

Stress in the banking sector, either in the form of a liability side crisis or of asset side deterioration will be reflected on the balance sheet of the banks (Mishkin 1992). Inclusion of both market data and balance sheet data of the banking sector has been shown to improve substantially an index of financial conditions by allowing several symptoms of stress to be identified (Hanschel and Monnin, 2005). Thus, we include balance sheet data as these may reflect sudden changes in the operation of banks which may be related to stressful events. For example, bank runs or a retardation of credit expansion, or both, signify a banking crisis. Specifically, we include the following variables:

- ***Deposit Gap*****:** The deposit gap is defined as the cyclical component of total deposits and it is estimated using the Hodrick-Prescott filter with $\lambda = 14400$ as suggested by Hodrick and Prescott (1997). Hanschel and Monnin noted that the advantage of using gaps lies in that gaps "underline the cumulative process of the imbalances: a large trend deviation can develop either in one period with string above (or below) trend growth or through a sequence of years with above (or below) trend growth" (Hanschel and Monnin 2005, pp. 431-32). In this sense, gaps may be a more suitable measure of imbalances than simple growth rates.[7] A negative deposit gap i.e. deposits below trend is a sign of stress as banks will be hard pressed for liquidity and they may have to liquidate assets at fire sale prices and destroy their balance sheet (Reinhart and Rogoff 2009, p. 144 ff.). Problems on the liability side have been traditionally been identified with banking crises (see e.g. Calomiris and Gorton 1991).

[7] Calomiris and Gorton (1991, p. 112 ff.) define a banking panic by a *sudden* withdrawal of deposits and explicitly rule out protracted withdrawals. However, when measuring financial stress it seems more accurate to take into consideration the contribution of less dramatic events and in this respect the use of gaps seems to be well justified.

- ***Loan gap:*** The loan gap is defined in a manner analogous to the deposit gap. A negative loan gap can be interpreted as either a sign of unwillingness, on the part of the banks, to lend (due, for example, to problems on the liability side) or a decreased demand for credit.

- ***Bank Profitability (Interest margin)*****:** As a measure of profitability we use the interest margin. A high interest margin constitutes a measure of bank's ability to obtain profit from their lending activities.

3.4. Equity markets

Stock market crashes constitute one of the primary forms of financial crises (Kindleberger and Aliber 2005, Mishkin 1992, Reinhart and Rogoff 2009). Thus, the inclusion of equity market data is needed in order to capture facets of stress related to the stock market.

- ***Stock market prices:*** An abrupt and prolonged decrease in equity prices is a symptom of market stress. As in the case of the banking index, we use again the CMAX transformation of the General Index of Athens Stock Exchange (ASE) to identify periods of sharp declines in Greek stock market.

- ***Realized volatility****:* We estimated the monthly realized volatility of the General Index of Athens Stock Exchange (ASE). Increased stock market volatility reflects increased uncertainty about fundamentals and the behaviour of other investors (Hakkio and Keeton, 2009).

- ***Earnings per share (EPS)****:* Earnings per share are utilized as a proxy variable for the profitability of the whole market. We expect that during periods of financial crisis profits are squeezed and thus a decline in the earnings per share can be interpreted as a sign of stress (Grimaldi, 2010).

3.5. Money markets

The money market is a primary source of liquidity for the financial sector and, consequently, the inclusion of money market variables enhances the ability of the index to identify financial stress. Holthausen and Pill (2010) note that until the outbreak of the current financial crisis, money markets had been a neglected subject for academic research as they seemed to function rather smoothly. However, tensions in the money market were marked during the latest financial crisis and as Taylor and Williams (2009) remarked, a “black swan” was observed in the money market. See further the *ECB Financial Integration Report 2011* for a chronology of the different phases through which the money market has gone, following interbank market tensions, since August 2007. In order to measure stress in money markets we used the following variable:

- ***3 month Euribor/3 month German T-bill spread:*** The Euribor is considered to be a benchmark for the interbank short-term lending rate. The spread between the 3 month Euribor and the 3 month T-bill represents counterparty risk and liquidity risk. Additionally, during periods of financial stress, asymmetry of information is aggravated and thus the problem of adverse selection intensifies. Thus the Euribor/T-bill spread represents three types of risk: flight to quality, flight to liquidity and asymmetry of information (Hakkio and Keeton 2009).

We take into account the fact that for the periods prior to joining the Eurozone in 2001 and after the outbreak of Greek debt crisis, the Euribor spread cannot be considered as a suitable proxy for the cost of funding of the Greek banks. Following Reinhart and Rogoff (2010), we assume that the Greek sovereign spread poses a floor on the market evaluation of the credibility of national banks. Therefore, for these two periods, in line with the approach used above, we construct a proxy for the cost of funding as follows: we

regress the Euribor spread on the sovereign spread

$$EuriborSpread_t = d_0 + d_1 SovereignSpread_t + e_t$$

for the period January 2001 to December 2009 and we use the estimated equation to extrapolate the values of the cost of funding proxy.

4. The Financial Systemic Stress Index (FSSI) – methodology

4.1 Construction of sub-indices

The first step towards the computation of the Financial Systemic Stress Index (FSSI) is the construction of five sub-indices that correspond to each of the five sets of variables presented in section 3. We adopt the principal components methodology to generate a factor that embodies most of the common variation for each set of variables. The underlying assumption is that variables belonging to the same set possess common information content, pertaining to the particular market segment. Therefore, we define the sub-indices as the first principal component which explains most of the variation within each set of raw stress indicators. In this way we ignore some of the minor variations since these might be viewed as 'noise' (Alexander, 2008).[8] This is also the approach followed in the construction of the Chicago Fed National Activity Index (CFNAI) and proposed by Stock and Watson (1989, 1999). The five stress sub-indices are then scaled from 0 to 100 by using the standardized logistic transformation (ECB, 2009b):

$$y_{it} = 100/\left[1+\exp\left(\tilde{y}_{it}\right)\right] \qquad (4)$$

where y_{it} are the transformed sub-indices for $i=1,\ldots,5$ which take values from 0 to 100 and $\tilde{y}_{it}$ are standardized sub-indices. This scaling is useful in order to enable their aggregation into a single financial stress index.

4.2. A portfolio based approach to systemic risk

In order to aggregate the five stress sub-indices into a systemic risk indicator i.e. the FSSI, we follow the methodology suggested in Hollo et al. (2012), where insights from the portfolio theory are used. In portfolio theory, when we aggregate highly correlated risky assets, total portfolio risk increases as all assets tend to move together following the markets' movements. By contrast, when the correlation between assets is low, non-systematic or diversifiable risk is reduced reducing the total portfolio's riskiness. In this setting, the rationale underlying Hollo's et al. (2012) approach is that the correlation between key stress indicators i.e. the sub-indices is an indicative measure of the systemic risk in the financial segment. In a way, analogous to portfolio theory, a high degree of correlation depicts a widespread stress situation in several segments of the market which, in turn, may lead to increased systemic risk.

[8] For an exact method of determining how many components to use, see Plerou *et al.* (2002).

Specifically, assuming that $\boldsymbol{y}_t$ is the 5x1 vector of the five (5) stress indicators, y_{it}, and $\boldsymbol{w}$ is the $5x1$ vector of weights attached to each of the 5 stress indicators, then $\boldsymbol{s}_t = \boldsymbol{w} \otimes \boldsymbol{y}_t$ is the vector of the weighted stress variables used for the construction of the index.[9] The Financial Systemic Stress Index (FSSI) is defined as:

$$FSSI_t = \sqrt{\boldsymbol{s}_t' \boldsymbol{C}_t \boldsymbol{s}_t} \tag{5}$$

where $\boldsymbol{C}_t$ is the 5x5 time-varying correlation matrix of the sub-indices, y_{it}, which is given by (for a detailed description of the estimation of time-varying correlations see section 4.3 below):

$$\boldsymbol{C}_t = \begin{bmatrix} 1 & \rho_{12,t} & \rho_{13,t} & \rho_{14,t} & \rho_{15,t} \\ \rho_{21,t} & 1 & \rho_{23,t} & \rho_{24,t} & \rho_{25,t} \\ \rho_{31,t} & \rho_{32,t} & 1 & \rho_{34,t} & \rho_{35,t} \\ \rho_{41,t} & \rho_{42,t} & \rho_{43,t} & 1 & \rho_{45,t} \\ \rho_{51,t} & \rho_{52,t} & \rho_{53,t} & \rho_{54,t} & 1 \end{bmatrix} \tag{6}$$

From (5) it is obvious that, as the cross-correlations converge towards 1, the FSSI converge to a weighted average of $\boldsymbol{y}_t$. This implies that the weighted average poses an upper limit to the FSSI.

We calibrated the weights in order to maximize the ability of the index to correctly identify crisis periods (using Eq. 10, see Section 5.3). The resulting weights were: Greek economy fundamentals: 24%, banking sector – market data: 25%, banking sector – balance sheet data: 13%, equity markets: 12%, and money market: 25%.

4.3. Estimation of the time-varying correlations

In order to calculate the FSSI in Eq. (5) we need estimates for the time-varying correlation matrix, $\boldsymbol{C}_t$, in Eq. (6). We implement a Multivariate GARCH (MGARCH) approach for the

[9] $\otimes$ is the element-by-element multiplication.

estimation of $\boldsymbol{C}_t$, which uses the information provided by the data in order to estimate the parameters of the model.

A commonly used MGARCH model is the BEKK model proposed by Engle and Kroner (1995). In its general form a BEKK(p,q,K) model is defined as:

$$\boldsymbol{\Sigma_t} = \boldsymbol{CC}' + \sum_{i=1}^{p}\sum_{k=1}^{K} \boldsymbol{A}'_{ki}\bar{\boldsymbol{s}}_{t-i}\bar{\boldsymbol{s}}'_{t-i}\boldsymbol{A}_{ki} + \sum_{j=1}^{q}\sum_{k=1}^{K} \boldsymbol{B}'_{kj}\boldsymbol{\Sigma}_{t-j}\boldsymbol{B}_{kj} \tag{8}$$

where $\boldsymbol{C}$ is nxn lower triangular matrix, $\boldsymbol{A}_{ki}$, $\boldsymbol{B}_{kj}$ are nxn parameter matrices, k specifies the generality of the process while the p and q are the lags used. The parameters of the BEKK model are estimated by maximizing the Gaussian likelihood function of the multivariate process. The most appealing property of the BEKK model is that ensures the positive definiteness of the conditional covariance matrices, $\boldsymbol{\Sigma_t}$, by utilizing as a constant term the product of two lower triangular matrices. However, the interpretation of the estimated parameters is somewhat tricky as they do not correspond to the impact of lagged values of $\bar{\boldsymbol{s}}_t\bar{\boldsymbol{s}}'_t$ and $\boldsymbol{\Sigma}_t$ as in the EWMA or the VEC model of Bollerslev et al. (1988). The first order BEKK model i.e. p=q=k=1 for the bivariate case i.e. n=2 can be written analytically as:

$$\begin{aligned}\begin{bmatrix} \sigma^2_{1,t} & \sigma_{12,t} \\ \sigma_{12,t} & \sigma^2_{2,t} \end{bmatrix} = \boldsymbol{C}'\boldsymbol{C} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \bar{s}^2_{1,t-1} & \bar{s}_{1,t-1}\bar{s}_{2,t-1} \\ \bar{s}_{2,t-1}\bar{s}_{1,t-1} & \bar{s}^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \\ + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} \sigma^2_{1,t-1} & \sigma_{12,t-1} \\ \sigma_{12,t-1} & \sigma^2_{2,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}\end{aligned} \tag{9}$$

Even if the BEKK model is relatively parsimonious compared to other MGARCH specifications (e.g. see the VEC model of Bollerslev et al., 1988), the number of parameters that have to be estimated is still high even in bivariate case, see (9). In order to cope with the dimensionality problem we impose a diagonal BEKK representation where the $\boldsymbol{A}_{ki}$ and $\boldsymbol{B}_{kj}$ are restricted to be diagonal matrices. Although less general, the diagonal BEKK model is one of the most common approaches in empirical applications, as it is parsimonious and produces positive definite covariances matrices (see also Caporin and McAleer, 2010).

5. Empirical analysis

5.1. The Financial Systemic Stress Index (FSSI)

The five sub-indices used for the construction of the FSSI are presented in Figure 1.[10] The shaded areas in the figure correspond to the crisis periods as identified by the survey results (see section 5.2 for details). From Figure 1, we can see the contribution of each of the sub-indices to the increase in the overall stress in the financial system. The most striking feature of the graph is that the money market sub-index is the prevailing factor in almost all six stress episodes in our sample. Still, during the Greek sovereign debt crisis period the sub-index of economic fundamentals is the main contributing factor to financial stress, as expected, with other sub-indicators making a close call. It is also worth noting that the sub-index for banks' balance sheets does not contribute significantly to stress during the peak of the global financial crisis at the end of 2008. This characteristic can be attributed to the fact that Greek banks were not exposed to "toxic assets" and thus they did not suffer substantial losses during this period. Moreover, the Greek banking sector was shielded from the global financial turmoil as it was highly profitable and well capitalized.

[Insert Figure 1 about here]

As pointed out in section 4, the main feature of a systemic stress indicator is that it utilizes the time-varying cross correlations between the sub-indices in order to capture and quantify

[10] All market data series were obtained from Datastream, while balance sheet data were obtained from the Bank of Greece.

systemic risk. Thus, Figure 2 depict the correlations between the five sub-indices estimated with the diagonal BEKK model. Once again the shaded areas show the periods of financial distress.

[Insert Figure 2 about here]

An interesting point is the negative correlations between the bank balance-sheet sub-index and the market-based sub-indices during the peak of the global financial crisis at the end of 2008. This can be attributed mainly to the aforementioned shielding of the Greek banking system from the losses caused by “toxic assets”. Thus, as most of the market variables deteriorated, bank balance-sheet data remained unaffected until the mid of 2009.

[Insert Figure 3 about here]

In Figure 3 we present the Financial Systemic Stress Indicator (FSSI) (henceforth the FSSI is the index calculated using the BEKK correlation model). We have also included in our analysis a weighted average of the sub-indices, which is the upper limit of both correlation based indices considered here, as it implies that the sub-indices are perfectly correlated. Therefore, we expect that during crisis periods the correlation-based indices would converge to the weighted average index as correlations converge to unity.

The FSSI presented in Figure 3 depicts the relative peaks during the crisis periods (shaded areas). Overall, the FSSI seems able to accurately capture the crisis periods, while at the same time does not exaggerate the level of stress during calm periods. Nonetheless, a more formal approach to the validation of the FSSI is required; sections 5.2 and 5.3 describe the FSSI evaluation process and results.

5.2. Survey results

An issue of concern to all attempts to construct indices of the financial system is how to evaluate the derived index. In the first place, in contrast to an index of economic activity which can be judged against real GDP or industrial production, there is no natural observable variable against which to judge an index of financial stress. In addition, business cycle chronologies may be available or easy to construct while this is not the case for crisis events in the financial sector.

Our strategy was to construct a chronology of financial crises (i.e. periods of intense stress) in the Greek financial sector, for the period 1998-2010 based on evaluations of financial experts regarding events that are commonly regarded to have influenced the Greek financial system. We choose a number of potentially stressful events, based on judgment and observation of the time series used to construct the index, and asked the participants to evaluate the level of stress that these events caused to the Greek financial system in a scale of 0 to 4 (see Appendix A for the survey). Specifically, we selected a total of 15 events, 12 of them being international in nature and 3 of domestic origin. The list of events along with the average value and standard deviation of the expert's answers are presented in Table 2. This approach has also been used by Illing and Liu (2006) in order to evaluate their financial stress index for Canada.

The answers we received from the survey were utilized in order to construct a binary index of crises for the Greek financial sector. Financial crises were identified with events in which the average value of the answers exceeded the mean of the stress scale, i.e. two (2). For the limiting cases of events seven (7) and eight (8) in which their average value, i.e. 1.85 and 1.98 respectively, was at the threshold, we took decisions regarding their classification as financial crises by looking at the raw data and exercising judgment. In both cases, we finally rejected these events as periods of financial crises. This derived chronology of crises was used as a benchmark against which the FSSI was tested. In Appenxi B we describe in detail the construction of the binary index.

[Insert Table 2 about here**]**

5.3. Evaluation of the FSSI

The binary index derived from the survey was used in order to judge the corresponding crises chronology as derived from the FSSI, and also to compare the FSSI chronology to the alternative stress indices.

Specifically, given the crises chronology constructed from the survey, the question was posed: do current and past changes in the FSSI are good indicators for financial crises? We would expect that current and past increases in the FSSI, implying intensification of stress, would lead to a financial crisis with increasing probability and thus we estimated the following probit model:

$$\Pr\left(Crisis_t\right) = \Phi\left(c + \sum_{k=0}^{1} b_k \Delta x_{t-k} + e_t\right) \tag{10}$$

where $Crisis_t$ is the binary index derived by the survey, and Φ is normal cumulative distribution function (cdf) and x_t is the FSSI i.e. $x_t = FSSI_t$.

We use the specification of Eq. 10 in order to gauge the performance of the FSSI. Specifically, we also estimated Eq. 10 using the weighted average stress index i.e.where $x_t = SI_t^{WA}$ is the weighted average stress index. After estimating these two regressions we evaluate the indices on the basis of their ability to match the constructed binary index.

The probit regression results for all stress indices are presented in Table 3. The FSSI provides a better fitting, measured by the Mc-Fadden pseudo R^2, compared to the the weighted average stress index which does not take into account time-changing correlations. Overall, the FSSI leads to estimated probabilities of crisis which conform closely to the constructed timing of crises (see Figs. 5,6).

[Insert Table 3 about here]

[Insert Figure 4 about here]

[Insert Figure 5 about here]

6. Conclusions

We have proposed a financial systemic stress index for Greece. We extended the portfolio-theory based approach, suggested by Hollo et al. (2010), by modeling the time-varying cross-correlations between composite stress indicators using a multivariate GARCH model. The variables used for the construction of the composite stress indicators included both market and balance sheet data thus enhancing the set of stress symptoms identified.

Validation of the FSSI was based on a survey conducted among financial experts, which led to the construction of a chronology of crises for the Greek financial system. It was found that the FSSI can timely identify the crisis periods as well as the level of systemic stress in the Greek financial system. The ability of the FSSI to successfully diagnose stress levels rests crucially on the adopted diagonal BEKK specification, which is able to capture abrupt changes in conditional correlations.

REFERENCES

Alexander, C. (2008). *Market risk analysis Vol II: Practical financial econometrics*. John Wiley & Sons, Ltd.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review*, *39*, 885–905.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Ebens, H. (2001a). The distribution of realized stock returns volatility. *Journal of Financial Economics*, *6*, 43-76.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2001b). The distribution of realized exchange rate volatility. *Journal of the American Statistical Association*, *96*, 42-55.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modelling and forecasting realized volatility. *Econometrica*, *71*, 579– 625.

Andersson, M., Krylova, E. & Vahamaa, S. (2008). Why Does the Correlation between Stock and Bond Returns Vary Over Time. *Applied Financial Economics*, *18*(2), 139-151.

Barndorff-Nielsen, O. E., & Shephard, N. (2002). Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of the Royal Statistical Society. B*, *64*, 253-280.

Bell, J., & Pain, D. (2000). Leading indicator model of banking crisis – a critical review. Bank of England Financial Stability Review, 113-129.

Bernanke, B. & James, H. (1991). The Gold Standard, Deflation and Financial Crisis in the Great Depression: An International Comparison. in Hubard R. G. (ed.), *Financial Markets and Financial Crises*, Chicago and London: University of Chicago Press.

Bollerslev, T., Engle, R. F., & Wooldridge, J. M. (1988). A capital asset pricing model with time varying covariances. *Journal of Political Economy*, *96*, 116–131.

Bordo, M., Dueker, M., & Wheelock, D. (2001). Aggregate Price shocks and financial stability: A historical analysis. Federal Reserve Bank of st. Louis Working Paper 2000-005B.

Brave, S., & Butters, R. A. (2010). Gathering insights on the forest from the trees: A new metric for financial conditions. Federal Reserve Bank of Chicago Working Paper, WP 2010-07.

Calomiris, C. W., & Gorton, G. (1991). The Origins of Banking Panics: Models, Facts, and Bank Regulation. In Hubbard, G. (ed.), *Financial Markets and Financial Crises*, Chicago: University of Chicago Press, 109-173

Cardarelli, R., Elekdag, S., & Lall, S. (2009). Financial stress, downturns and recoveries. IMF Working Paper, WP/09/100.

Caporin, M., & McAleer, M. (2011). Do we really need both BEKK and DCC? A tale of two multivariate GARCH models. *Journal of Economic Surveys.* doi: 10.1111/j.1467-6419.2011.00683.x

Connolly, R., Stivers, C., & Sun, L. (2005). Stock market uncertainty and stock-bond relation. *Journal of Financial and Quantitative Analysis*, *40*(1), 161-194.

Duca, M. L., & Peltonen, T. (2011). Macro-financial vulnerabilities and future financial stress: Assessing systemic risks and predicting systemic events. ECB Working Paper 1311.

ECB, 2009a. The concept of systemic risk. ECB Financial Stability Review, December 2009.

ECB, 2009b. Global Index for Financial Turbulence. ECB Financial Stability Review, December 2009.

ECB, 2011. Financial Integration Report.

Engle, R. F., & Bollerslev, T. (1986). Modelling the persistence of conditional variances. Econometric Reviews, 5, 1–50.

Engle, R., & Kroner, F. K. (1995). Multivariate simultaneous generalized ARCH. *Econometric Theory*, *11*, 122–150.

Grimaldi, M. B. (2010). Detecting and Interpreting Financial Stress in the Euro Area. *ECB Working Paper*, No 1024.

Hall, S. G., & Zonzilos, N. G. (2003). An Indicator Measuring Underlying Economic Activity in Greece", Bank of Greece Working Paper, 4-2003.

Hatzious, J., Hooper, P., Mishkin, F., Schoenholtz, K. L., & Watson, M.W. (2010). Financial Conditions Indexes: A fresh look after the financial crisis. *NBER Working Paper Series*, No. w16150.

Hakkio, C. S., & Keeton, W. R. (2009). Financial Stress: What Is It, How Can It Be Measured, and Why Does It Matter? *Federal Reserve Bank of Kansas City Economic Review*. Second Quarter, 5-50.

Hanschel, E., & Monnin, P. (2005). Measuring and forecasting stress in the banking sector: Evidence from Switzerland. BIS Working Paper No 22.

Hodrick, R., & Prescott, E. C. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking*, 29(1), 1-16.

Hollo, D., Kremer, M., & Duca, M. (2012). CISS – A 'Composite Indicator of Systemic Stress' in the Financial System. ECB Working Paper 1426.

Holthausen, C., & Pill, H. (2010). The Forgotten Markets: How Understanding Money Markets Helps Us To Understand the Financial Crisis. *ECB Research Bulletin*, *9*, 2-5.

Hull, J., Predescu, M., & White, A. (2004). The relationship between credit default swap rates, bond yields, and credit rating announcements. *Journal of Banking and Finance*, 2, 2789-2811.

Illing, M., & Liu, Y. (2006). Measuring financial stress in a developed country: An application to Canada. *Journal of Financial Stability*, 2, 243-265.

Kindleberger, C. P., & Aliber, R. Z. (2005). Manias, Panics and Crashes: A History of Financial Crises. John Wiley & Sons.

McMillan, D. G., & Kambouridis, D. (2009). Are RiskMetrics good enough? Evidence from 31 stock markets. *International Review of Financial Analysis*, 18, 117-124.

Mishkin, F. S. (1991). Asymmetric Information and Financial Crises: A Historical Perspective. In Hubbard, R. G., (ed.) *Financial Markets and Financial Crises* Chicago: University of Chicago Press, 69-108.

Mishkin, F. S. (1992). Anatomy of a Financial Crisis. *Journal of Evolutionary Economics*, *2*(2), 115-130.

Morales, M. A., & Estrada, D. (2010). A financial stability index for Columbia. *Annals of Finance*, *6*, 555-581.

Monnin, P., & Jokipii, T. (2010). The Impact of Banking Sector Stability on the Real Economy. Swiss National Bank Working Paper, 2010-5.

Nelson, W.R., & Perli, R. (2007). Selected indicators of financial stability. *Irving Fisher Committee's Bulletin on Central Bank Statistics*, *23*, 92-105.

Plerou, V., Gopikrishnan, P., Rosenow, B., Amaral, N., Guhr, T., & Stanley, E. (2002). Random matrix approach to cross correlations in financial data. *Physical Review, E 65*, 1–18.

Reinhart, C. M. & Rogoff, K. S. (2009). *This Time is Different*. Oxford: Princeton University Press.

Reinhart, C. M., & Rogoff K. S. (2010). From Financial Crash to Debt Crisis. *NBER Working Paper*, 15795.

Stock, J. H., & Watson, M. W. (1989). New indexes of coincident and leading economic indicators. In: *NBER Macroeconomic Annual*, 351–409.

Stock, J. H., & Watson, M. W. (1999). Forecasting inflation. *Journal of Monetary Economics*, *44*, 293–335.

Taylor, J., & J. Williams (2009). A Black Swan in the money market. *American Economic Journal: Macroeconomics*, *1*(1), 58-83.

Patel, S., & Sarkar, A. (1998). Crises in developed and emerging stock markets. *Financial Analyst Journal*, *November/December*, 50-61.

Appendix A: Survey

We are developing a financial stress index (as defined below) for the Greek financial system. We would be grateful if you could provide us with your view regarding the impact of certain historical events on financial stress. The aim of this survey is to compare the level of financial stress, as measured by the constructed financial stress index, with your view of historical events.

Financial stress can be defined as a disruption (or an expectation of disruption) of the normal functioning of financial markets and/or financial institutions. Certain key phenomena that can be associated with episodes of financial stress are:

- Increased uncertainty about fundamental value of assets
- Increased uncertainty about the behaviour of other investors
- Risk aversion (flight-to-quality)
- Unwillingness to hold illiquid assets (flight-to-liquidity)
- Increased asymmetry of information

Although the relative severity of the abovementioned phenomena may differ form one episode to another, each of the stress episodes includes at least one of these phenomena.

Based on the above, we would like you to rank the following events in a scale from 0(not stressful) to 4(extremely stressful) or DK (=don't know) in terms of how stressful they were for the Greek financial system.

---

1) August/September 1998: Russian crisis
2) October 1999: Crash of the Athens Stock Exchange
3) 2000: Burst of dot com bubble
4) 2001: Terrorist attack of 9/11
5) 2001: Argentinian financial crisis
6) 2003: War in Iraq

7) May 2006: Worldwide uncertainty regarding interest rate increases from Fed and ECB
8) 2007: 1st phase of the Financial Turmoil (Liquidity Squeeze)
9) August/September 2007: Liquidity stress and bank run of the Northern Rock
10) March 2008: Bear Stearns Bailout
11) First months of 2008: Banking crisis in Ireland/Iceland
12) September/December 2008: Collapse of Lehman Brothers – Bail-out of AIG, Fannie Mae and Freddie Mac
13) October 2009: Announcement of statistical figures for the Greek budget deficit – Beginning of the Greek sovereign debt crisis
14) November 2009: Dubai default
15) April/May 2010: Greece applies for the Financial Support Mechanism and signs the Memorandum

Please feel free to add comments in the space provided.

Appendix B: Constructing a binary index of crises

In this appendix, we describe the construction of the binary index of crises. Given the results of the survey and the selection of crisis episodes, we decided on the definition of the exact timing of the crises based on informed judgment, considering the time series.

1) 1998m8 – 1998m10 (Russian crisis)

The impact of the Russian crisis was strong in the pricing of sovereign risk, stock market index and banks' balance sheet items. Specifically, as it is shown in Fig. B.1, the sovereign spread escalated to almost 4.5% from 1998m8 to 1998m9 and only on 1998m10 did it revert to a descending trend. A trough during the 3 months 1998m8-1998m10 is also evident for the banking index of the Athens stock exchange. In contrast, from 1998m11 a steep rise is observed (see Fig. B.2). Finally, the deposit gap is highly negative during the period 1998m8-1998m10. Given the timing observed in these time series, we decided to define the crisis as lasting for 3 months, starting in 1998m8.

Figure B.6: Greek government bond/German Bund spread

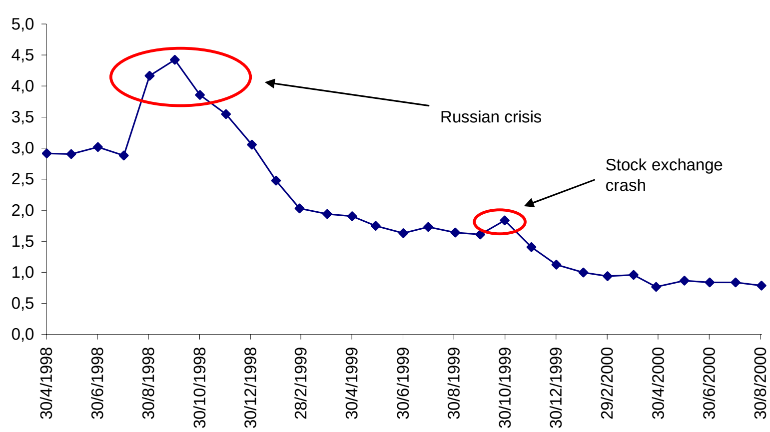


Figure B.7: Stock exchange – banking index

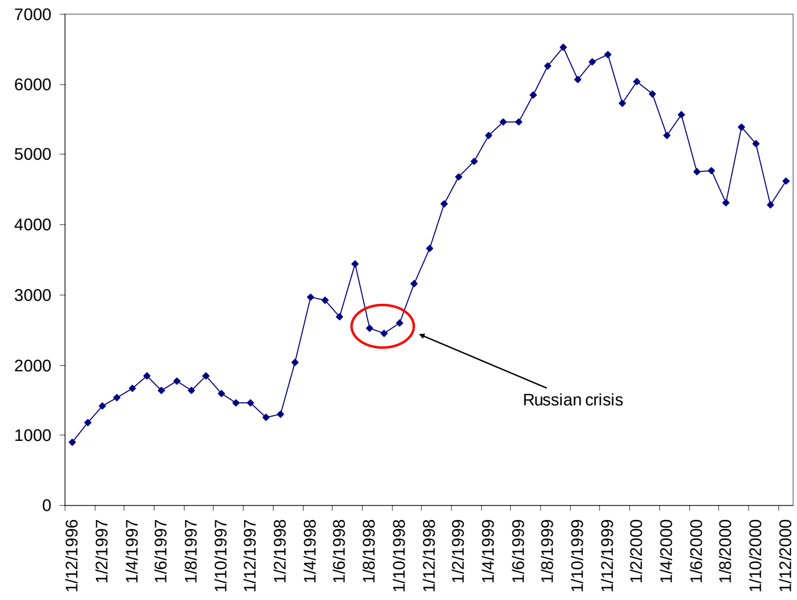
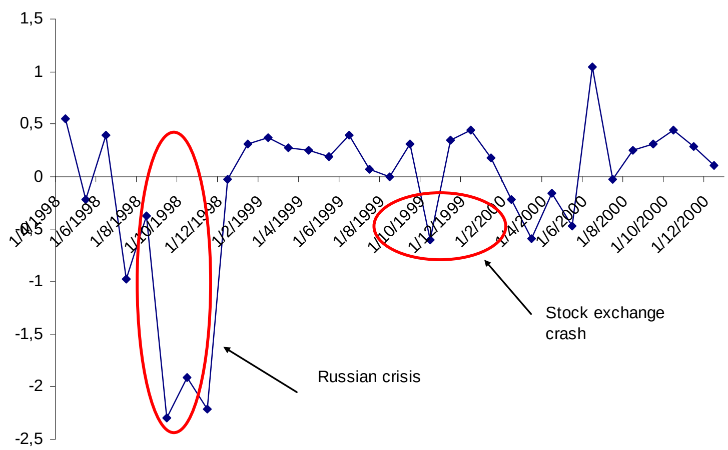


Figure B.8: Deposit gap (standardized)



2) 1999m10 (Crash of the Athens Stock Exchange)

After a long period of continuous upward trend, the Athens Stock Exchange index fell significantly in October 1999; the index fell to 5442 in October 1999 from 5668 in September. We chose to define the binary crisis index equal to 1 for just this month. Our decision took into account the time series of the stock index (Fig.B.4), the deposit gap (Fig. B.3), the sovereign spread (Fig. B.1), and the average CDS for Greek banks. Despite the consequent prolonged downward trend of the stock index we did not deem it meaningful to extend the crisis defined period further since the other indicators, except from the stock index, did not show signs of stress.

Figure B.9: Stock index

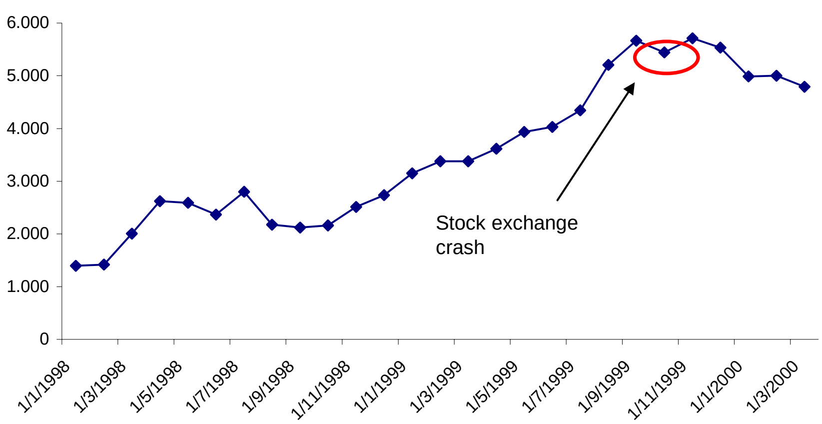
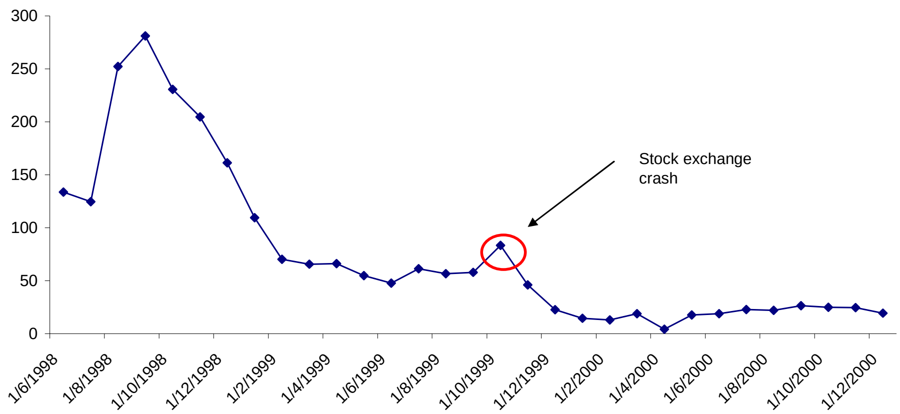


Figure B.10: Average CDS of Greek banks

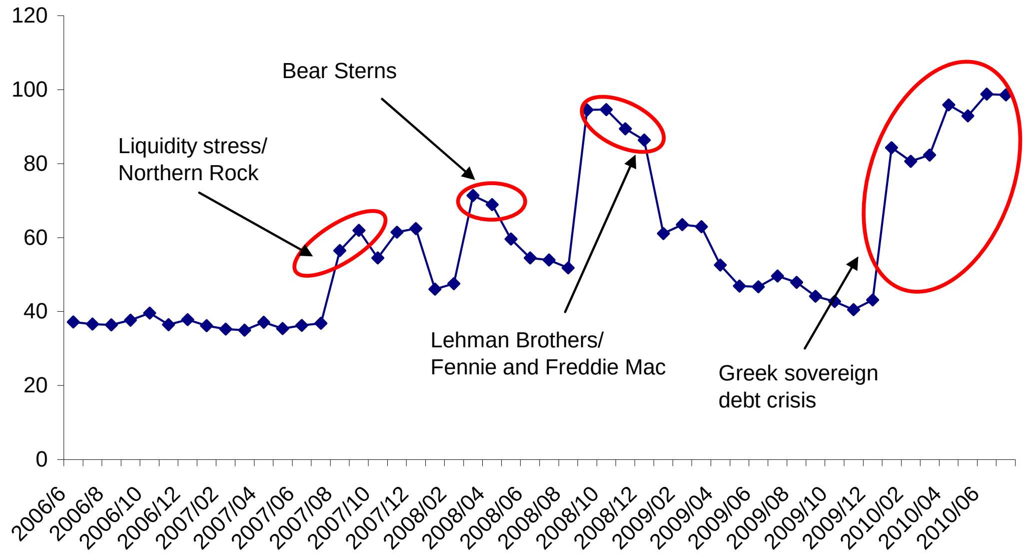


3) 2007m8 - 2007m9 (Liquidity stress and bank run of the Northern Rock)

The timing of the liquidity-stress/Northern-Rock-bank-run event was defined by the dates 2007m8 and 2007m9. From Fig. B.6, it is clear that euribor spread increased sharply from 2007m8. It remained at high levels until 2007m12. Given, however, that other basic indicators (e.g. banks CDS and sovereign spread) did not show any noticeable sign of stress during this period, we decided to define the crisis as lasting until 2007m9.

This definition is consistent with the actual course of events. In fact, during August 2007, concerns regarding the valuation of mortgage-backed securities had intensified. The ECB intervened by offering low-interest credit lines to troubled banks. Finally, September 2007 saw the request of funding by Northern Rock from the Bank of England followed by bank run on its deposits.

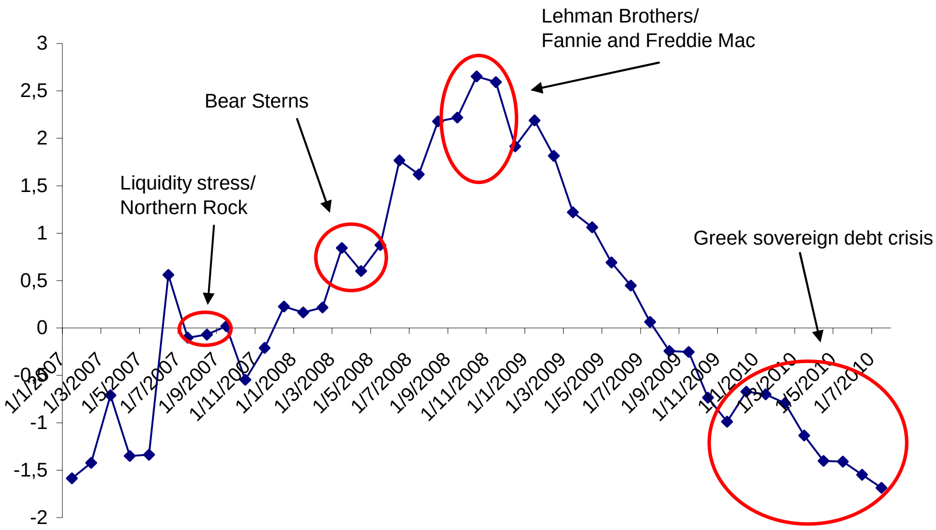
Figure B.11: Euribor spread



4) 2008m3-2008m4 (Bear Sterns Bailout)

As in the Northern Rock event, the impact of the Bear Sterns episode was clearly felt in the interbank market. A spike in the euribor spread is apparent during 2008m3-2008m4 (see Fig. B.6). Clear signs of markets calming down can be observed from 2008m5. In addition, this episode had some effect on the loan gap, which reflects a credit slowdown on 2008m4 (Fig. B.7).

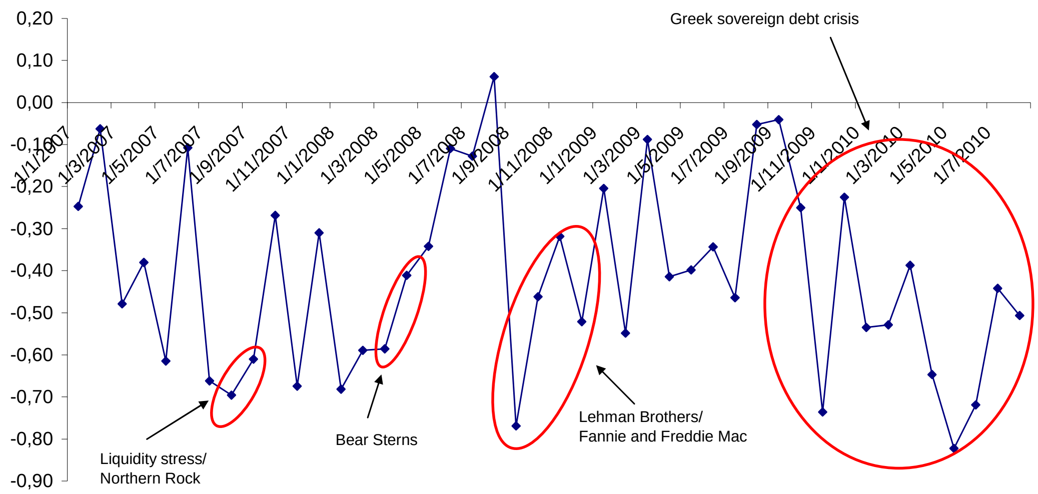
Figure B.12: Loan gap (standardized)



5) 2008m9-2008m12 (Collapse of Lehman Brothers – Bail out of AIG, Fannie Mae and Freddie Mac)

During September 2008 the US government announced it will bail out Fannie Mae and Freddie Mac, the Lehman Brothers investment bank was allowed to collapse while AIG was bailed out. Consequently, we define 2008m9 as the initial date of this crisis episode. It is striking how swiftly the correlation between returns on Greek stocks and the German Bund turned to negative during this event (from slightly positive to almost -0.8!) – see Fig.B.8. Both this correlation and the evolution of Euribor spread (Fig.B.6) led us to the decision to mark 2008m12 as the end of this event.

Figure B.13: Correlation between returns on Greek stocks and the German Bund



6) 2009m11-2010m7 (Beginning of the Greek sovereign debt crisis)

Following the announcement of statistical figures for the Greek budget deficit (October 2009) the market perception of the Greek debt sustainability was revised downwards and gradually unfolded to a severe sovereign debt crisis. The crisis is, obviously, marked to last until the end of our sample. We mark the November of 2009 as the onset of the crisis, based on the evolution of time series, especially, sovereign spread (Fig. B.9), average bank CDS (Fig. B.10), banking sector's idiosyncratic risk (Fig. B.11), and the deposit gap (Fig. B.12).

Figure B.14: **Greek government bond/German Bund spread**

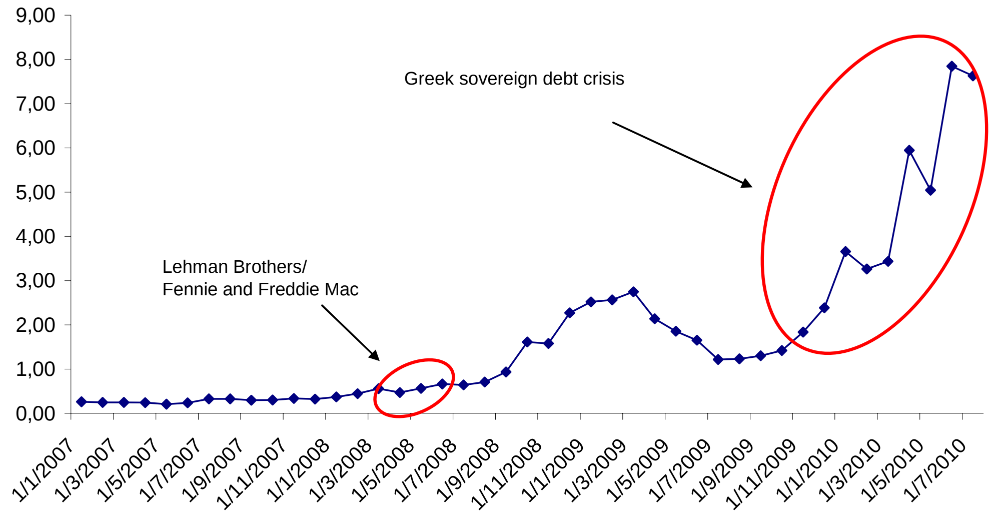


Figure B.15: Average CDSs

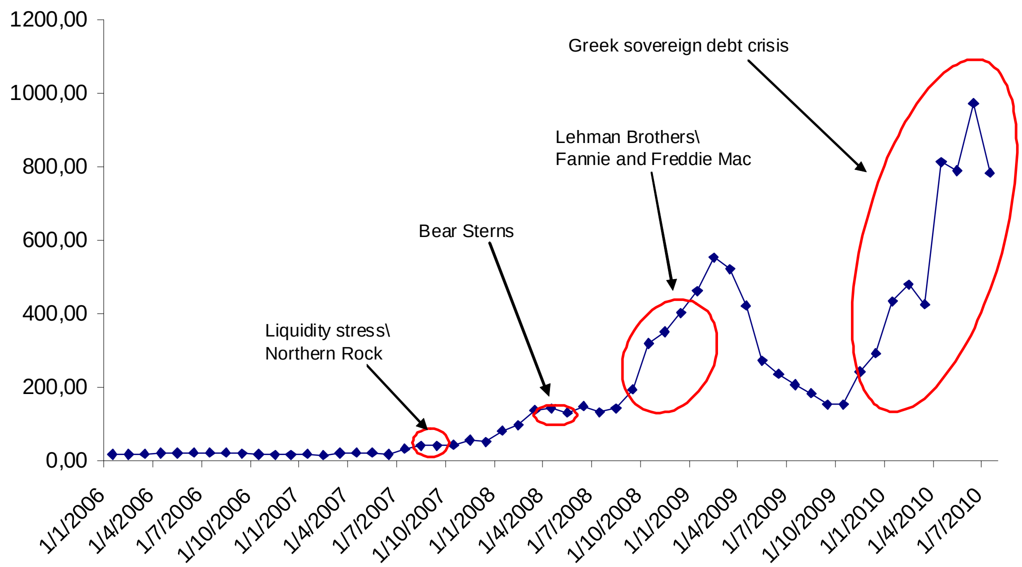


Figure B.16: Banking sector's idiosyncratic risk

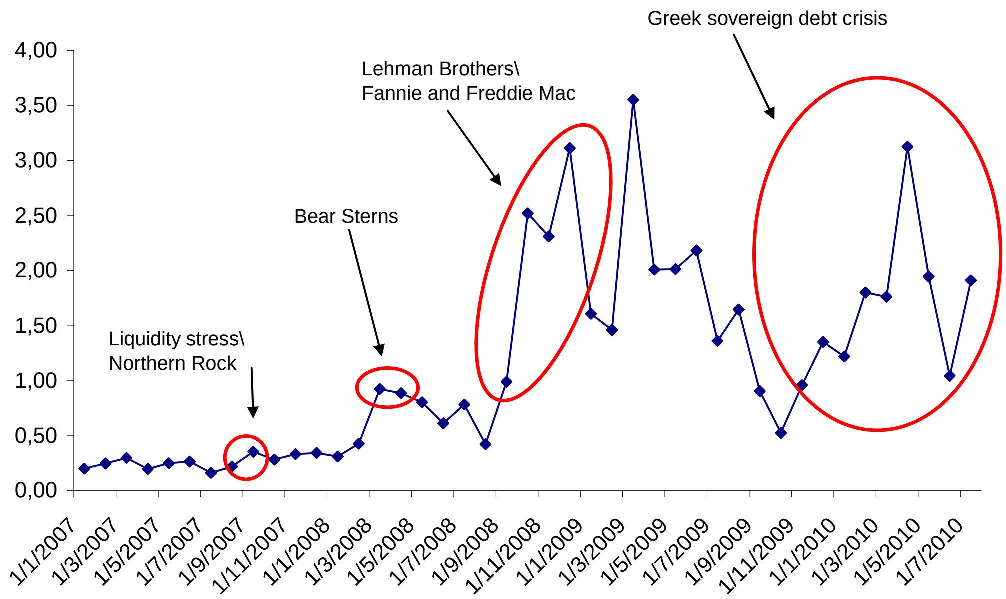
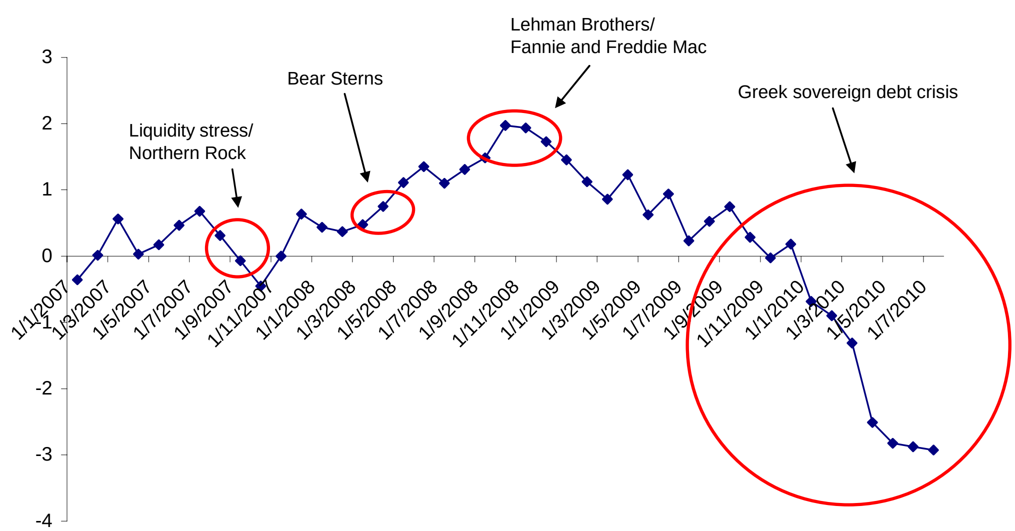


Figure B.17: Deposit gap (standardized)



Appendix C: Robustness checks

In this appendix we provide a number of robustness checks regarding the methods followed for the construction of the FSSI.

First, we experiment with the choice of the weights applied to the five sub-indices. Although the FSSI is developed so as to cover almost all elements of the financial system, we suspect that the variables related to the stock market may not be as important as the variables related to the money market or the banking sector. For this reason, we eliminate the impact of the sub-indices that are designed to capture the stress in the stock markets.

In the first "constrained" version of the stress indices we set the weight of the equity-markets sub-index equal to zero and we increase equally the weight for the banking sector – balance sheet sub-index. The probit regression results are presented in Table C.1.

Table C.1 Probit regression results for the first version of the "constrained" stress indices

	FSSI	Stress Index (weighted average)
Constant	-1.654***	-1.662***
	(0.216)	(0.226)
Δx_t	0.152***	0.153***
	(0.032)	(0.036)
Δx_{t-1}	0.140***	0.210***
	(0.034)	(0.051)
Mc Fadden R-square	0.462	0.402

This table presents the probit regression results where the explanatory variable, x_t , is the FSSI, the stress index using the EWMA model and the weighted average stress index respectively. The dependent variable is the *,** and *** indicate significance at a 10%, 5% and 1% significance level. The standard errors are depicted in parenthesis under the parameter estimations. In the last row, we present the fiiting of the equation

The results indicate that the performance of the three indices is almost unchanged relative to the "unconstrained" indices presented in this paper, since the fitting of regression has only deteriorated slightly. This evidence shows that the stock –market related sub-index is relatively less significant than the others for the identification of the systemic crisis. Nonetheless, the ranking of the indices does not change and the FSSI still outperforms its competitors.

In the second "constrained" version of the FSSI the weights for the banking sector market data and the equity sub-index are set equal to zero and the weights for the money market and the banking sector balance-sheet are increased by 15% and 22% respectively. The probit regression results are presented in Table C.2.

Table C.2 Probit regression results for the second version of the "constrained" stress indices

	FSSI	Stress Index (weighted average)
constant	-1.602***	-1.541***
	(0.206)	(0.202)
Δx_t	0.121***	0.119***
	(0.026)	(0.030)
Δx_{t-1}	0.115***	0.154***
	(0.029)	(0.038)
Mc Fadden R-square	0.398	0.337

This table presents the probit regression results where the explanatory variable, x_t , is the FSSI, the stress index using the EWMA model and the weighted average stress index respectively. The dependent variable is the *,** and *** indicate significance at a 10%, 5% and 1% significance level. The standard errors are depicted in parenthesis under the parameter estimations. In the last row, we present the fiiting of the equation.

The empirical results in Table C.2 suggest that the exclusion of the banking sector stock market related variables from the stress indices have a significant impact on the capability of the index to track the systemic events in our sample. However, once again the ranking of the competing indices does not change and the FSSI maximizes the Mc Fadden R square metric.

Overall, we show that the FSSI is robust against alternative weight choices with the stock market related variables being the less significant contributor to the identification of the systemic events. Nevertheless, the unconstrained FSSI version presented in the paper is, overall, the best performing stress index.

The second robustness check refers to the methodology used for the construction of the FSSI. In particular, the principal components used for the sub-indices and the portfolio based approach used for the summation of the sub-indices in a single index. These methods may average out the "idiosyncratic" crises which appear in the form of extreme values of individual variables and in some parts of the financial system. Thus, in order to test whether the FSSI is able to capture these type of crises we build a stress index of the form: $\max(y_{1t},...,y_{13t})$, where y_{it} is given in (4). This stress index consists only of the maximum transformed values of the individual variables, y_{it}, meaning that each time, *t*, the index indicates the presence of idiosyncratic shocks in each aspect of the financial system.[11] However, the empirical results show that this kind of index has poor fitting results in our probit regression testing procedure with the Mc Fadden R-square being only 0.091. A possible explanation for this result is that during the non-crisis periods the index is very sensitive to random changes of the individual variables. This implies that the index points to a crisis which does not have a systemic nature.

[11] We use only the maximum values for each of the transformed variables as we have used the logistic transformation in a way that an increase indicates a crisis.

Figure 1 Composite stress indicators

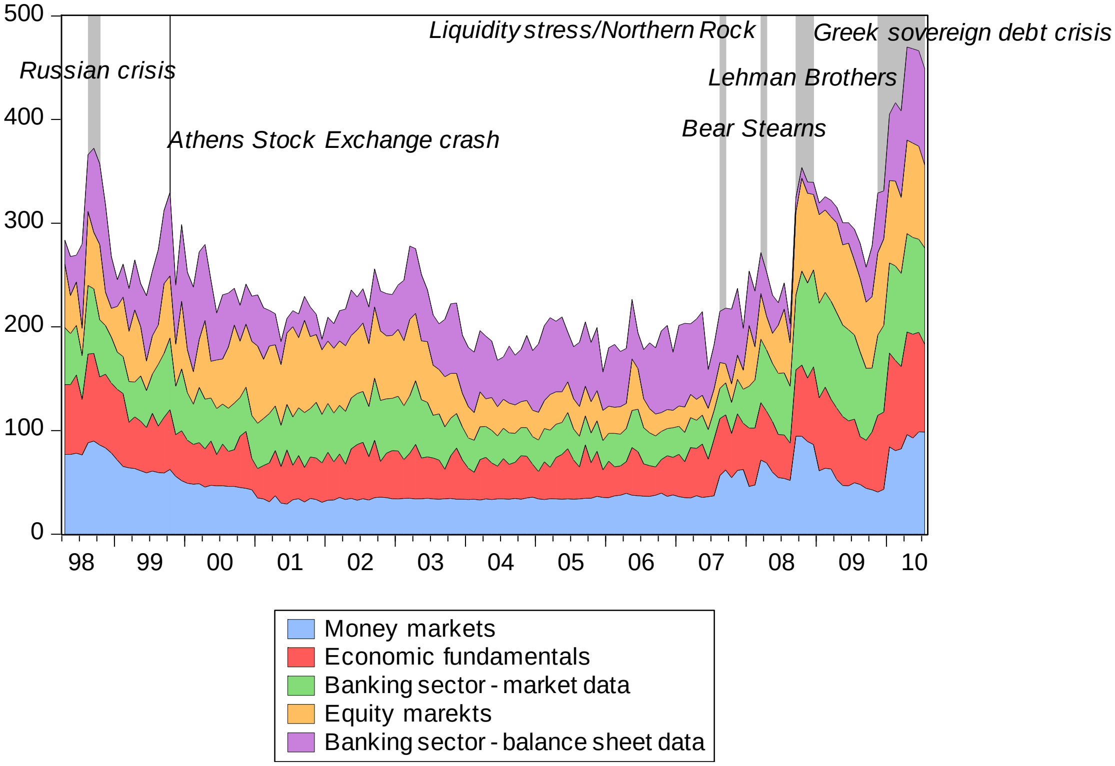


Figure 2 Time varying correlations estimated with a diagonal BEKK model

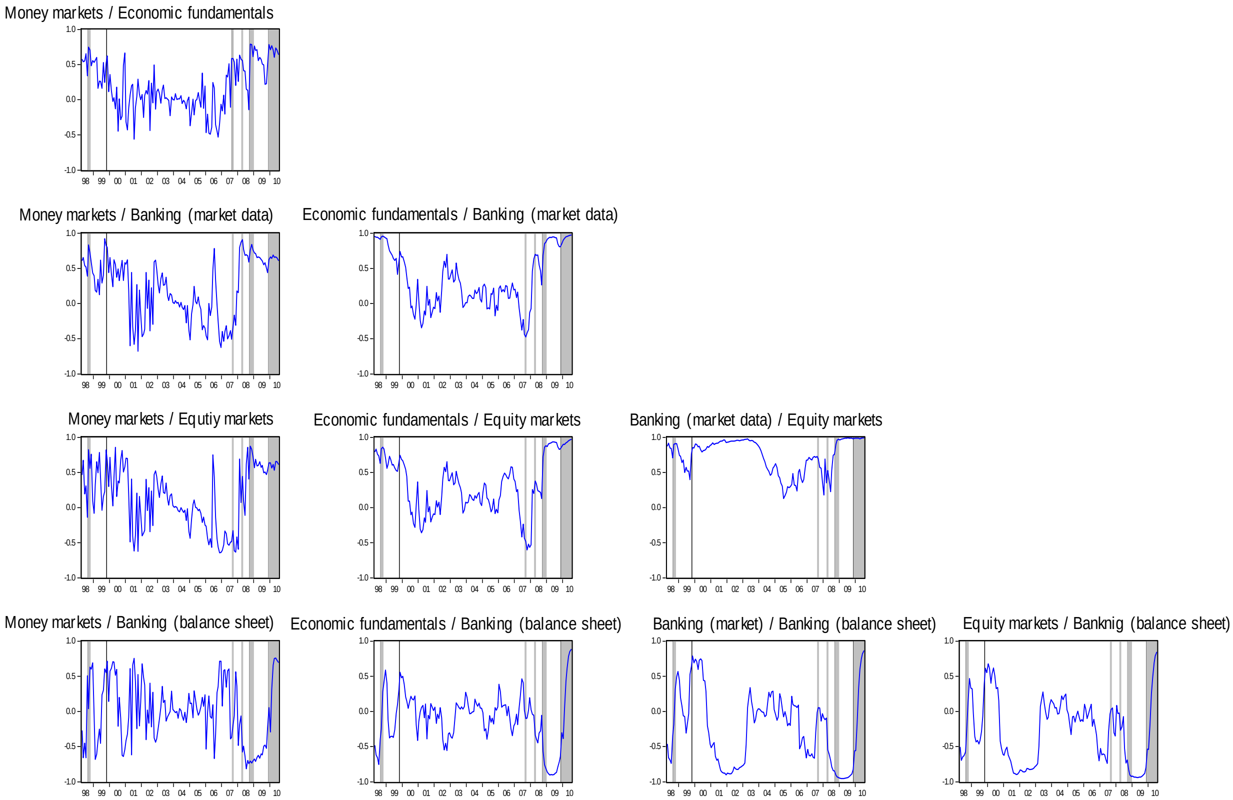


Figure 3 Financial Systemic Stress Index (FSSI)

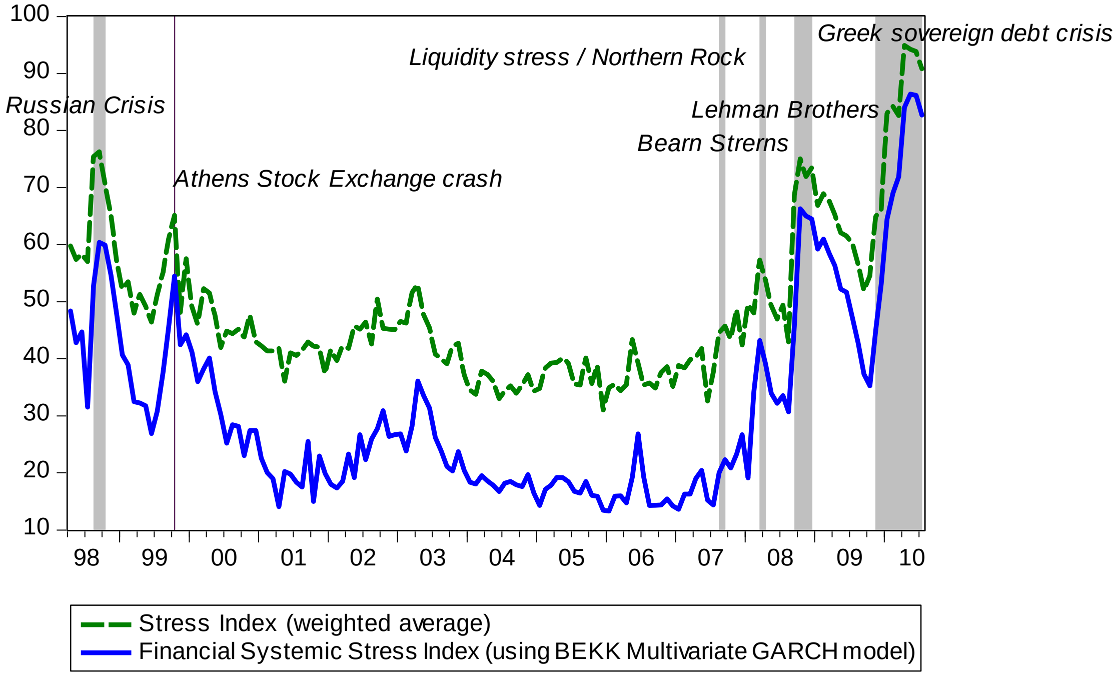


Figure 4 Probit regression results for the FSSI

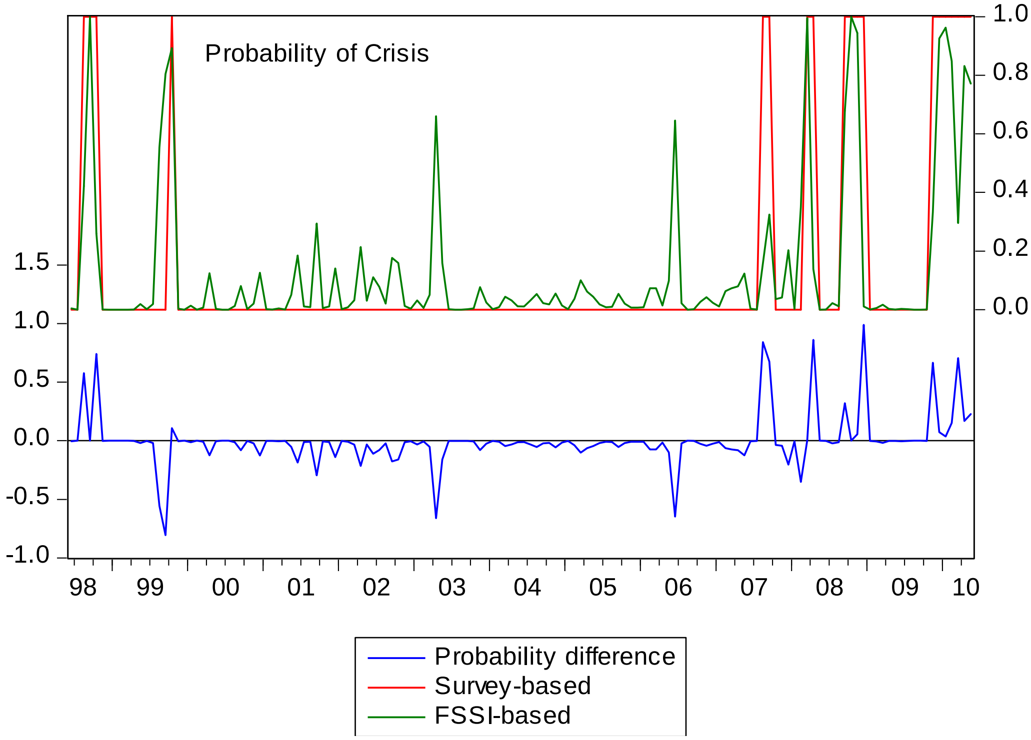


Figure 5 Probit regression results for the weighted average stress index

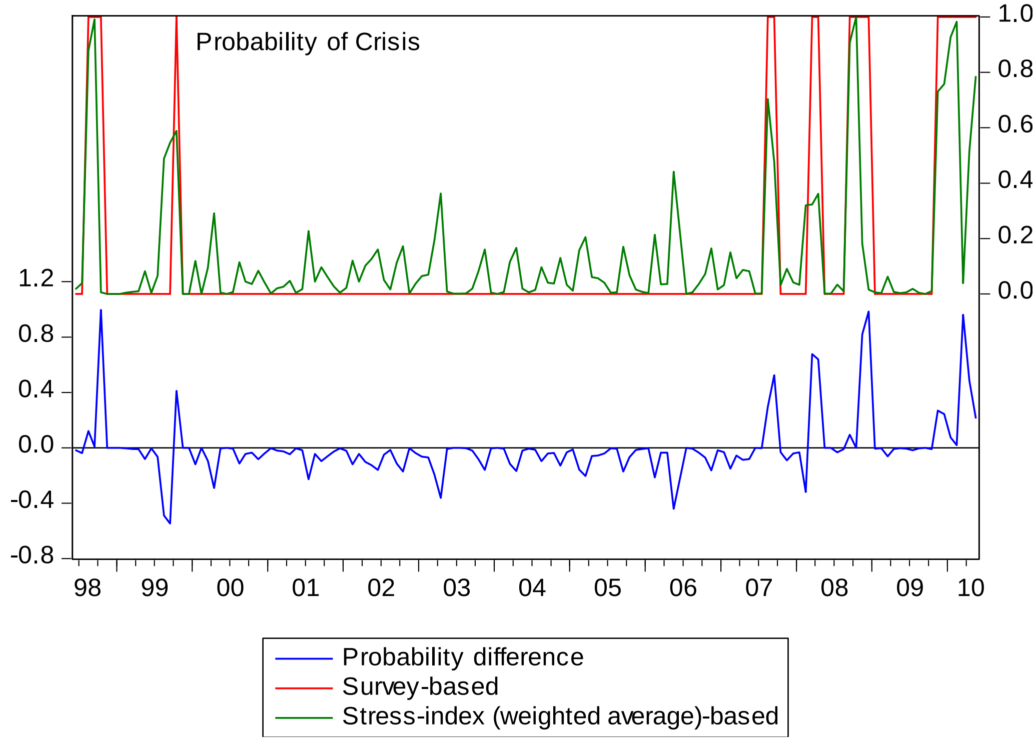


Table 1 Literature review for the construction of financial stress index[12]

Authors	Country(ies) (time period)	Methodology	Type of data used	Evaluation method
Bordo et al. (2001)	US (1790 – 1997)	A yearly Financial Conditions Index (FCI) was constructed as the sum of standardized raw stress variables (using the median instead of the mean). Each year was classified into five categories covering a range from "financial distress" to "financial euphoria". The classification was done according to the value of the index relative to its sample standard deviation.	1790-1869: Narrative sources. 1870-1997: Business and bank failure rates, bank loan charge-offs, real interest rates, yield spreads.	-
Hanscel & Monnin (2005)	Switzerland (1987 – 2002)	A quarterly "stress index" was developed for the Swiss banking sector. The raw stress indicators were aggregated into a single index using the variance-equal weight method (taking the average of standardized variables). Macroeconomic imbalances were found to be useful as early warning signals of banking stress.	Market and balance sheet data	The identification of crisis periods was based on known facts and the index constructed was compared with these periods of high stress.
Illing & Liu (2006)	Canada (1981-2005)	Daily data from banking sector, foreign exchange, debt and equity markets were combined into a Financial Stress Index (FSI) using various methods (Principal Components Analysis (PCA), credit weights, variance-equal weights and transformations using sample CDFs). "Refined" measures of financial stress i.e. modified raw variables that capture more systematically the stress conditions and GARCH techniques were also proposed. An event was characterized as highly stressful if the index was above a two standard	Market data	The various indices were compared in terms of Type I and Type II errors in signaling a crisis episode. The results of a survey were used to determine which of the episodes are characterized as crisis.

[12] Table 1 presents academic efforts for the quantification of financial stress in a single index. There are also non-academic approaches such as the monthly Financial Stress Index (FSI) developed by the Bank Credit Analysts (BCA) for the US economy (see further Illing and Liu, 2006; Hatzius et al., 2010). See also Lekkos et al. (2010) for a financial stress index for Greece.

		deviation threshold.		
Nelson & Perli (2007)	US (1994-2005)	The Financial Fragility Indicator was based on weekly data and shows the probability of crisis in the US economy. A set of twelve financial variables was ustilized to construct three subindicators combined into a single probability index by estimating a logit model.	Market data	-
Cardarelli et al. (2009)	17 advanced economies (1981-2009)	A quarterly FSI for each country was constructed as a variance-equal weighted average of seven variables grouped into three subindices (banking sector, securities and foreign exchange). The authors identified as episodes of financial stress, those periods that the FSI is greater than one standard deviation from its trend (which is calculated using a Hodrich-Prescott filter).	Market data	The episodes of financial stress identified by the FSI were compared with major financial stress episodes identified in the literature.
ECB (2009b)	World's main 29 economies (1994 – 2010)	The raw stress variables for each country were standardized and converted through logistic transformation. They were categorized into three market segments corresponding to fixed income, equity and foreign exchange markets. The Global Index of Financial Turbulence (GIFT) is a weighted average of individual country and market-specific indices.	Market data	The identification of crisis periods was based on known facts and the GIFT was compared with these periods of high stress.
Hakkio & Keeton (2009)	US (1990 – 2009)	The monthly Kansas City FSI (KCFSI) emphasized on the selection of market variables that can capture five key features of financial stress, specifically: (i) increased uncertainty about fundamental value of assets, (ii) increased uncertainty about the behaviour of other investors, (iii) increased asymmetry of information, (iv) decreased willingness to hold to risky assets (flight-to-quality), (v) decreased willingness to hold illiquid assts (flight-to-liquidity). A Principal	Market data	The index was compared to known periods of financial stress.

		Component Analysis (PCA) was applied in order to produce the index.		
Brave & Butters (2010)	US (1970 – 2010)	An unbalanced panel of 100 mixed frequency financial variables was used to construct the Financial Conditions Index (FCI). Kalman filter, EM algorithm and Harvey accumulator techniques were utilized to produce the index.	Market data	Markov-switching techniques were applied to the FCI to identify financial crisis periods. These crisis period were compared with major events in U.S. financial history.
Duca & Peltonen (2011)	10 advanced and 18 emerging economies (1990 – 2010)	For each country the FSI was constructed as the average of five stress components transformed into an integer that ranged from 0 to 3 according to the country specific quartile of the distribution the observation belongs to.	Market data	The index was compared to known periods of financial stress.
Grimaldi (2010)	Euro area (1999 – 2009)	A list of stressful events defining the crisis periods were linked with sixteen market variables through a logit model in order to construct the weekly FSI, which shows the probability of crisis (see also Nelson and Perli, 2007).	Market data	The FSI was compared with the implied volatility VSTOXX index in order to assess its signal/noise content.
Hatzius et al., (2010)	US (1970 – 2010)	A modified PCA was used in order to combine 44 financial stress indicators in a single FCI. The main differences compared with other methods are: (i) the use of an unbalanced panel of financial variables, (ii) elimination of the variability of financial variables that is explained by current and past real activity and (iii) the aggregation of the variables was done using more than one principal component.	Market data	The FCI was evaluated in terms of the ability to forecast real economic activity.
Hollo et al. (2012)	Euro area (1987-2011)	Five subindices consisting of money, bond, equity, foreign exchange market data and financial intermediaries data were used to construct the Composite Indicator of Systemic Stress (CISS). The systemic risk was taken into account by estimating the time	Market data and balance sheet data	Two methods to endogenously identify stress regimes: i) autoregressive Markov-switching model, and ii) TVAR (threshold VAR)

		varying correlation matrix of the subindices with an EWMA model. The aggregation of the subindices was based on the portfolio risk theory.		
Morales & Estrada (2010)	Colombia (1995-2008)	Three different weighting schemes (Variance-equal weights, Principal components and a qualitative response approach) were used to construct a single stress index. Using the same methodology they also constructed separate indices per type of financial institution.	Balance sheet data	Identification of known stress periods.

Table 2 List events and their impact on Greek financial system

Date/Event	Average	Standard Deviation
1) August/September 1998: Russian crisis	3.39	0.72
2) October 1999: Crash of the Athens Stock Exchange	2.30	0.34
3) 2000: Burst of dot com bubble	1.05	0.18
4) 2001: Terrorist attack of 9/11	1.14	0.17
5) 2001: Argentinian financial crisis	0.23	0.03
6) 2003: War in Iraq	0.98	0.17
7) May 2006: Worldwide uncertainty regarding interest rate increases from Fed and ECB	1.85	0.35
8) 2007: 1st phase of the Financial Turmoil (Liquidity Squeeze)	1.98	0.33
9) August/September 2007: Liquidity stress and bank run of the Northern Rock	2.08	0.34
10) March 2008: Bear Stearns Bailout	2.11	0.34
11) First months of 2008: Banking crisis in Ireland/Iceland	2.05	0.35
12) September/December 2008: Collapse of Lehman Brothers – Bail-out of AIG, Fannie Mae and Freddie Mac	3.86	0.65
13) October 2009: Announcement of statistical figures for the Greek budget deficit – Beginning of the Greek sovereign debt crisis	3.91	0.65
14) November 2009: Dubai default	2.24	0.34
15) April/May 2010: Greece applies for the Financial Support Mechanism and signs the Memorandum	3.94	0.67

This table presents the list of events that are commonly regarded to have influenced the Greek financial system. Twenty six (26) financial experts were asked to evaluate the level of stress that these events caused to the Greek financial system in a scale of 0 to 4. The last two columns of the table present the average value and standard deviations of the experts' answers respectively. An event is identified as financial crisis if the average level of stress is above the mean of the stress scale i.e. two (2).

Table 3 Fitting of the stress indices to the constructed binary index

	FSSI	Stress Index (weighted average)
constant	-1.631***	-1.501***
	(0.215)	(0.1888)
Δx_t	0.159***	0.145
	(0.033)	(0.033)
Δx_{t-1}	0.160***	0.180
	(0.037)	(0.042)
R-square	0.467	0.384

This table presents the probit regression results where the explanatory variable, x_t , is the FSSI, the stress index using the EWMA model and the weighted average stress index respectively. The dependent variable is the *,** and *** indicate significance at a 10%, 5% and 1% significance level. The standard errors are depicted in parenthesis under the parameter estimations. In the last row, we present the fiiting of the equation

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