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Financial Stress Index: A Lens for Supervising the Financial System

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Mikhail V. Oet, Timothy Bianco, Dieter Gramlich, and Stephen Ong

This paper develops a new financial stress measure (Cleveland Financial Stress Index, CFSI) that considers the supervisory objective of identifying risks to the stability of the financial system. The index provides a continuous signal of financial stress and broad coverage of the areas that could indicate it. The construction methodology uses daily public market data collected from different sectors of financial markets. A unique feature of the index is that it employs a dynamic weighting method that captures the changing relative importance of the different sectors of the financial system. This study shows how the index can be applied to monitoring and analyzing financial system conditions.

Keywords: financial system stability, systemic risk, financial stress, financial supervision, financial stress index.

JEL classification: G01, G10, C22, C52, E32, E44, E66.

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1. Introduction

A major finding from analyses of the recent financial crisis from a systemic perspective (Allen and Carletti 2010, IMF 2009, UNCTAD 2009) is that principal problems originated due to inherent information asymmetry among interconnected market participants and propagated significantly via information uncertainty in financial markets. The market participants had not recognized this susceptibility to information uncertainty—as a systemic dimension—sufficiently in advance. Put simply, market observers did not know how to watch for signs of trouble in the financial system and did not know what to watch out for.

This finding is particularly troublesome for any risk managers as guardians of organizational stability, including the financial supervisors as guardians of stability of the financial system. A critical hurdle is the lack of transparency about the system´s conditions and their causes. The absence of a proverbial flashlight for observing financial system conditions keeps in the dark not only the financial system observers and market participants, but also the risk managers. For all watchers of the financial system, this lack of transparency makes it difficult to recognize an evolving critical episode and to assess the nature of developing stress adequately. For any guardians of stability, the lack of ability to observe system conditions is bad news indeed: challenging the design of efficient crisis management strategies, and, from a broader point of view, hampering ability to prevent future systemic crises. Consequently, an appropriate monitoring instrument may specifically support the ability to intelligently observe systemic risk and to continuously assess financial system conditions. This tool would enable the public to observe drivers of stress in the financial system, and—by providing alerts—help to diffuse the information uncertainty and give the risk managers time to counteract. Such a tool for monitoring stress in financial markets may particularly be constructed as a financial stress index (FSI).

2. Research Objectives

The objective of this study is to frame a discussion of *supervision* of *stress* in a financial system. The primary research questions include how to reveal a financial system's stress to observers and what factors of stress the observers should mind. Furthermore, the research asks

how to consider a system's financial stress supervision efficiently to monitor stress development and to provide alerts. Figure 1 shows the conceptual model used in this study.

Financial stress is defined to be "observable, continuous manifestations of forces exerted on economic agents" (Oet et al. 2011a, p. 12). Illing and Liu (2003, 2006, p. 243) examine financial stress "as a continuous variable with a spectrum of values, where extreme values are called a crisis." This concept of financial stress extends Bordo, Dueker, and Wheelock (2000) notion of "an index of financial conditions" which studies whether aggregate price shocks are useful for dating financial instability. Oet et al. (2011a) provide a historical review of the financial stress measures. In the context of this paper, supervision is defined plainly as the action and process of critical watching.

Among the recent research contributions to financial stress are studies by Hakkio and Keeton (2009), Hatzius et al. (2010), Kliesen and Smith (2010), Oet et al. (2011a), Brave and Butters (2011), Holló, Kremer, and Lo Duca (2012), and Carlson, Lewis, and Nelson (2012). Principally, an FSI design conception follows the users' functional objectives. Predominantly, alternative measures of financial system stress are designed from non-supervisory perspectives and focus on techniques of combining quantitative data rather than on the theoretical meaning of stress observation.[1] The pursuit of purely methodological objectives tends to narrow the conceptual considerations for the scope of observed variables and structures suitable for the architecture of an FSI as a measure of financial system's state. Here, Holló, Kremer, and Lo Duca (2012) research stands out by explicitly addressing the underlying financial system architecture and

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[1] For example, Hatzius et al. (2010) and Brave and Butters (2011) pursue an objective to monitor and forecast economic activity. These studies confront critical questions of differentiating financial stress from varying cyclical effects of economic activity. Hatzius et al. (2010) select among candidate indexes one with optimal performance in forecasting economic growth.
Hakkio and Keeton (2009) and Carlson, Lewis, and Nelson pursue policymakers' perspectives. Hakkio and Keeton (2009, pp. 5-6) set policy objectives to find a single measure of financial stress to guide timing of monetary policy tightening when "financial stress is no longer high enough to endanger economic recovery." Carlson, Lewis, and Nelson (2012, p.2) seek an index construction that indicates "the degree to which conditions in financial markets are similar to periods when policymakers were concerned enough about systemic risks to intervene."
Kliesen and Smith (2010) and Hollo, Kremer, and Lo Duca (2012) focus on techniques to distill a systemic feature of various financial variables. Following Hakkio and Keeton (2009), Kliesen and Smith (2010, p. 1) "assume that financial stress is the primary factor influencing … comovement [of a group of financial variables], and by extracting this factor (the first principal component)… create an index with a useful economic interpretation." Hollo, Kremer, and Lo Duca (2012, p. 2) "measure the current state of instability…in the financial system and condense that state of financial instability into a single statistic…to emphasise the systemic nature of existing stresses in the financial system."

designing a stress measure "that aims to measure the current state of instability in the financial system as a whole."[2]

A supervision of stress, as a critical observation of financial system, calls forth the consistency between the underlying financial system composition, the variables that describe its state, and the meaning of stress observation. To those that supervise in order to manage institutional risk, stress observation means the ability to use a FSI to see and manage the unchecked development of stress across markets and institutions that otherwise would be difficult to handle in highly dynamic or opaque markets. In addition, the early use of FSIs may help to avoid feedback that comes from supervisory actions themselves and that are supposed to be more extensive the more elevated the level of stress is (Boyd, De Nicolò, and Loukoianova 2010, Berger et al. 2011).

While providing answers to these questions, this study offers three main contributions to the literature:

- The first contribution is developing a modeling framework for FSIs both from general considerations and specific supervisory needs (section 3). This comprises an operational definition of systemic risk for supervision and allows stress episode dating as well as the exploration of functional services of FSI for supervision.
- The second contribution is constructing and implementing a new FSI (the Cleveland Financial Stress Index—CFSI) while describing a specific, objective method for verification and benchmarking of financial stress for supervision (section 4). To benchmark financial stress, the method utilizes a related concept of financial risk as volatility and establishes an independent signaling time series of markets' price volatilities to verify the performance of the CFSI.
- The third contribution is an application of use of the benchmarking method in an expanded interpretation of past U.S. financial episodes and an objective assessment of current observations (section 5).

Various data, technical considerations and applications of CFSI are addressed. It is shown that the construction method for CFSI is optimal under a variety of monitoring cycles: from weekly to quarterly. As a quarterly series, CFSI provides dependable filtering of idiosyncratic stress episodes, making it useful as a dependent variable in an early warning system (EWS) for

[2] Hollo, Kremer, and Lo Duca (2012, p. 8).

systemic risk.[3] Decomposition of CFSI into its components allows for intriguing interpretations of economic conditions and particularly, while referring to specific financial stress components, permits detailed observations of the effects of regulatory measures to reduce systemic risk. To this extent, we consider the evidence of structural connection between the pattern of systemic stress episodes and financial deregulation. Our evidence suggests that while the frequency of systemic stress episodes remains consistent before and after financial deregulation in the U.S., (resulting from the Financial Services Modernization Act in the late 1990s) the duration pattern of systemic stress episodes changes. We observe that while in post-deregulation, the speed of systemic stress propagation slows (the benefit of risk diversification for individual institutions) and the length of the recovery from systemic stress also slows substantially (the penalty of universal banking).

3. Modeling Requirements for Supervisory Financial Stress Indexes

3.1. Theoretical Framework and General Modeling Principles

An FSI assesses the level of risk in a financial system.[4] Its construction builds on a definition of what is considered as financial stress (modeling subject), the objectives associated with the index use, and the indexes' architectural principles, e.g. a set of rules to fix and link the different index components consistently. The definition of systemic financial stress has gone through transformations. In the early 1980s and 1990s, the concepts of systemic risk and systemic crises tended to be synonymous, leading to binary measurement of systemic risk —either crisis or no crisis— and identification relied on professional consensus.[5] Systemic risk conditions manifest differently in the banking system, in a broader set of financial companies, or securities and foreign exchange (FX) markets.[6] Investigating the definitions applied in 13 research studies, Ishihara (2005) finds six different types of financial crises, then defines and measures them individually.[7]

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3 The use of CFSI in the EWS for systemic risk is discussed in Oet et al. (2011b).

4 Financial systems are analyzed in Allen and Gale (2001), Song and Thakor (2010), Thakor (1996).

5 See, for example, Demirgüc-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999).

6 EWSs in finance started in the 1990s with models for predicting currency and national debt crises. Specific EWSs for banking system distress have been proposed more recently, for example, by Berg, Borensztein, and Pattillo (2004), pp. 4, 7.

7 Ishihara (2005), p. 8. The types of crises are: banking liquidity, banking solvency, balance of payments, currency, external debt, growth rate, and financial crisis.

Literature from late 1990s and 2000s focuses on the search for a reassessment and a new definition of systemic risk. Caprio and Klingebiel (1996), Demirgüç-Kunt and Detragiache (1998), and De Bandt and Hartmann (2000) connect systemic risk to the point that most of the capital in financial firms is exhausted and that a considerable number of financial institutions are affected. Even more sophisticated conditions are defined by Demirgüç-Kunt and Detragiache (2005), Reinhart and Rogoff (2008), or Laeven and Valencia (2008) who link systemic crises to the existence of at least one of the four conditions: (i) deposit runs, (ii) introduction of deposit freezes or blanket guarantees, (iii) liquidity support, (iv) bank interventions. Another dimension is introduced by Hendricks, Kambhu, and Mosser (2007, p. 65) who emphasize disrupted transmission structures as characteristics of systemic crises where "systemic risk is the movement from one stable (positive) equilibrium to another stable (negative) equilibrium".

These concepts of systemic risk, however, have several drawbacks. The binary and the three-regime (Bussière and Fratzscher 2002) approaches ignore market stresses that approached, but never met crisis standards. They also exclude situations that were successfully managed but might otherwise have become crises. Further, the definitions include either en-masse bank insolvencies or government interventions. Both of these are antithetical to the supervisory objective for a definition that allows time to avert these outcomes. In addition, these definitions inherently lack the ability to describe continuous states of the financial system and to differentiate the severity of systemic episodes.[8] Consequently, more recent research suggests a richer approach to systemic financial risk as a continuous variable, with crisis as an extreme value. First, Bordo, Dueker, and Wheelock (2000) develop the concept of "an index of financial conditions" (FCI) examining whether aggregate price shocks are useful for dating financial instability. Further studies extend this approach by combining different price vectors on financial markets, principally vectors related to interest rates and equity prices.[9]

In a further approach, systemic indexes pursuing supervisory objectives of averting risk manifestations in the financial system develop along the lines of Illing and Liu (2003 and 2006) research as FSIs. Illing and Liu examine financial stress "as a continuous variable with a spectrum of values, where extreme values are called a crisis," allowing more information to be

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8 The IMF (2009), p. 145, emphasizes that binary variables do not measure the intensity of the stress.

9 An overview is given by Swiston (2008), pp. 3-5. For example, Bloomberg uses a set of three vectors— money market rates, bond market spreads, and equity prices—equally weighted and calculated for the period 1994-2008. See Rosenberg (2008), p. 8.

contained in the stress measure and avoiding some arbitrary boundaries for the beginnings and ends of crises.[10] Their index for systemic risk in Canada relies principally on spreads, betas, and interest rates with the level of financial stress determined as a weighted aggregation of various sub-indexes. Hanschel and Monnin (2005) use the same type of stress index to investigate systemic risk in Switzerland.

To synthesize, systemic risk may be referred to as the risk of correlated default of financial institutions affecting largely the system's risk capital and liquidity with subsequent negative feedback effects on real markets. Given the richer information from a continuing variable as well as the interconnected behavior of financial variables, modern stress indexes should be conceived as continuous and comprising several major financial areas. A continuity of stress is a feature of state conditions of each market in a financial system. To identify systemic stress as a common factor affecting the financial system, the index should consider concurrent stress states in several distinct markets as well as the persistence of significant stress in a particular market.

Operationally, a continuous index definition must allow for the resolution of ensuing crisis identification problems, specifically precise timing of episodes and differentiation of their relative severity. While representing an aggregation of variables and weights, the FSI has to remain coherent, transparent and modular, thus allowing the observer to retrace the drivers of systemic stress. In this sense the Illing and Liu (2006) approach provides a promising guideline for conceptualizing an FSI. As will be shown later, certain inconsistencies in the Illing and Liu construction method have to be corrected and several new observable component market factors will be introduced.

3.2. Supervisory Requirements

From a supervisor's point of view, there are three main applications for a measure of financial stress: monitoring, alerting, and analyzing. Monitoring reduces information uncertainty, by providing a supervisor with concurrent information on the state of financial markets. It also comprises identifying episodes of systemic stress and supports the assessment of the observer's relative position in the markets. Alerting focuses on the sources of financial stress and supplies sufficient transparency and time to manage the observer's response with required exactness. Analyzing involves assessing the likelihood of a developing systemic stress state.

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[10] Illing and Liu show that crises in Canada have been influenced by three broad sets of issues: by country-specific issues, by North American issues, and by issues elsewhere.

As has been argued (Gramlich et al. 2010), the first of these applications, identification of systemic stress, is based on a continuous notion of what constitutes financial stress (transmission of distress), the extent of distress (intensity of distress), and the financial markets involved (type of distress). More specifically, transmission of distress involves the selection of observable market characteristics (e.g. spreads and betas) and the choice of thresholds above which the observable characteristics are considered to be in distress. Intensity of distress involves the selection of time over which the persistence of distress is observed. Finally, type of distress involves the selection of markets that in combination may be deemed to raise systemic concerns. The choices made operationally may vary to yield more or less sensitive interpretations of systemic stress, resulting in a flexible identification scheme.

The sensitivity of the identification of systemic stress is important, because the supervisory remedy would be based on balancing the costs of regulatory actions against their benefits. If the supervisor sets the definition of systemic stress too low, the supervisory action may be inefficient as markets would otherwise be able to resolve and stabilize the conditions. By contrast, if the supervisors were to identify systemic stress conservatively, then they would fail to understand and act on the systemic stress in a timely fashion to arrest its evolvement. Worse, the supervisory action itself may be destabilizing by causing adverse effects and generating undesirable feedback effects. Boyd, De Nicolò, and Loukoianova (2010) point out that defining systemic risk from crises perspectives involves the mixing of economy-driven shocks and governmental (supervisory) response.[11] If the effects of supervisory actions were not integrated, systemic conditions would arise much earlier, and conventional indicators would recognize them too late.

Exclusion of idiosyncratic events serves as a useful additional constraint on the identification of systemic stress. For example, setting the extent of distress to daily or weekly data results in a very volatile stress index with too many idiosyncratic stress episodes: market rumors, unsubstantiated fears, political events, etc.[12] Given that supervision of the financial system involves monitoring, analyzing, and alerting, financial stress is a more fitting focus than financial conditions: FSI components must be directly observable in the markets. They can be explained in terms of loss expectations, risk, and uncertainty, among others, but are not equivalent to risk in

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[11] Similarly, Berger et al. (2011) discuss feedbacks from supervision.

[12] As it is shown in this study, quarterly extent of distress excludes random and idiosyncratic events and is useful for supervisory purpose.

its standard computational finance sense of statistical volatility. Economically, financial stresses are observable continuous manifestations of "forces exerted on economic agents." This is a critical point guiding the selection of components of an FSI.

Freixas and Rochet (2008) discuss that the importance of external finance spread for monetary policy transmission has been affirmed both by theoretical and empirical studies.[13] The critical role of the external finance spread emerges differently in alternative models. In the Bernanke and Gertler (1990) theoretical study, the importance of the spread for financial fragility emerges from the perspective of investment and agency costs. Bernanke and Gertler (1995) consider various types of spreads empirically for their role in the credit channel of monetary policy transmission. In Holmström and Tirole (1997), the spread results from "scarcity of bank capital." In Bolton and Freixas (2000), the spread is due to "adverse selection in the capital markets." As Freixas and Rochet (2008) point out, the key role of the spread in various monetary policy transmission channels is due to its amplification effect on interest rates and generating the financial accelerator effect.

Existing FSIs allow use of both spreads and the conceptually similar volatility indexes as index components. While both volatility indexes and spreads provide observations of market stress, one critique from supervisory point of view of their concurrent use is that they provide qualitatively different insights. Volatility indexes are blends of prices of many securities. They hide the causal transmission mechanism by which the factors entering the volatility series influence the stress index, making the mechanism a "black box."[14] By contrast, spreads are differences between two related financial positions, very often between two securities. A change in spread communicates relative activity of the two positions (securities). Thus, the spread change contains information of the market-perceived risk associated with the two positions. In addition, the sources of a given change in spread are directly observable in the rise and fall of the

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[13] Freixas and Rochet (2008), p. 198: "external finance premium, defined as the wedge between the cost of funds raised externally and the opportunity cost of internal funds, [is] an essential key in understanding of the transmission mechanism."

[14] We use the term "black box" in a sense similar to Bernanke and Gertler (1995) – "Inside the Black Box: The Credit Channel of Monetary Policy Transmission." Given supervisory objectives, the advantage of clear observations of underlying factors of market distress is obvious.

two positions. Empirically, it is also interesting to note that spread-based FSI appears to identify stress episodes before alternative indexes using mixed methods.[15]

To synthesize, a survey of current literature on FSIs reveals an absence of a consistent application of the theoretical framework to the construction and application of financial stress for supervising the financial system. Current FSIs are mostly constructed for general use and combine different modeling perspectives and index components. A more specific and consistent architecture for application in supervision is essential.

4. Index Construction for Supervision

4.1. Index Concept

Insert Fig. 1 about here

As has been argued from a supervisor's perspective, the FSI is constructed as a continuous stress variable, using spread measures instead of volatility measures, because spreads contain information on market-perceived risk. This fact also means that spreads will be functionally related to the quality of this information among other factors. Specifically, spreads will be adversely affected by increased uncertainty in the market. Of course, numerous other factors affect movement of spreads in individual markets over time. Such factors affect spreads frequently, are difficult to anticipate, and have little meaning to the financial system, i.e. are idiosyncratic. Put another way, spreads are noisy communicators of underlying stress. Conceptually, increased underlying systemic stress should affect spreads in all markets. This means that a measure of underlying systemic financial stress should consider spreads from a variety of different markets.

Further, there is generally little correlation between the widening of spreads in separate markets arising because of non-systematic stress. In contrast, events due to systematic stress ought to affect spreads across market segments. Since spreads in each market carry some amount of market-specific idiosyncratic noise simultaneously with any underlying signal of systematic stress, considering spreads together, across different markets and over time, would tend to reduce

[15] In addition, Appendix A.2 (Table 3A) shows that spread-based financial index frequently leads the volatility indexes in the funding, credit, and FX markets.

aggregate idiosyncratic noise through diversification (mean reversion) and emphasize the underlying, non-diversifiable signals of systematic stress. Put another way: considering multiple spreads in different markets together reduces the likelihood of common idiosyncratic cause and increases the likelihood that spreads move due to a common factor, which can be interpreted as systemic financial stress. Thus, by aggregating the individual spreads into an index, the researcher hopes to improve the signal to noise ratio and isolate the movements in spreads due to the underlying systemic stress.

Methodologically, in the formulation of financial stress, the construction elements are linked to the financial system's markets, the variables that describe the market activity, the necessary transformation and aggregation of these variables, and the choice of the unit of time for the stress measure. FSI's consideration of a financial system's markets has to recognize findings of precedent literature as well as recent transformations in the financial system. For the U.S. financial system, the relevant markets have to be chosen; the unit of time for supervisory objectives has to be specified; and the relevant market variables have to be selected, transformed, and aggregated. A further request is to calibrate the data series representing the financial stress appropriately.

Beyond the use of spreads as a conceptually adequate variable for stress in individual markets, a further question is to the necessary transformation and further aggregation of these variables to describe systemic conditions. Bordo, Dueker, and Wheelock (2000) transform variable data by standardizing: measured distance between each observation and the subperiod median is divided by the variable's standard deviation (std). The overall index is aggregated simply as unweighted average of these standardized distances across component variables. While the authors do not offer a definition of systemic conditions, they offer a methodology to measure them continuously and suggest a rating system approach to the classification of stress episodes. Illing and Liu (2003 and 2006) test a number of alternative weighting schemes for FSI in Canada, calibrating the alternative stress series against an expert survey and finding that credit-weighted aggregation provides optimal identification of stress episodes for Canada.[16]

The calibrating choices made in the construction of a FSI rely on a prior benchmark identification of stress episodes, identified in turn by the extent to which a host of market

[16] Illing and Liu (2006, p. 255) credit weights correspond to "the relative size of each market…as a share of total credit in the economy."

variables deviates from some long-term trend. The notion of an abnormal event in market A causing substantial deviations in values within market B (the contagion effect) necessarily complicates identification of stress episodes by introducing a feedback effect. This makes the identification of leading indicators of stress difficult in that the researcher's choice of indicators may move in response to propagation events rather than as the first rumblings of distress. Additionally, in the course of normal business cycle fluctuations, a supervisor expects some movement in market indicators as part of rational resource allocation. The researcher must be wary of selecting indicators that move regularly with the business cycle.

In order to aggregate the selected markets' stress variables into an overall systemic FSI, further aspects for each variable have to be considered: what is the precedent set by the variable's value and how much that precedent matters. Mathematically, an FSI is generated using the following basic equation:

$$FSI_t = \sum_j \left[w_{jt} \times \int_{-\infty}^{x_j} f\left(x_{jt}\right) dx_{jt} \right] \times 100 \qquad (1)$$

where the x_{jt} term is the value of variable j at time t, the integration term is the cumulative density function (CDF) of variable j, and the w_{jt} term is the weight given to variable j in the FSI at time t. A key technical challenge to be overcome by an appropriate choice of the weighting methodology is the potential for false alarms. This potential has to be balanced against the risk of missing important events when setting warning standards too high.[17]

4.2. Variable Selection and Data

To enable the consistent choice of FSI variables within an overall framework, the financial system is considered to comprise of financial intermediaries and financial markets.[18] Financial intermediaries involve commercial and investment banks as well as different types of financial service institutions, particularly investment funds, securitization vehicles, and finance companies. Financial markets include all marketplaces to adjust differences in liquidity and risk/return profiles. In representing the U.S. financial markets and considering previous

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17 Gramlich et al. (2010), p. 207

18 "The term *financial system* is typically used to describe the collection of financial intermediaries—venture capitalist, investment banks, commercial banks, insurance companies, and so on—and stock, bond, and contingent claims (derivatives) markets that are collectively responsible for allocating resources and redistributing risks in the economy" (Thakor 2001, p. 577). See Merton and Bodie (1995), Thakor (1996), and Allen and Gale (2001) for extensive discussion.

research[19], the CFSI captures stress in six distinct financial markets: funding markets, FX markets, credit markets, equity markets, real estate markets, and securitization markets (Table 1).

In each distinct financial market, the typical products involved in the financial institutions' interaction and the corresponding applied stresses can be distinguished through spreads. For example, reasonable measures of stress in the funding markets would consist of spreads capturing pressures on bonds of financial institutions, interbank borrowing, and interbank liquidity because financial institutions access the funding market seeking direct (through bonds) and indirect financing (through interbank borrowing) to manage liquidity and interest rate risk. In the credit markets, financial institutions act as intermediaries for short- and long-term borrowing. Thus, measures of stress in the credit markets would include spreads capturing pressures on corporate bonds, commercial papers, and treasury yield curve, as well as liquidity (bid-ask) pressures on treasuries. In addition, the relative stress on U.S. vs. international credit markets may be observed through the covered interest rate parity spreads.[20] In the equity markets, it is reasonable to include observable measures that describe the extent to which financial equities in the S&P 500 have collapsed over the previous year. Similarly, in the foreign exchange market observable measures of flight from the U.S. dollar toward a set of foreign currencies are included. The real estate markets enable transactions in physical commercial and residential properties, where financial institutions act as various intermediaries including finance and investment. Stress in the real estate markets may be observed through asset pricing pressures relative to alternative risk-free investments of like maturity. The securitization markets facilitate transactions in securities backed by pools of transformed assets. Financial institutions in these markets provide a large array of services including origination, pooling, structuring, credit enhancement, transfer, insurance, and investment. It is reasonable to observe stress in the securitization markets through relative asset pricing pressures of securitization assets—i.e. asset-backed securities (ABS), commercial mortgage-backed securities (CMBS), residential mortgage-backed securities (RMBS)—to risk-free investments of like maturity.

Calibration of parameters starts with an initial setting and is modified further in several iterations. For transmission of distress, we test a number of distress thresholds from ¼ std to 1 ½

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[19] See Illing and Liu (2003, 2006). The derivatives market is indirectly included, since derivatives refer to prices in the selected six markets as an underlying.

[20] The comparison here is made between US and UK markets that were the strongest competitive currency markets in the 1990s.

std paying attention to possible structural breaks in the benchmark time series of stress episodes. We select a distress threshold changing regime of ¾ std (from 4Q 1991–Q1 1998) and ¼ std (from 2Q 1998–current). For extent of distress, we test durations from weekly to quarterly and select two consecutive fortnights of distress. For type of distress, we consider distress conditions across different financial markets and select those that affect at least two distinct markets. The choices result in the following operational definition used for identification of systemic stress episodes with CFSI: *systemic stress is two consecutive fortnights of distress above previous biweekly thresholds, or concurrent biweekly distress in at least two distinct markets.* The intent of this approach is to set a lower threshold for monitoring systemic stress to improve ability for concurrent identification of episodes that have a potential to become critical.[21]

Current literature on continuous index measures, both financial conditions and financial stress, generally reports the indexes as Z_t standardized distances without providing explicit thresholds for identification of distress severity. Bordo, Dueker, and Wheelock (2000) show that a continuous index can be used for identification of distress severity independently of dating of systemic conditions, using Z_t standardized distances from the median. They suggest a five category differentiation of distress: "severe distress," "moderate distress," "normal," moderate expansion," and "euphoria."[22] Certainly, use of a common scale facilitates the comparison among alternative indexes. Establishing thresholds for identification of distress severity is an even more useful application of the standardized distance method of index measurement.[23]

The CFSI uses daily observable financial markets' data to capture continuity of stress in financial markets. The data is of high quality, sourced from the Federal Reserve FRED database, the Bank of England, Bloomberg, Haver Analytics, and the Securities Industry and Financial Markets Association (SIFMA). Restricted by the availability of major data series,[24] the development data set starts in the fourth quarter 1991. The variables for each of the six financial markets and their construction are outlined in Table 1.

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21 Oet et al. (2011a).

22 In reference to the subperiod mean, Bordo, Dueker, and Wheelock (2000, p. 27) propose a five-state empirical calibration of FCI: severe distress with $Z_t > 1.5$ standard deviation (std), moderate distress with $Z_t > 0.75$ std, normal with $0.75 > Z_t > -0.75$ std, moderate expansion where $-1.5 < Z_t < -0.75$ std, euphoria with $Z_t < -1.5$ std.

23 In section 4.3 of this study, we extend Bordo, Dueker, and Wheelock's idea for identification of distress severity by using a probit model of CFSI to optimally calibrate a distress severity rating system.

24 The most severe constraint is Bloomberg 10 year A Bank Bond Index that is not available prior to 09/26/1991.

Insert Table 1 about here

4.3. Variable Transformation and Aggregation

After the sixteen single variables are computed as set up in Table 1, the individual time series must be transformed in preparation for aggregation into the overall FSI. The process involves the generation of a CDF for each variable. To ensure commensurate percentiles, the CDF time series for each variable j are generated using a common set of dates where data is fully populated for all variables included in the computation of the FSI[25]:

$$CDF_{jt} = \int_{-\infty}^{x_j} f(x_{jt})\, dx_{jt} \tag{2}$$

The process for converting any given variable into its CDF requires an intermediate step of computing $Rank(x_{jt})$, a rank ordering of the data in the series. Once the corresponding rank series is generated for each variable, the CDFs at each point in time are computed by the following:

$$CDF_{jt} = f(x_{jt}) = \frac{Rank\ (\mathrm{x}_{jt})}{number\ of\ daily\ observations} \tag{3}$$

In most cases, the higher the computed value of a variable, the higher the rank associated with the value. For instance, in the initial construction a rank of 4,237 would be associated with the largest daily observation in the variable's time series while a rank of 1 would belong to the smallest daily observation. However, there are several series where this convention is reversed: Weighted Dollar Crashes, Stock Market Crashes, and Treasury Yield Curve spread.[26]

For determining the contribution (weighting) of a single variable to the overall FSI, different weighting methods are discussed in literature.[27] To find the most appropriate, several non-parametric tests are run and the results assessed in light of the CFSI's monitoring efficacy in identifying episodes of systemic stress. These are Type I/Type II error analysis, Receiver Operating Characteristic (ROC), and Somers D analysis – a measure of association describing

[25] For example, in the initial construction, common dates spanned from 9/26/1991 through 3/31/2009, resulting in 4,237 daily observations.

[26] The reason for the reverse rank ordering for Weight Dollar Crashes and Stock Market Crashes comes from their computation as outlined in Section 3.2. Since the observed values of both of these variables are computed as current value over the past year's high value, a larger output implies smaller deviation of current value to recent past data and, therefore, a lower precedent.

[27] Index construction may involve four competing aggregation methods: 1) equal weights, 2) equal variance weights, 3) credit weights, and 4) principal component weights. See Illing and Liu (2004, 2006).

the difference in the conditional probabilities of observing a systemic stress episode given groups of standardized FSI distances to mean.[28] The above tests show the CFSI calibration using credit weights to be optimal under competing weighting methods and within a range of possible alternative monitoring and forecasting frequencies.[29]

In addition to statistical optimality, the CFSI calibration using dynamic credit weights is conceptually appealing since it lends economic significance to the different FSI components and considers the different market sectors contributing to overall stress. The weights are determined using data from the Federal Reserve Board's Flow of Funds statistical release (Z.1), supplemented by real estate volume data from Haver Analytics and securitization volume data from SIFMA.[30] This data is separated into the six market sectors: funding (FD), foreign exchange (FX), equity (EQ), credit (CR), real estate (RE), and securitization (SR). For any given quarter, total dollar flows through each sector are converted into a proportion of total dollar flows through all sectors, using the following equation:[31]

$$Z\ Proportion_t = \frac{Z_t}{FD_t + FX_t + EQ_t + CR_t + RE_t + SR_t},\ Z \in \{FD, FX, EQ, CR, RE, SR\} \qquad (4)$$

The proportions are then used as weights for the aggregation of the sixteen CDF functions generated above. Each variable is identified as belonging to one of the six market sectors and is weighted appropriately. When multiple variables belong to a single market sector, the fractional allocation of weight within the sector is calculated by transaction volume data, where available, and by the number of variables in the sector otherwise.[32] With the fractional proportions calculated, a daily CFSI time series is computed by the following equation:

$$\begin{gathered} CFSI_t = (CDFSI1A_t + CDFSI2E_t + CDFSI10A_t + CDFSI11A_t) \times \frac{FD\ Proportion_t}{4} \\ +(CDFSI3A_t) \times FX\ Proportion_t \\ +(CDFSI4A_t + CDFSI5A_t + CDFSI6A_t + CDFSI7A_t + CDFSI8A_t) \times \frac{CR\ Proportion_t}{5} \\ +\ (CDFSI9A_t) \times EQ\ Proportion_t \end{gathered}$$

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28 Somers (1962).

29 Oet et al. (2011a).

30 The FSI construction involved four competing aggregation methods: equal weights; equal variance weights; credit weights; and principal component weights.

31 In the data gathered, FX flows were missing until 3Q: 1997. To impute the data, the relative proportion of FX dollar flow to total flow of funds in each quarter prior to 3Q: 1997 was assumed to be constant, held to its known weight in 3Q: 1997 flow of funds data.

32 In absence of transaction volumes, the weight allocation within sector seems to suffer from the same claim of arbitrariness that plagues the equal weights approach, though, not as severe given the weights' sensitivity to change in total credit composition.

$$+[CDFSI12A_t, CDFSI13A_t] \times [CRE\ Proportion, RRE\ Proportion]^T$$
$$+[CDFSI14A_t, CDFSI15A_t, CDFSI16A_t] \times$$
$$[ABS\ Proportion, CMBS\ Proportion, RMBS\ Proportion]^T \quad (5)$$

The daily CFSI series filters idiosyncratic noise through a daily 10-observation moving average for the supervisory applications of monitoring, analyzing, and alerting.

5. CFSI Applications for Supervision

5.1. Benchmark index as a reference for stress episodes

In order to assess the suitability of the CFSI for monitoring and forecasting financial systemic stress, a reference set of episodes of financial stress is needed. A first possibility is relying on literature precedents for identifying stress episodes.[33] Typically, authors recognize only two U.S. systemic crises since 1980: savings and loans crisis generally dated in 1988 and the subprime crisis of 2007, with other significant stress episodes conspicuously missing.[34] Here, a possible setback is that supervisors are interested in a nuanced dated series of potential systemic stress, whereas literature mostly aims to date realized episodes of crises. The second major limitation of existing studies is their reliance on survey-based crisis dating. This leads to subjective interpretation of dating and tends to define systemic conditions through crisis response. Thus, as Boyd, De Nicolò, and Loukoianova (2010) point out, the crises series tend to show crises too late.

The Bordo, Dueker, and Wheelock (2000) annual FCI index is able to differentiate 3 distinct episodes from 1980 to 2000: severe distress of 1982-1986, and two periods of moderate distress: 1981 and 1987-1992. One important advantage of this approach is availability of a historically deep index series. Unfortunately, from the standpoint of supervisory objectives, the annual FCI is sub-optimal, as its frequency means that supervisors lack ability to observe any conditions until annual data is collected. The resulting lag thus seriously undermines the ability of the annual FCI to serve supervisors. Clearly, data that is more frequent is essential to supervisors.

Taking into account these limitations, a further possibility is constructing a benchmark index for dating systemic stress episodes. This benchmark parallels the design of CFSI, but grounds on volatility as an alternative measure of stress in the financial markets. Six volatility indexes,

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[33] See Caprio and Klingebiel (1996), Demirgüc-Kunt and Detragiache (1998).
[34] For example the LTCM crisis and the Asian crisis.

MOVE, VDAX, LBOX[35], and VIX in addition to calculated volatilty indexes for real estate and securitization are used that analogously reflect the six financial markets represented in the CFSI—funding, FX, credit, equity, real estate, and securitization—respectively. To ensure further comparability between the indices, the benchmark index is built and applied for a consistent set of episode monitoring frequencies from daily to quarterly.

From a computational perspective, the final set of six volatility benchmarks is transformed into six monthly[36] time series of stress in the representative markets. We benchmark that an individual market is in stress if the level of the market's volatility index surpasses a predetermined threshold. Specifically, a signal of stress may be indicated by the difference in the signaling time series of the individual volatility indexes exceeding the distress threshold $\bar{\beta}$ standard deviations.[37] The calculation is as follows:

$$S_{i,t,q} = Variable\ Benchmark\ Stress\ Signal_{i,t,q} = \mu_{Index_{i,t,q}} - \left[\mu_{Index_{i,q-1}} + \bar{\beta}\sigma_{Index_{i,q-1}}\right] \quad (6)$$

where, for each market i, t is the period number in the series and q is the quarter number in which the given period resides. The first term in the variable equation is the mean of the benchmark index over the current period, the second term is the mean of the benchmark index over the previous quarter, and the third term is the value of the distress threshold of the benchmark index over the previous quarter. For each volatility index, if the $S_{i,t,q}$ is non-negative, the market described by the index is considered in stress for the period.

As none of the six benchmark indices represents a broad enough measure to singularly identify a period of systemic stress across financial markets, the indices are combined into an overall benchmark stress index (BSI), a binary signal of stress (see Fig. 2). For this overall BSI, a systemically stressful period is identified as satisfying at least one of the following conditions:

- No less than two of the market benchmark indices signal stress for the same period.
- A single benchmark index signals stress for at least the second period in a row.

The BSI tested at a varying set of frequencies allows selection of frequency that is optimal in filtering out any idiosyncratic episodes where policy actions may not be warranted. For the

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35 LBOX (Lehman Swaptions Volatility Index) was used in the original benchmarking through September 4, 2009. LBOX was superseded by In July 2009 by BOX (Barclays Swaptions Volatility Index).

36 Developmentally, the tested volatility benchmarks' frequencies ranged from daily to quarterly.

37 Different thresholds for the benchmark are tested in correspondence with tested CFSI frequency. Accordingly, the benchmark selected distress threshold is a changing regime of ¾ std (from 4Q 1991–Q1 1998) and ¼ std (from 2Q 1998–current). See Section 5.2.

biweekly BSI, the combined signals of systemic stress are found in 5.1 percent of biweekly periods from the third quarter of 1991 to the fourth quarter of 2011, as summarized in Table 2 (panel A).

Insert Table 2 about here

Applying this identification scheme results in six systemic stress episodes from 4th quarter 1991 to 4th quarter 2011 confirms that many of these episodes have been previously identified in literature. The absence of idiosyncratic events in the identified benchmark episodes supports the efficacy of the biweekly BSI in identifying systemic stress episodes and filtering out inappropriate events.

Insert Fig. 2 about here

5.2. Monitoring Financial Stress

Functionally, as a principal requirement from a supervisor´s point of view, an FSI has to provide a substantial and reliable picture of financial markets' level of systemic stress. Particularly, financial stress has to be identified distinctly from other (idiosyncratic) types of market stress,[38] and an FSI should provide sufficient insight into market sectors to indicate the causes of stress. Accordingly, applications of the CFSI for monitoring are developed from different perspectives: to maintain researcher confidence the CFSI is compared to the benchmark index (BSI) for timing of stress episodes, a rating system for providing grades of stress thresholds is developed, and the overall results from the CFSI are decomposed into single market factors.

As a monitoring tool, the CFSI's main benefit is to allow insight on stress in a number of financial markets. A meaningful reading of the CFSI rides on the underlying assumption of 'no aggregate noise' in the index. Yet, noise is always present in the financial markets. Therefore, the 'no aggregate noise' assumption is really an assumption that uncorrelated simultaneous stress in the normally-functioning markets tends to be arbitraged away through interconnections and transfers between these markets. When this assumption holds, any remaining stress may indicate

[38] Non-financial stress mainly includes shocks from political events, e.g. 9/11, Desert Storm, Iraq War, etc.

a structural 'ailment' in the markets that may not be quickly or easily arbitraged away through normal markets' function.

The increase in the index is seen as an indication of a probable increase in underlying stress, while a possible accidental coincidence is always an underlying explanation (index noise, spurious correlation). For example, the same stress index taken on two consecutive days may represent two vastly different levels of stress, when one day's stress is fueled by spurious coincidences in different markets, while another day's stress is driven by correlated events due to a common structural causal factor. Use of a very high frequency CFSI, such as a daily CFSI, therefore presents a problem of including too much noise. By contrast, use of a very low frequency CFSI, such as an annual CFSI, becomes questionable due to the interim evolution and transformation of the financial markets. To summarize, in using and interpreting the CFSI, it is important to keep in mind that, the aggregate stress index, at best, is only a relative weathervane of directional change in the aggregate stress. Knowledge of such directional change in the CFSI sheds light on the monitoring of systemic stress and helps to relate the probability of an economically meaningful event.

5.2.1. Optimal Monitoring Frequency

Selection of optimal monitoring frequency using the CFSI is sensitive to several considerations. The most significant of these is the ability of the CFSI at a given frequency to filter out idiosyncratic stress episodes. An unbiased evaluation of the filtering properties of the CFSI requires appropriate independent benchmarks. The volatility benchmarks are used to mirror stress in the six markets considered in the CFSI construction. A critical question is how to choose the threshold for determining if a market is in stress. Theoretical precedent for answering this question has been established by prior researchers applying the signaling method.[39] By comparing signaling outcomes of a set of volatility thresholds, we can establish a set of thresholds that minimizes idiosyncratic episodes in a given time period.

Figure 3 shows the results of the Credit Weights financial stress index series selected as CFSI. Shown from September 1991 to January 2012 are the various CFSI frequencies from daily to quarterly. The values of the CFSI are being continually updated (with daily frequency) based

[39] Kaminsky, Lizondo, and Reinhart (1998), Kaminsky and Reinhart (1996, 1999), Borio and Lowe (2002, Asset), Borio and Lowe (2002, Crises), Borio and Drehmann (2009).

on evolution of observed financial stress components. This means that new observations of stress change the components' CDF. The figure provides useful insights about the CFSI's ability to differentiate idiosyncratic (that is, political and non-financial stress) in the markets. As the figure shows, the daily CFSI captures high-frequency market stress, including idiosyncratic stress. The weekly CFSI is only marginally better in reducing the impact on CFSI of very-short-lived idiosyncratic events. The 10-day moving average and quarterly CFSI are significantly better at sifting out episodes of idiosyncratic events that make no lasting fundamental impact on market stress. These results are also observed in Table 2 (panel B).

Insert Fig. 3 about here

To establish an optimal monitoring regime using CFSI, we proceed to establish and test alternative CFSI-based stress rating systems for systemic stress. An optimal CFSI rating system can facilitate monitoring of systemic stress and guide interpretation, similar to Bordo's et al. (2000) use of five grade ranges in the FCI. In addition, the rating approach can help in the determination of the optimal CFSI monitoring frequency. The logic of the CFSI-based rating system is as follows: When the CFSI has a low Z-score, it is unlikely that we are experiencing a stress episode; when the Z-score is high, it is more likely; and when it is moderate, the diagnosis is unclear. As a result, a CFSI rating system that effectively differentiates Z-score ranges vis-à-vis frequency of stress episodes can be ideal for selecting optimal monitoring frequencies and for supervision.

To construct such a system, we divide the range of the Z-score of CFSI into grades, determine how many observations fall into each grade, and compare those observations to the benchmark binary stress series. We use two metrics for the effectiveness of the rating system, Somers' D and the area under the receiver operating characteristic (ROC) curve. Somers' D is a broad metric that shows the degree to which a low rating within the system contains more stress events.[40]

$$Somers'\ D = 2\left[\frac{P(Rating\ Grade_{stress} > Rating\ Grade_{no\ stress}) + P(Rating\ Grade_{stress} = Rating\ Grade_{no\ stress})}{2}\right] - 1 \qquad (7)$$

[40] Technically, it is a measure of association describing the difference of the conditional probabilities. See Somers (1962).

The area under the ROC curve is a measure of the differentiating power of the rating system. For a perfect rating system the ROC statistic measures 100, while ROC for a rating system that is not better than random measures 50.

The results of testing are shown in Table 3. The optimal number of grades depends on the frequency chosen. Overall, it is clear that the rating system at a biweekly frequency with four grades is optimal as it has an ROC of 68.6, Somers' D of 37.1, and is not equivalent to a random rating system at 5% significance.

Insert Table 3 about here

5.2.2. Decomposition of CFSI

A further requirement for FSIs is the ability to provide insight into market sectors and thus the drivers of market stress. As has been argued, the weights of the CFSI's six market components fluctuate as the structure of the financial system evolves. In turn, as these weights change, some market sectors become more or less pertinent relative to others. For example, the weight for the credit markets increased from 0.14 to 0.17 during the subprime crisis, and this sector played an increasing role in the change in CFSI over the crisis. Conversely, the weight for the equity markets decreased from nearly 0.4 in the late 1990s to roughly 0.15 in 2009. Clearly, the equity rebound in the S&P500 Financials after 2007 played a significant role in the decrease in CFSI from its height during the subprime crisis; however, this effect would have been larger if the weight had been as large as in the late 1990s.

Figure 4 shows the movements of specific components within the monthly CFSI, providing insight into the amount of stress that the six distinct markets contributed to the overall stress series. Measures from all markets tend to contribute significantly to the overall financial stress. Their contributions in periods of financial stress tend to rise and fall together, amplifying overall changes on the financial stress. This correlated behavior of stress components does have some exceptions. See Table 6 for a cross-correlation matrix of the sub-indexes and CFSI over time. Consider, for example, the evolution of the subprime crisis of 2007–10. There was an observed initial stress increase in all six markets composing the CFSI at differing times. As the crisis progressed and the Federal Reserve took extraordinary steps to mitigate this stress, CFSI shows a decrease in overall stress starting in late-2009. The most marked drop-offs in stress were first

apparent in the CFSI's risk transfer market component, followed by stress declines in others such as equity and foreign exchange. A similar, but less dramatic pattern can be observed in the latent phase of the LTCM crisis of 1998, as Federal Reserve stabilizing measures were put in place, first reducing stress in the credit markets, then relieving stress in the funding and equity markets.

Insert Fig. 4 about here

This is where observations from individual components of the financial stress offer substantial benefit. Figure 5 decomposes stress in the funding and credit markets respectively from 2Q: 2006 to 2Q: 2012. Figure 5 shows that in the initial phase of the subprime crisis, from March to July 2007, funding markets' stress was primarily driven by growing interbank liquidity spread and bank bond spread. The financial beta accentuated stress only after December 2007. Interbank cost of borrowing became a factor at the height of the crisis, from March 2008 to May 2009. Beginning in May 2009, interbank costs decreased as the Federal Reserve began decreasing the federal funds rate among other less conventional tools.

Figure 5 also shows the components of stress in the credit markets. At the onset of the subprime crisis, from March to July 2007, credit markets' change in stress was mainly driven by increases in the covered interest spread and the commercial paper–T-bill spread, with other spreads remaining relatively steady. At the height of the crisis, from March 2008 to October 2009, increases in the covered interest spread, corporate bond spread, and commercial paper–T-bill spread were the most significant, accentuated by the liquidity spread. As stress in the credit markets subsided toward December 2009, only the corporate bond spread and the liquidity spread remained wide.

Insert Fig. 5 about here

5.3. Alerting Financial Stress

The use of a stress index for supervisory alerts entails two key challenges: first, to the FSI´s ability to identify contemporaneous financial stress and second, to the FSI's ability to allow sufficient alerting time for supervisory actions. The first challenge is the demonstration that a particular set of FSI frequencies is capable of efficiently filtering out idiosyncratic noise events temporarily affecting the markets. To the extent that CFSI fails to do so, a reasonable objection may be made that an EWS model with the CFSI as a dependent variable would aim to predict

political or other non-financial events, which is neither possible nor desirable from a supervisors´ point of view. The second challenge is the acceptability of time losses resulting from a natural lag in the FSI construction. The FSI construction and frequency impose a certain natural lag that sets a minimum tolerance for alerting. For example, a possible application of the Bordo, Dueker, and Wheelock (2000) annual FCI index to EWS would require tolerance of FCI's inability to register the intra-year propagation of unanticipated adverse financial conditions and the loss of up to one year of possible supervisory action. Similarly, the natural limitation of a quarterly CFSI for a EWS is its inability to register the propagation of intra-period systemic stress and the loss of one quarter of supervisory alerting.

Figures 6 and 7 show that the quarterly CFSI indeed possesses these desirable filtering characteristics important for EWS use. The figures compare filtering ability of daily, weekly, monthly, and quarterly CFSIs. While higher-frequency financial stress indexes (daily and weekly) reflect concurrent volatility during systemic stress episodes of both financial and idiosyncratic nature, the quarterly CFSI instead eschews idiosyncratic volatility, reflecting a slower accumulation of financial imbalances.

Insert Fig. 6 about here

Insert Fig. 7 about here

5.3.1. Application of the CFSI rating system to quantification of probability of stress episodes

Analysis of the CFSI-based rating system leads to the determination of optimal thresholds for monitoring financial stress and optimal grades for rating stress episodes.[41] This analytical setting for the continuous CFSI series can also be applied to estimate probability of a systemic stress episode given the timing reference established by the benchmark index. To do so, a probit model has been employed to obtain the implied probability of a stress episode. The probability estimate can be beneficial for guiding supervision as well as for future modeling of systemic stress. The

[41] See Section 5.2 and Table 3. The optimal grade-frequency combination was determined by Somers' D and ROC analysis considering a grade range from 2 to 5 and a frequency range from daily to quarterly. The optimal number of grades for the rating system is four, the optimal monitoring frequency is biweekly, and the optimal threshold is ¾ standard deviations through Q1 1998 and ¼ standard deviations thereafter.

probit model takes the form of

$$Stress = \alpha_0 + \alpha_1 Z_{CFSI} + u \quad (8)$$

$$Stress = -1.344444 + 0.370646 Z_{CFSI} + u \quad (9)$$

As of September of 2011, the range of Z-scores of CFSI (Z_{CFSI}) are divided into grades which have a minimum threshold of 1.84 std (grade 4), 0.57 std (grade 3), -0.70 std (grade 2), and less than -0.70 std (grade 1) (see Table 4 and Figure 9). A higher grade implies a higher probability of stress. Considering figure 8, it is clear that the probability of a systemic stress episode has fluctuated significantly since the peak of the Subprime crisis.

Insert Table 4 about here

Insert Fig. 8 about here

Comparing these results to the Bordo, Dueker, and Wheelock (2000) conjecture for severe and moderate distress thresholds of their annual FCI, our results indicate the need to revise the recommended thresholds. Moderate distress threshold should decrease from 0.75 standard deviations to 0.57 standard deviations. Severe distress threshold should increase from 1.5 standard deviations to 1.84 standard deviations, based on the biweekly CFSI series during 4th quarter 1991 - 4th quarter 2011.

5.3.2. Robustness

Use of the quarterly CFSI (CFSIq) as a dependent variable in a EWS is predicated by the confirmation of its econometric robustness and the analysis of its time series properties. Tests for stationarity and causal relationship (spurious correlation) are essential. To the extent that statistics of a stress series follows a random walk, explaining and forecasting future behavior of stress statistics becomes impossible. If CFSIq is found to be non-stationary, then the EWS researcher would need to verify cointegration, before further EWS model adjustments.

A useful question to ponder is to what extent does CFSIq stress series self predict. The first step toward answering this question is to determine the underlying data generation process for stress. Appendix A (Figure 1A) provides a summary of CFSIq autoregressive properties. As the CFSI correlogram, autocorrelation and partial autocorrelation functions show, the effects of lagged levels of CFSIq tend to dissipate after six quarters. A fairly fast decline indicates that the

long-run development of time series is not affected beyond a certain horizon. This aspect of correlogram is more consistent with a deterministic time series with stationary AR(1) component rather than with a nonstationary series. Thus, the decay of the autocorrelation function suggests a significant autoregressive component to CFSIq in absence of a moving average component.

A possible reason for the autoregressive significance may be the nonstationarity of CFSIq time series. We conduct extensive graphical analysis, including the correlogram analysis, and unit root tests of the quarterly CFSI series and conclude that the quarterly series of the financial stress index can be considered stationary around a deterministic trend at 5% critical level. Results of the CFSI stationarity testing are given in Appendix A (Table 1A). This is a welcome finding as this process shows that CFSI can be used in level form as a dependent variable in a forecasting EWS.

5.4. Analyzing Financial Stress

In addition to monitoring and forecasting functions an FSI may be used for analyzing the pattern of systemic stress series. As discussed by Boyd, De Nicolò, and Loukoianova (2010), Berger et al. (2011), the pattern of systemic episodes can be influenced dynamically by the supervisory and regulatory actions. Thus, from a supervisors perspective, it is particularly important to carefully consider the dynamic effects of these actions on the pattern of systemic stress. Particularly, in this section evidence is presented that the CFSI time series supports a structural connection between the pattern of systemic stress episodes and financial deregulation. Drawing on literature and own data, there appears to be “no free lunch” in reducing risk. Greater growth and risk reduction for individual institutions in good times are accompanied by adverse systemic risk effects in bad times. Our evidence first suggests that the frequency of systemic stress episodes remains consistent pre- and post-U.S. financial deregulation. Second, we observe that in post-deregulation the speed of systemic stress propagation slows (the benefit of risk diversification for individual institutions). However, the length of the recovery from systemic stress also slows substantially (the penalty of universal banking for the financial system).

Considering figure 9, a pronounced difference in patterns of stress volatility prior to and after 1998 can be noted. While the frequency of stress episodes is generally similar among the different candidate series, their duration appears substantially different. Pre-1998 stress episodes tend to be short relative to post-1998 episodes which tend to last longer, taking more time to dissipate. Additional insight into the apparent pattern in stress episode duration can be obtained

by considering the rate of change in financial stress series per unit of time (dZ_{FSI}/dt). The physical meaning of this is the velocity or variation over time (volatility) of financial stress. Higher values of velocity (volatility) of stress at the episode's onset (resp. recovery) indicate faster evolution of critical states (resp. faster recovery). Lower values of velocity (volatility) of stress at onset (resp. recovery) indicate longer onset of stress (resp. slower recovery).

Insert Fig. 9 about here

Figure 9 supports the observation, that there may be a change in the stress pattern pre-1998 and post-1998. Pre-1998 stress velocity is characterized by sharp swings in Z_{CFSI} prior to crises episodes within a more volatile bandwidth: generally from -0.5 std to +0.5 std and 2 to 4 times higher at onset of crises. Post-1998 stress velocity bandwidth is roughly half: from -0.25 std to +0.25 std along with some outliers, while also amplifying something like 2 to 4 times at onset of crises. This describes a slower evolution of crisis (a welcome pattern) and slower recovery from crisis (an unwelcome pattern) after 1998. Further clarity can be obtained by directly considering the distribution of duration of stress episodes pre- and post-1998, shown in figures 10 and 11. Both the CFSI and volatility benchmarks indicate a similar pattern of increase in duration of stress episodes in the post-1998 period.

Insert Fig. 10 and Fig.11 about here

Our evidence supports the idea that the change in pattern only affects the duration of stress episodes and not their frequency. Table 5 confirms the observation that frequency of systemic stress episodes remains generally consistent in both pre-1998 and post-1998 periods.

Insert Table 5 about here

5.4.1. Financial deregulation and structural change

One possible explanation for this pattern is a structural change in the U.S. financial system. Indeed, 1998 was marked by the groundbreaking of a re-built U.S. financial architecture and the summoning of a new era of financial consolidation and universal banking.[42] The U.S. Financial Services Modernization Act (aka Gramm-Leach-Bliley Act) became law in 1999, bringing down

[42] See Calomiris (2000) and Wilmarth (2005).

structural separation that existed between commercial banks, investment banks, securities firms, and insurance companies.

There is a strong empirical link between regulation and systemic crises. Miron (1986) finds that prior to the creation of the Federal Reserve, banking panics in the United States were seasonal. Freixas and Rochet (2008) find that many financial crises worldwide have been in part initiated by a global movement toward financial deregulation as supported by a large number of empirical studies of the relationship between crises and regulation. Kaminsky and Reinhart (1999, p. 480) suggest that "crises may have common origins in the deregulation of the financial system and the boom-bust cycles and asset bubbles that, all too often, accompany financial liberalization." Caprio and Klingebiel (1996, pp. 24, 30) provide cross-country evidence of a natural lag between financial liberalization and adjustment of regulatory structure and supervisory practices, which may partially explain the link between deregulation and banking crises. Mishkin (1997, p. 28) emphasizes this point in discussing the U.S. savings and loan crisis: "deregulation of a financial system and rapid credit growth can be disastrous if banking institutions and their regulators do not have sufficient expertise to keep risk taking in check." There are numerous empirical studies supporting this connection, for example McKinnon and Huw (1996), Sachs et al. (1996), and Weller (2001). In an extensive empirical review of U.S. bank deregulation, Calomiris (2000, p. 3) finds that "the single most important factor in banking instability has been the organization of the banking industry."

Another mechanism linking deregulation and systemic risk is risk diversification. Universal banking allows financial intermediaries to grow larger and more diverse, thereby benefiting from more efficient portfolio diversification to take larger risk. Post Glass-Steagall Act of 1933 and the Bank Holding Company Act of 1956 and prior to the financial deregulation of 1999, U.S. financial intermediaries were not allowed to become universal banks. From the viewpoint of an individual universal bank, a larger and more diverse bank is more insulated from the risk of failure and, thus, could be individually safer. Paradoxically, as more institutions become larger and universally alike, once crisis sets in, contagion among institutions can be expected to persist longer and recovery can be expected to take more time. The apparent safety of an individual large and diversified financial institution is also the source of moral hazard and an implicit too-big-to-fail subsidy. Reviewing studies of systemic risk in a post deregulation era, Wilmarth (2005) writes that "doubts about the claimed advantages of universal banks are buttressed by

concerns that financial conglomeration will aggravate the problem of systemic risk in financial markets."

We can deduce that at least one structural break occurred over the period around August 1998. A formal test is appropriate to interpret such breaks empirically. We make use of the Quandt likelihood ratio statistic[43] to test for breaks at dates within the 15 percent trimmed monthly series. We consider the first order difference equation with one lag of Z_{CFSI} to test for a structure break. As Fig. 12 shows, the maximum Quandt likelihood ratio statistic occurs in August 1998 (F-statistic = 12.12) which is statistically significant at a 1 percent critical value. There is an additional statistically significant period in July 2007 (F-statistic = 6.70) which is statistically significant at a 5 percent critical value.

Insert Fig.12 about here

These results are welcome as they yield the possibility of multiple structure breaks. The first break, indicated likely in August 1998, corresponds to the announcement of Financial Services Act passage by the U.S. Senate, leading up to the U.S. Financial Services Modernization Act later in the year. The second break, indicated likely in July 2007(see Fig. 12), corresponds to mounting frictions in the financial markets that would result in the financial crisis.[44]

5.4.2. Comparison of sector stress, financial system stress, and alternative stress measures

As argued before, financial system stress can be considered a common, systematic factor affecting various markets that compose the financial system. In addition to the common factor, stress in each of these markets will also show idiosyncratic features. Thus, a supervisor may generally anticipate that correlation among stress in the various markets would not equal to +/- 1. As a critical observer of the markets, the supervisor is well aware of empirical findings that patterns of volatility of asset returns change over time and across markets.[45] Furthermore, a

[43] See Quandt (1960).

[44] Specifically, September 2007 marks several key crisis timeline events (see Federal Reserve Bank of New York 2010). August 2007 registers first signals of the subprime valuation shock (BNP Paribas). The immediate aftershocks are both domestic (tri-party repo financing issues at Countrywide) and international (Northern Rock run).

[45] See Fama and French (1989), Schwert (1989), Shiller (1989). Fama and French (1989, p. 23) find spread-based patterns of "common stocks and long-term bonds contain a term or maturity premium that has a clear business-cycle pattern (low near peaks, high near troughs)." They also find that spreads "contain a risk premium that is related to longer-term aspects of business conditions. The variation through time in this premium is stronger for

supervisor may also anticipate that stress patterns in different markets may generally also be different over time and across markets.[46] The supervisor then is particularly interested in the relationship of stress within a particular market to financial system stress, how it may change over time, and what aspects of the changing pattern the supervisor should watch out for.

Here, the operational logic of CFSIs systemic stress identification provides a valuable roadmap—*systemic stress is two consecutive periods of distress above previous period thresholds, or concurrent distress in at least two distinct markets.* This operational guide enables the supervisor to observe significant stress alerts both within a particular market and in the system, as stress signals that begin propagation through several markets. As argued below, this identification offers a supervisor significant time advantage in the interpretation of observations of the financial system stress.

A skeptic of the CFSI would point out the generally accepted fact that the housing bubble peaked in 2006, but financial system stress did not begin to accumulate until the 3rd quarter of 2007. The evidence shows that monthly housing prices[47] from April 2006 to March 2007 remain nearly flat and then decline in April 2007. Quarterly housing prices[48] flatten from September 2005 to June 2006, declining in September 2006. Both housing price indexes are observable with lags: three months lag for monthly data, and two quarters lag for quarterly data. This means that a critical supervisor focused on the housing prices will not be alarmed by quarterly data until the spring of 2007 and not until July 2007, if only higher frequency monthly data is observed. In fact, CFSI's rate of change is extraordinarily fast beginning spring 2007, but because CFSI remains at historically low levels of overall stress, observations of the CFSI trigger moderate stress alarms (grade 3) only in mid-August 2007, an important loss of several months of information.

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low-grade bonds than for high-grade bonds and stronger for stocks than for bonds." Shiller (1989, p. 1) finds that "Financial market prices, prices of stocks, bonds, foreign exchange, and other investment assets, have shown striking changes in volatility through time. For each of these kinds of assets there are years when prices show enormous unpredictable movements from day to day or month to month, and there are years of stable, uneventful markets."

46 Few would contend that market stress should be endogenously driven and significantly so. At the same time, Brock and Hommes (1997, 1998), and Hommes (2006) find that presence of heterogeneous beliefs of boundedly rational agents is sufficient for spread-based stress to evidence non-linear patterns of "strange chaotic attractors" across markets and time.

47 S&P/Case-Shiller Home Price Index: Composite 20 (seasonally adjusted). Source: Haver Analytics.

48 S&P/Case-Shiller Home Price Index: U.S. National (seasonally adjusted). Source: Haver Analytics.

However, the critical supervisor guided by the CFSI's operational roadmap to systemic stress does have a significant informational advantage. Observing stress in individual markets (Figure 13), the supervisor can observe systemic stress alarms almost one year earlier. In June 2006, both funding sector stress and FX sector stress ring alarm bells of a systemic episode by the operational definition of stress signal.[49] Raw data from funding and FX markets for the CFSI is available daily and accompanied by estimated sector weights. The market stress observations are adjusted with one quarter lag, when re-estimated sector weights become available. Therefore, observant supervisors should recognize a systemic stress episode sometime between June and September 2006.[50]

Insert Fig.13 about here

Table 6 compares correlation of stress within individual financial sectors of CFSI in various financial system regimes. Panel A shows the correlation over the entire period. Panel B recognizes distinct behavior based on three different regimes, bounded by the two structural breaks (in 1998 and 2007) discussed in Section 4.4.1., figure 13 compare stress in individual sectors to overall financial system.

Insert Table 6 about here

Table 6 and figure 13 taken together suggest three summary comments and several detailed observations. First, it is clear that information from correlations, and particularly from the change in correlations, provides additional insight into the changing patterns of stress. Second, correlations from Panel A provide a benchmark for the assessment of sector correlations in different regimes. They show the extent, relevance, and dynamics of stress in individual markets relative to the financial system. Third, the change in correlation pattern across regimes and markets clearly shows that single markets have unique and changing patterns of relationship with

[49] After 2Q 1998, stress is signaled when observed stress exceeds previous quarter's benchmark by ¼ std.

[50] It is appropriate to note those supervisors that observed the evolution of systemic stress episode at this time with foresight or intuition. There were many observers with critical insight (Subprime crisis impact timeline, n.d.)—institutions, including JPMorgan Chase, AIG, Commerzbank, and Goldman Sachs; regulators, including Federal Reserve and Bank of International Settlements; and academics, including Robert Shiller and Nouriel Roubini. In addition there were many named and nameless traders that acted on their observations of market stress and trends (Lewis, 2010), well in advance of the herd that was to emerge a year later: "By the fall of 2006, the housing market was dipping, and big insurance companies, pension funds and other institutional investors were turning away from any investments tied to mortgages" (Bernstein and Eisinger, 2010).

overall financial stress. The comparisons of sector stress with financial system stress supports the argument that individual sectors may not be considered redundant and overlapping. The different correlations, and particularly the change in correlations across regimes, make evident the idiosyncratic character of stress in individual markets and further substantiate a supervisor's logic in considering their contribution to overall stress. A market that consistently has a zero correlation with overall stress (say, a market for cotton) probably adds no new information. This market contrasts with markets like equity or credit which are always relevant and important to the financial system. The changing pattern of high and low correlations (as in the funding and real estate markets) or the positive and negative correlations (as in FX and securitization markets) means that these markets add significant information value to the financial system stress.

Table 6 also enables a supervisor to make several detailed observations with interesting economic interpretations. Correlation behavior of each sector from 1991 to 2012 provides indirect support for the occurrence during this timeframe of three distinct regimes bounded by two structural breaks in the CFSI. The funding sector is uncorrelated with the CFSI during regime 2 (1998-2007) which is characterized by the U.S. deregulation and the build-up of the real estate asset bubble. This is intuitive, as the funding sector experienced little stress in this boom period. At the same time, the funding sector is strongly positively correlated with the CFSI in the crisis regime (post 2007) and has a small positive correlation with CFSI in the pre-deregulation U.S. regime. The FX sector shows generally small positive correlation (regimes 1 and 2), except that during crisis (regime 3) it shows a medium negative correlation, i.e. tends to vary inversely with CFSI. This is intuitive, as the FX sector reflects the flight capacity of international capital away from the crisis regime. The equity sector appears the most stable sector over time that is strongly correlated with overall stress in all three regimes. This is consistent with the view that equity markets tend to efficiently arbitrage away the idiosyncratic (diversifiable) risk factors of publicly-traded companies. The credit sector shows medium positive correlation in regime 1, and strong positive correlation in regimes 2 and 3. In all regimes the credit sector is less strongly correlated with CFSI than the equity sector. This is also intuitive—as a market for private debt, the credit sector reflects greater opacity, greater information asymmetry, and greater need for monitoring than the equity sector. The real estate and securitization markets present arguably the most interesting comparisons with overall stress.

While overtime real estate appears non-correlated with CFSI, it shows a medium positive correlation with CFSI in regime 1, a strong positive correlation in regime 2, and no correlation in regime 3. This is somewhat intuitive, as real estate in regime 2 (deregulation before crisis) served as a principal asset class contributing to the expanding bubble and the corresponding euphoric reduction in overall stress. In regime 3 (crisis), the real estate sector has been squeezed and deflated and remains in this state, transferring practically no further impact on overall stress. The securitization sector shows medium negative correlation prior to financial deregulation, no correlation in regime 2 (deregulation prior to crisis), and strong positive correlation in regime 3 (crisis). These statistics suggest that securitization markets tended to offset financial system stress in regime 1, and that the nature of the interaction changed with deregulation.

Interestingly, Table 6 also provides evidence that the CFSI and alternative indexes such as indexes employed by The Federal Reserve Banks of Kansas City, St. Louis, and Chicago are not consistently correlated over time. Regime 1 data shows that the CFSI and alternative indexes are trivially or even negatively correlated, both contemporaneously and across time. This may be due to the nonexistence of substantial periods of financial stress. It may also be due to the diversity of components and weighting methodologies employed by such indexes. The correlation data implies that CFSI may be more accurate at capturing the stress episodes during the first regime. Moving to more recent regimes of deregulation and crisis, the correlations become somewhat stronger but remain relatively low. This pattern indicates that the differences between the various financial stress measures are significant with regards to the objective of supervising the financial system.

6. Conclusions

Based on an analysis of supervisory objectives and a definition of systemic stress a specific index to monitor risk in financial markets, the CFSI, is developed. While assessing both the level and factors of financial stress, the CFSI provides supervisors with a continuous alert in the context of stress development in the financial markets. A leading principle for the architecture of an FSI for supervision is to combine significant elements explaining stress in the distinct financial markets in a comprehensive way and consistent with the user's objectives of supervising the financial system. Considering this, the index construction methodology explores different indicators for systemic stress, alternative weighting schemes for aggregating them, as

well as various frequencies for monitoring and forecasting. For the U.S. financial markets, the CFSI extension of prior conceptual and empirical literature enables an assessment of concurrent financial system stress that is useful for supervision as an activity of critical observation. The factors of this measure are comprised of spread based variables from six distinct markets and are aggregated via dynamic credit weights. The CFSI results have been benchmarked to a reference series of financial stress signals recognized by literature and captured by price volatility measures in the relevant financial markets.

A specific challenge when assessing systemic stress is to discriminate stress signals reliably. Effective application of a stress index for early warning specifically hinges on the index capacity to differentiate idiosyncratic risk. A desirable FSI frequency would minimize presence of idiosyncratic stress episodes. The optimal stress-signaling regime and CFSI frequency are therefore investigated. It is shown that the construction method for CFSI is optimal under a variety of monitoring cycles. Particularly, as a quarterly series CFSI provides dependable filtering of idiosyncratic stress episodes, making it potentially useful as a dependent variable in an EWS for systemic risk.

The CFSI is applied for different supervisory purposes: monitoring, alerting, and analyzing. First, monitoring capacity of CFSI is activated by the transparency of its component decomposition. This allows for intriguing interpretations of economic conditions showing that individual CFSI components had a changing impact across different crises. Analysis of the CFSI levels and decomposition of its components permits as well detailed observations of the effects of regulatory measures to reduce systemic risk through specific financial stress components. Second, CFSI's suitability for alerts of systemic risk conditions is established by examining the autoregressive and Granger properties of CFSI. It is further extended by the use of signaling to identify systemic stress episodes, the establishment of CFSI grade thresholds and the corresponding probability of systemic stress. Third, the analytical potential of CFSI provides useful insights into the structural aspects of the financial system, particularly the connection between the pattern of systemic stress episodes and regulatory change.

While the CFSI displays promising results for assessing and analyzing financial stress and therefore providing information for supervisors to act, further aspects may be discussed to improve the CFSI as a measure of financial system stress. Additional data, technical considerations, and new applications are primarily to be considered. The construction of an FSI

may be enhanced by further tests of financial stress data from extended and more recent time series and from applying the CFSI to alternative financial markets. A particular focus can be extended to the use of an FSI in a supervisory EWS capable of monitoring and forecasting the effects of structural change in the system for systemic stress, including both regulatory and market driven changes. Given the multiplicity and dynamics of financial crises, it may be reasonable for these applications to consider the use of a specific measure of financial stress like CFSI in conjunction with other measures of systemic risk.

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Figures and Tables

Figure 1 - Conceptual model financial system's stress.

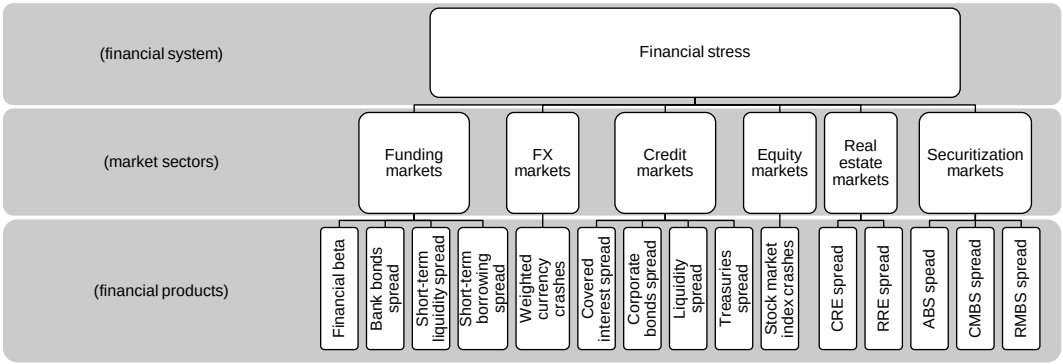


Figure 2 - CFSI vs. benchmark index of systemic stress episodes.

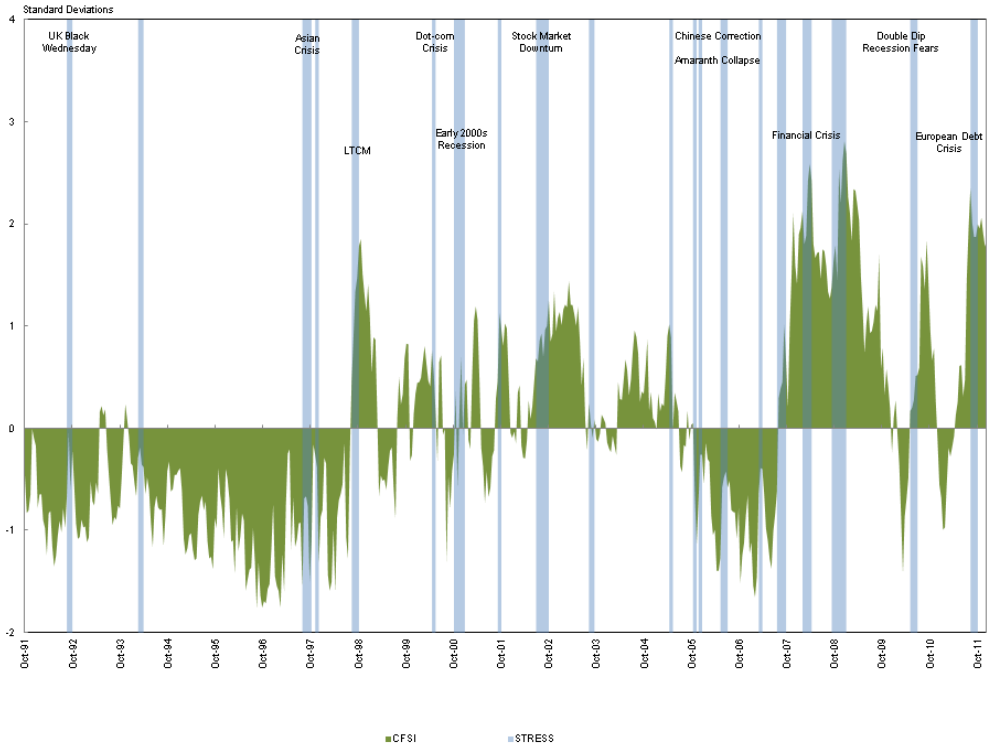


Figure 3 - CFSI (Sep. 1991 – Jan. 2012)

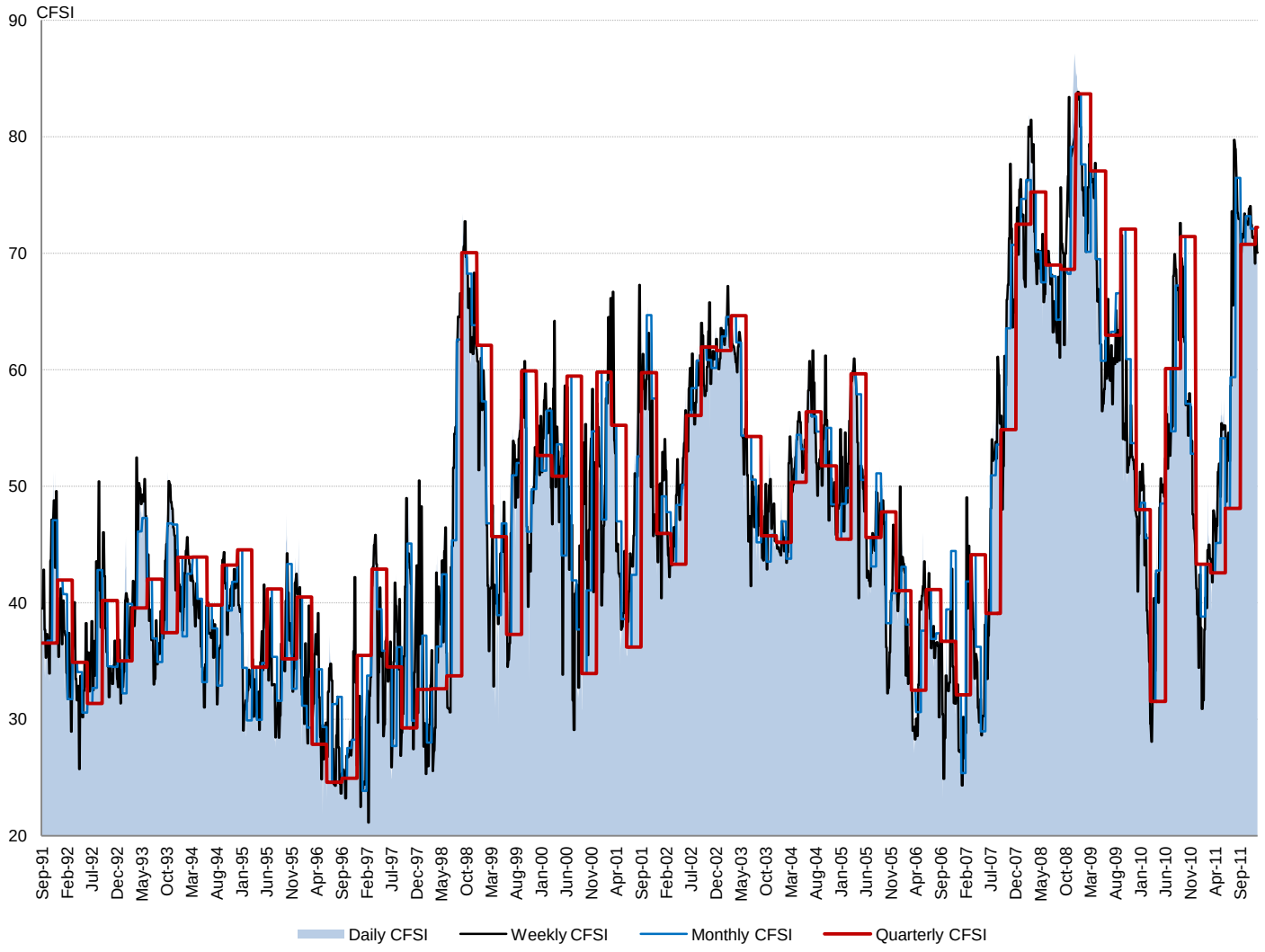


Figure 4 - CFSI components

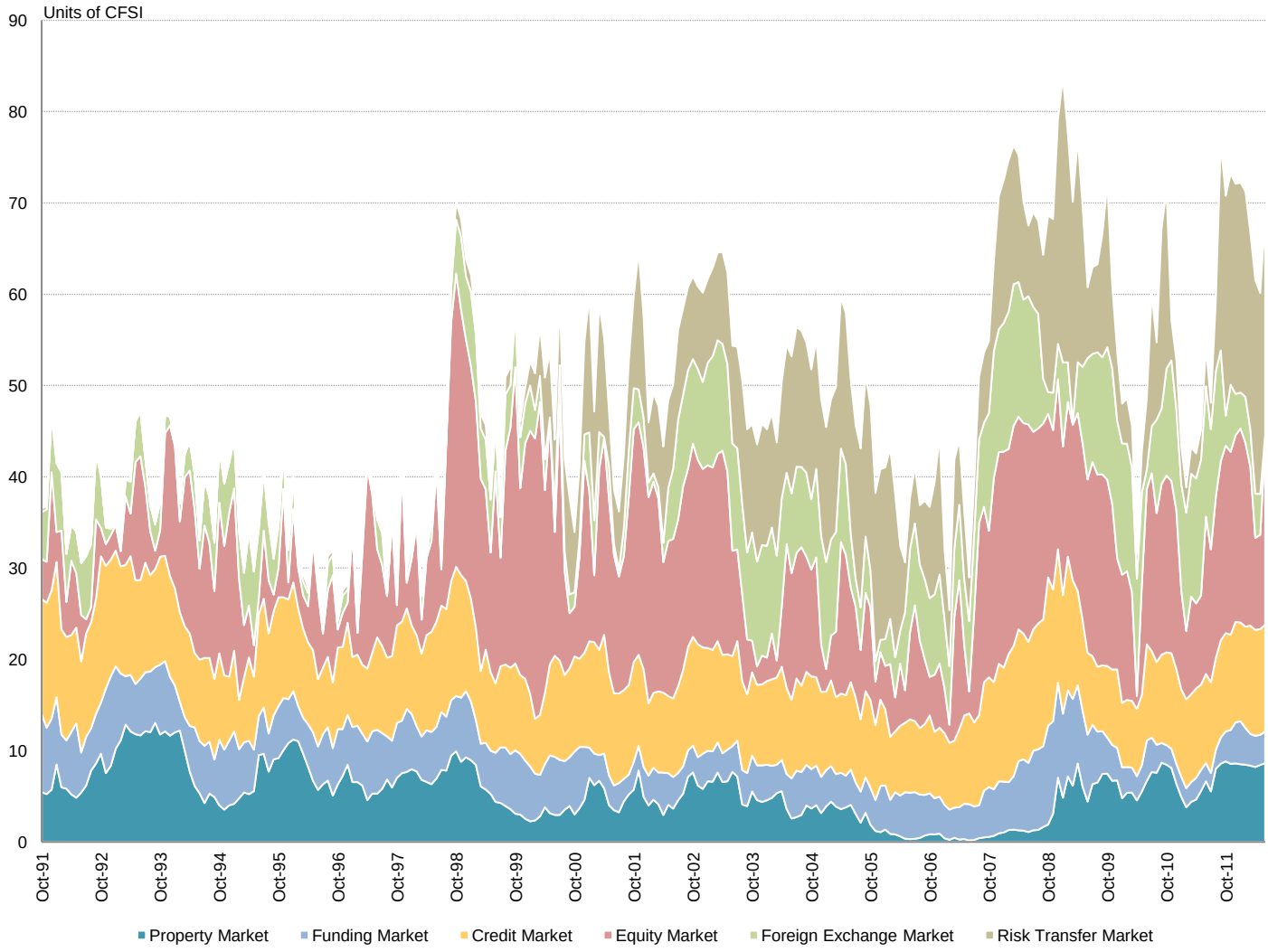
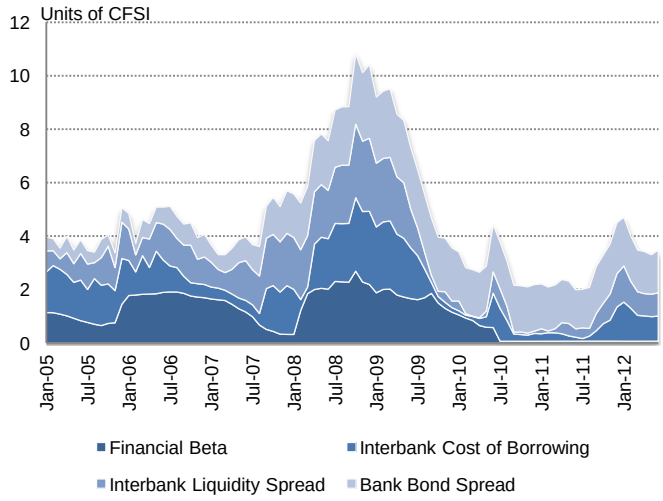


Figure 5 - Components of stress in funding and credit markets (1Q 2005 – 4Q 2011)



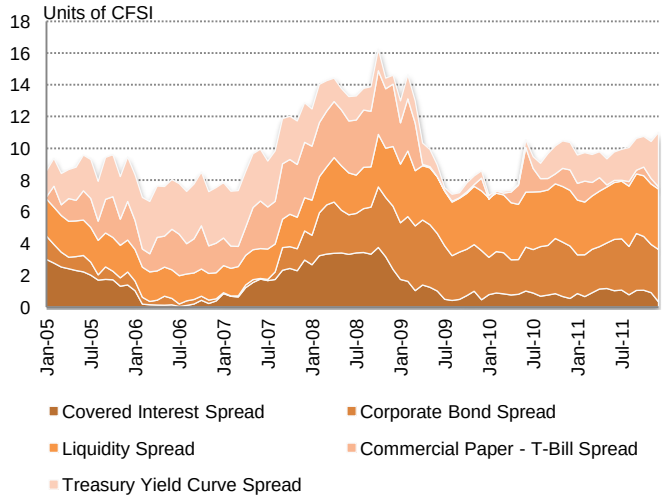


Figure 6 - Selected Financial Systemic Stress Episodes: Quarterly Dependent Variable vs. High Frequency FSI

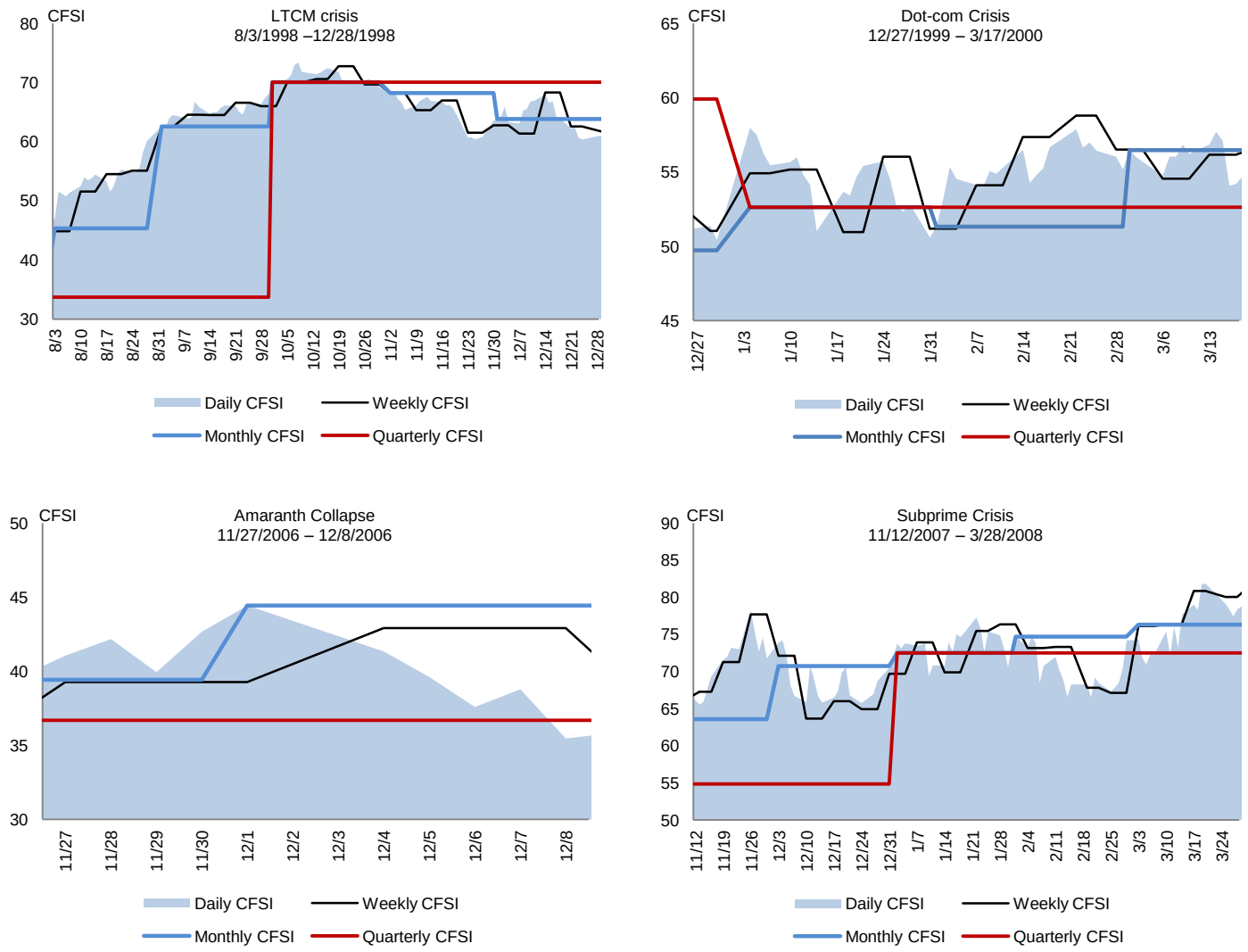


Figure 7 - Selected Idiosyncratic Systemic Stress Episodes: Quarterly Dependent Variable vs. High Frequency FSI

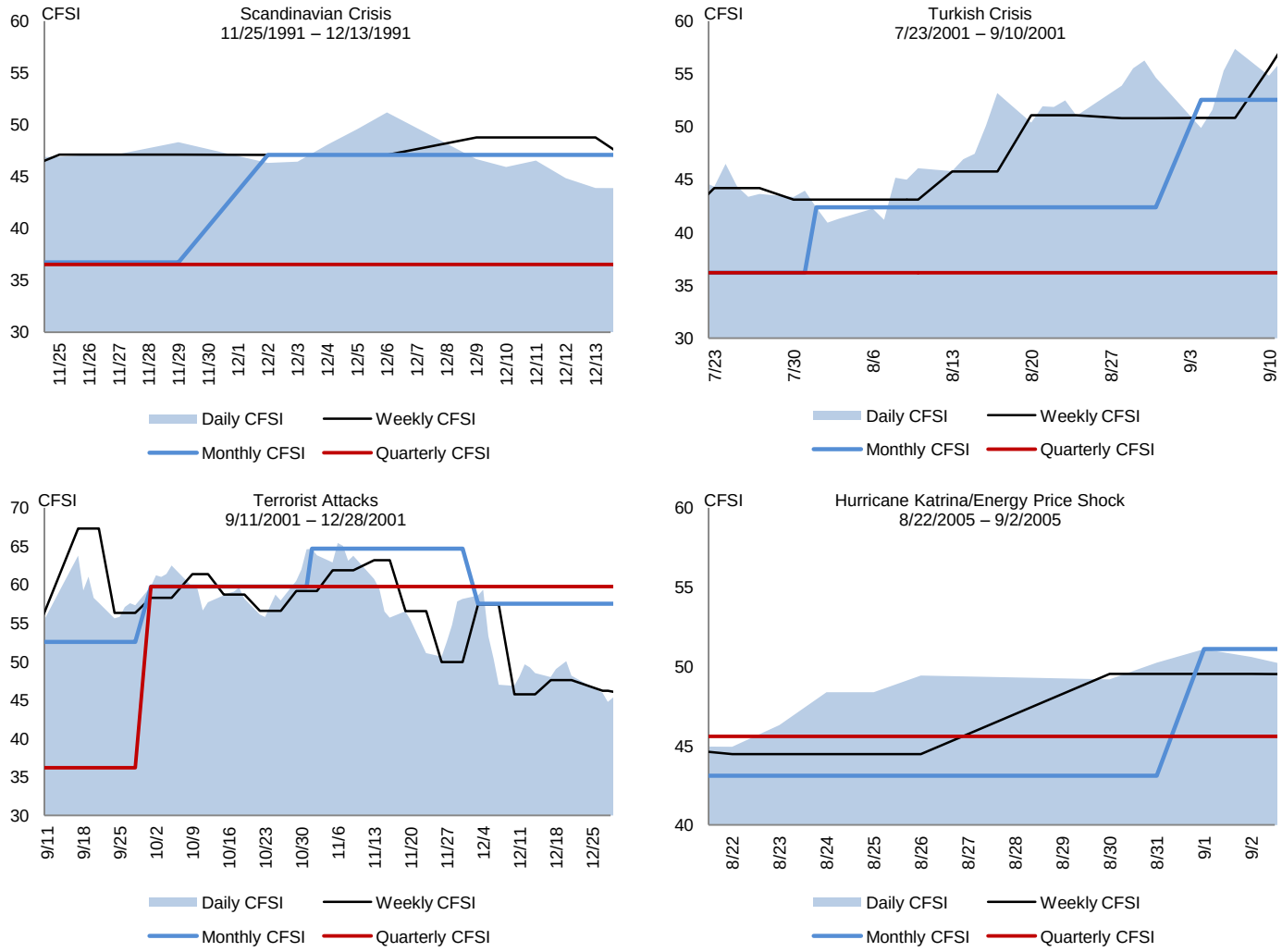


Figure 8 – Implied probability of systemic stress episode.

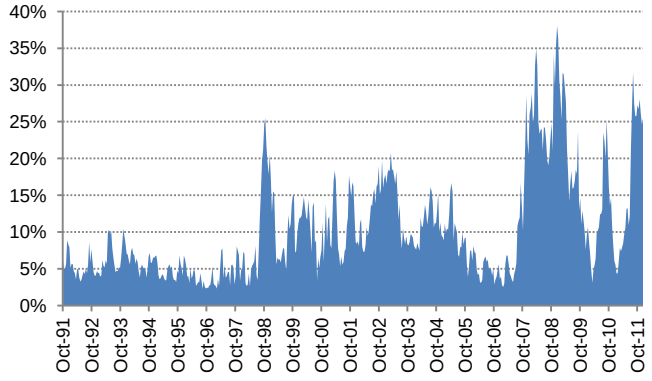


Figure 9 - Velocity of financial stress (4Q: 1991–4Q: 2008). Crisis bars are based on the Federal Reserve Bank of Cleveland's expert survey, in which larger bars reflect scaled judgment of greater significance.

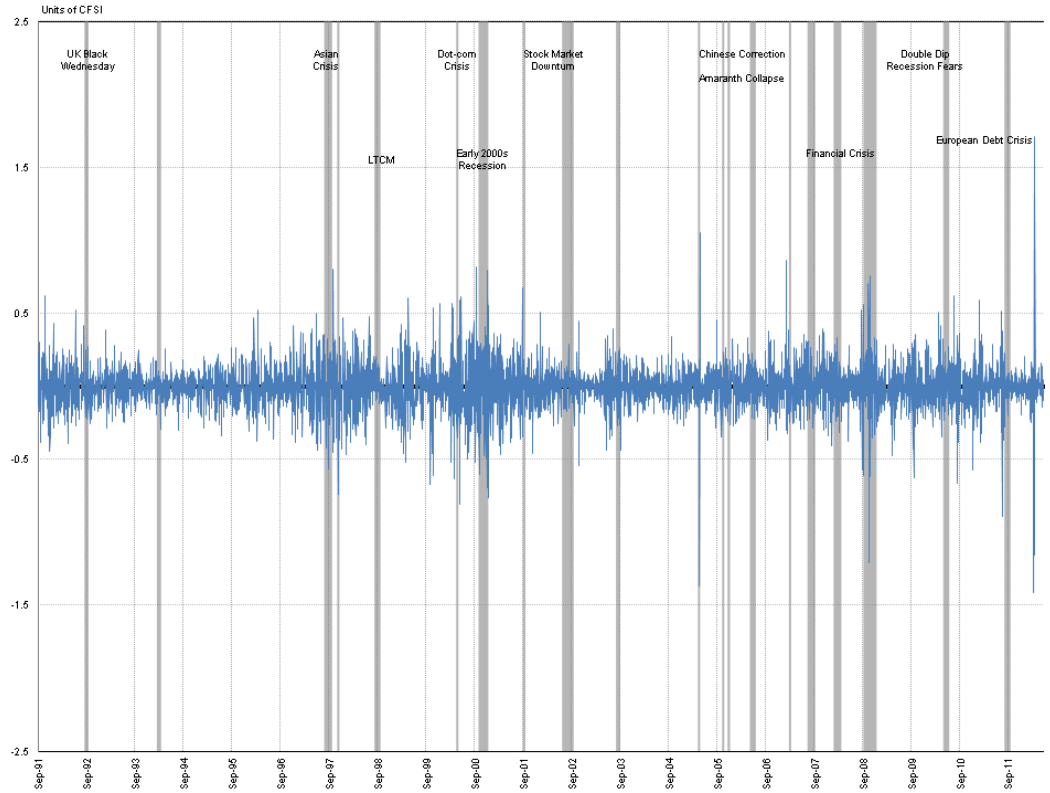


Figure 10 – Duration distribution of CFSI systemic stress episodes (months).

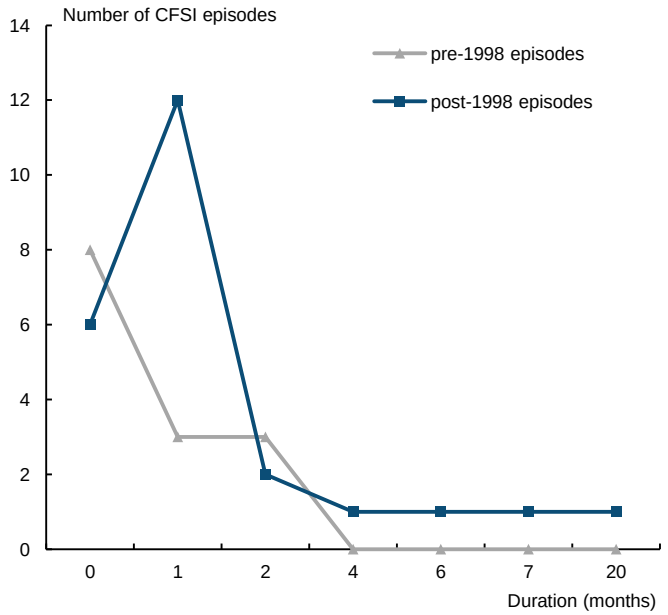


Figure 11 - Duration distribution of benchmark systemic stress episodes (quarters)

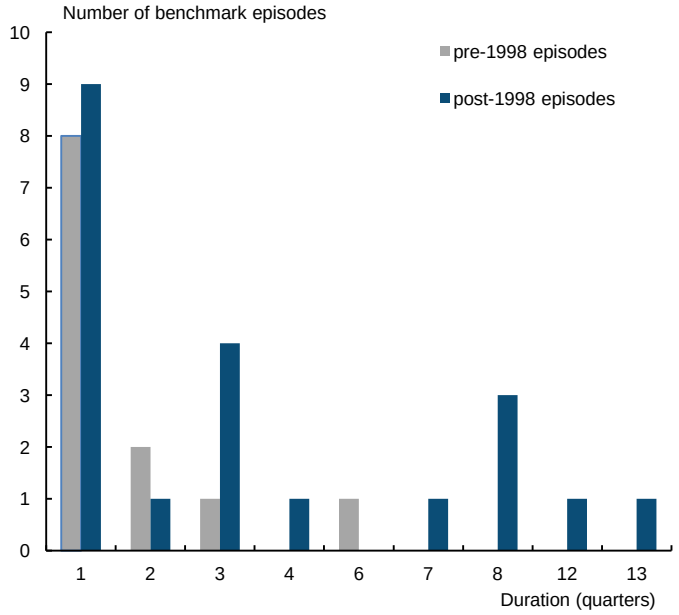


Figure 12 - Quandt likelihood ratio testing for structural break in Z_{CFSI}

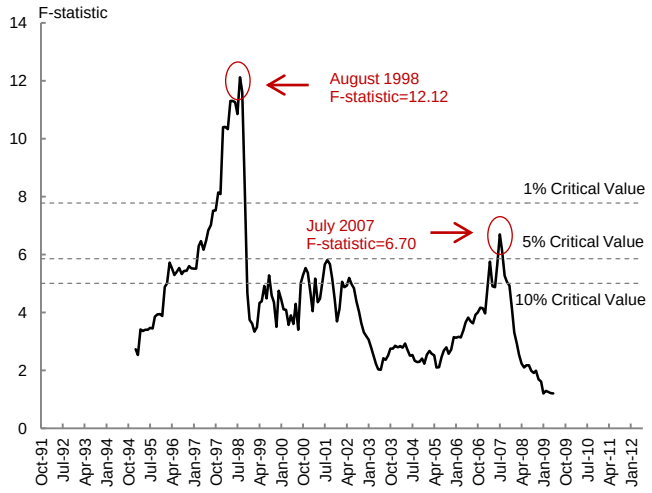


Figure 13 - Market sector stress and CFSI

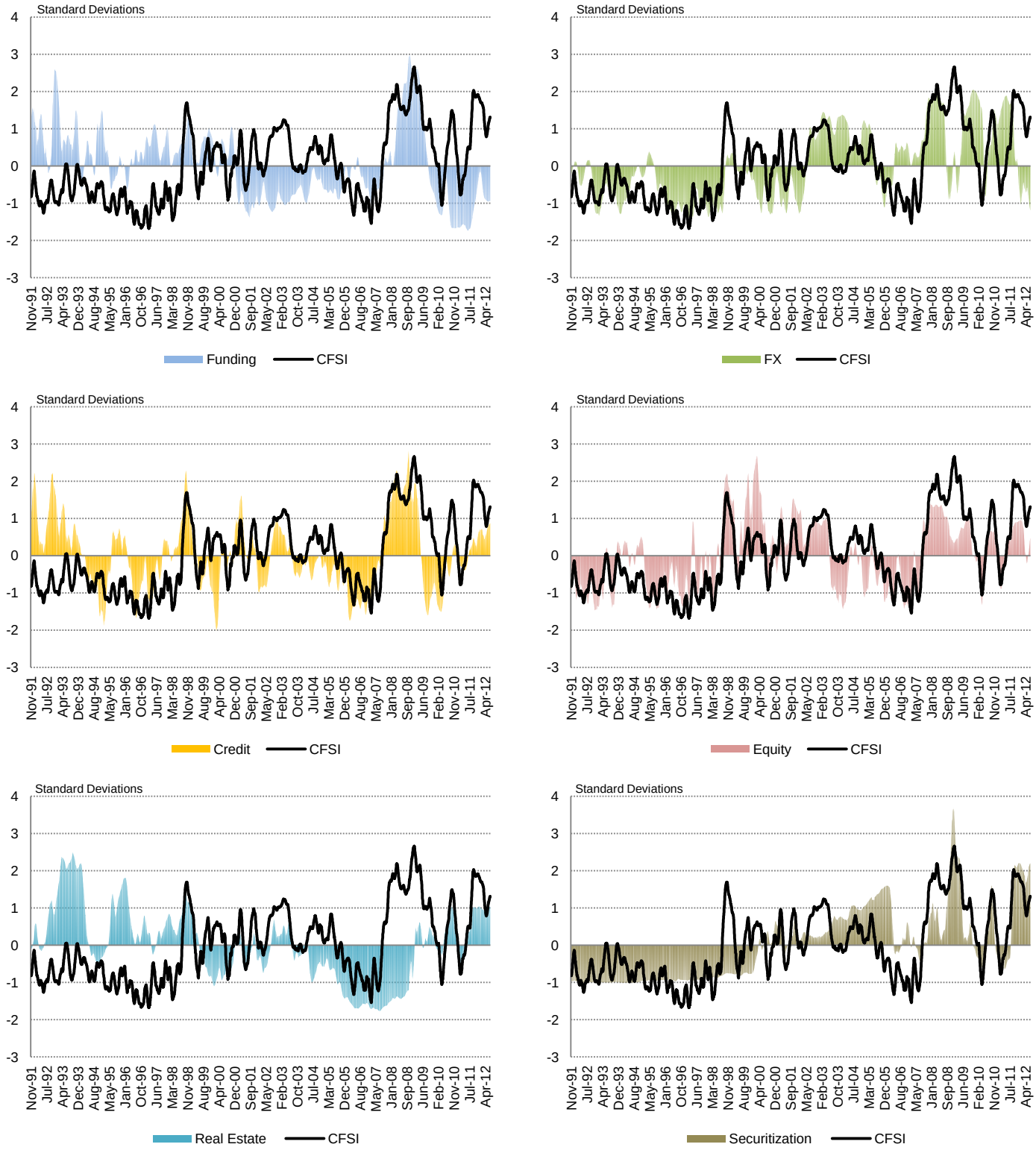


Table 1 - Financial Stress Index construction variables.

Market Sector	Financial Product	Significance	Calculation	Notes
Funding Markets	(1) Financial beta	strain on bank profitability, and potentially solvency, in light of changes in profitability of publicly-traded companies economy wide	$Financial\ Beta_t = cov(r_t\|_{t-1}^{t}, m_t\|_{t-1}^{t}) / var(m_t\|_{t-1}^{t})$	r is banking sector share prices (S&P 500 Financials), m is overall stock market share prices (S&P 500), (t, t-1) are observations from time t to one year prior
	(2) Bank Bond Spread	perceptions of medium- to long-term risk in banks issuing bonds rated A, medium- to long-range risk to high quality bank profits	$Bank\ Bond\ Spread_t = 10A_t - 10TB_t$	10A refers to ten-year A-rated bank bond yields and 10TB to ten-year Treasury yields (a composite computed by Bloomberg for its C07010Y Index – 10-year A-rated Bank Bond Index)
	(3) Interbank Liquidity Spread	TED spread, difference between the LIBOR and Treasuries rate, evidence on counterparty and liquidity risk in interbank lending	$Interbank\ Liquidity\ Spread_t = 3mo\ L_t - 3mo\ TB_t$	3mo L is 3 month LIBOR rate and 3mo TB is 90-day Treasury Bill secondary market rate
	(4) Interbank Cost of Borrowing	risk premium banks charge to borrow from one another, indicator of counterparty risk	$Interbank\ Cost\ of\ Borrowing_t = 3mo\ L_t - FFR_t$	3mo L is 3-month LIBOR and FFR is the Federal Funds Target Rate
Foreign Exchange (FX) Markets	(5) Weighted Dollar Crashes	quantifies flight from the U.S. dollar toward foreign currencies, sense of uncertainty or liquidity demand system-wide	$Weighted\ Dollar\ Crash_t = \frac{x_t}{max[x \in (x_{t-j} \| j = 0,1,\ldots,365]}$	x is the Trade weighted $U.S. Exchange Index
Credit Markets	(6) Covered Interest Spread	uncertainty regarding government bond markets, difficulty in acquiring liquidity for governments signaling the onset of stress	$Covered\ Interest\ Spread_t = (1 + r_t^*) - \left(\frac{F_t}{S_t^*}\right)(1 + r_t)$	r* is the 90-day UK Treasury Bill rate as of noon on day t, F is the 90-day forward rate for the UK-U.S. exchange rate, S* is the spot UK-U.S. exchange rate, and r is the 90-day U.S. Treasury Bill rate
	(7) Corporate Bond Spread	measures medium- to long-term risk, impressions of risk to corporations in all sectors	$Corporate\ Bond\ Spread_t = 10CB_t - 10TB_t$	10CB is the 10-year Moody's Aaa rated Corporate Bond yield and 10TB is the 10-year Treasury yield
	(8) Liquidity Spread	changes in the short-term trend of differences in Bid Prices (BP) and Ask Prices (AP) on 3 month Treasury Bills, measure of an instrument's liquidity	$Bid\ Ask\ Spread_t = (\frac{1}{30}) \sum_{i=0}^{29} \left[\frac{AP_{t-i} - BP_{t-i}}{\left(\frac{AP_{t-i} + BP_{t-i}}{2}\right)} \right]$	moving average is calculated over the previous thirty trading days
	(9) 90-Day Commercial Paper-Treasury Bill Spread	measures the short-term risk premium on financial companies' debt	$90day\ Commercial\ Paper\ Treas.Spread_t = (90day\ CP_t) - (3mo\ TB_t)$	90day CP 90-day is Financial Commercial Paper (CP) rate and 3mo TB is 90-day Treasury Bill secondary market rate
	(10) Treasury Yield Curve Spread	slope of the yield curve as a combination of long-term uncertainty and short-term liquidity needs, predictor of recessions	$Treasury\ Yield\ Curve_t = (\frac{1}{30}) \sum_{i=0}^{29} (10yr_{t-i} - 3mo_{t-i})$	thirty-day moving average, difference between three-month Treasury Bill yields (3mo) on a bond equivalent basis with ten-year constant maturity yields (10yr)
Equity Markets	(11) Stock Market Crashes	extent to which equity values in the S&P 500 have collapsed over the previous year, expectations about the state of banks	$Stock\ Market\ Crash_t = \frac{x_t}{max[x \in (x_{t-j} \| j = 0,1,\ldots,364]}$	x refers to the S&P 500 Financials Index
Real Estate Markets	(12) Commercial Real Estate Spread	measures the risk associated with investing in commercial real estate relative to a risk free financial instrument	$Commerical\ Real\ Estate\ Spread_t = CRE_t - 20TB_t$	CRE refers to the price of commercial property given by the NCREIF Commercial Property Index and 20TB is the price of a 20-year Treasury Bond
	(13) Residential Real Estate Spread	measures the risk associated with investing in residential real estate relative to a risk free financial instrument	$Residential\ Real\ Estate\ Spread_t = RRE_t - 20TB_t$	RRE refers to the seasonally adjusted price of residential property given by the S&P/Case-Shiller National Home Price Index and 20TB is the price of a 20-year Treasury Bond
Securitization Markets	(14) Asset-Backed Security Spread	measures the ability of originators to raise capital and the relative riskiness of the securitized asset	$Asset-backed\ Security\ Spread_t = ABS_t - 5TB_t$	ABS is the asset-backed bond yield (SYCAAB@USECON) and 5TB is the yield on a 5-year Treasury Note
	(15) Commercial Mortgage-Backed Security Spread	measures the ability of originators to raise capital and the relative riskiness of the securitized asset	$Commercial\ MBS\ Spread_t = CMBS_t - 5TB_t$	CMBS is the yield on commercial mortgage-backed securities and 5TB is the yield on a 5-year Treasury Note (CMBSAAA5 Index)
	(16) Residential Mortgage-Backed Security Spread	measures the ability of agencies to raise capital and the relative riskiness of the securitized asset	$Residential\ MBS\ Spread_t = RMBS_t - 30TB_t$	RMBS is the price of agency residential mortgage-backed securities (JPAGMBS Index) and 30TB is the price of a 30-year Treasury Bond

Table 2 - Systemic stress episodes as a function of monitoring frequency (3Q 1991- 4Q 2011).

	Frequency	Stress Episodes	Non-Stress Episodes
PANEL A: Benchmark series	Quarterly	6	75
	Monthly	29	213
	Biweekly	71	455
	Weekly	176	877
	Daily	1428	5944
PANEL B: CFSI	Quarterly	11	70
	Monthly	27	215
	Biweekly	56	470
	Weekly	117	936
	Daily	824	6548

Table 3 - Results of non-parametric testing for optimal CFSI-based rating system.

		# of grades=2	# of grades=3	# of grades=4	# of grades=5
Quarterly	Somers' D	2.7	-16.7	-30.2	-24.9
	ROC	51.3	41.7	34.9	37.6
Monthly	Somers' D	21.6	14.5	24.4 [a]	27.7 [a]
	ROC	60.6	57.2	62.2	63.9
Biweekly	Somers' D	23.6	30.0 [a]	37.1 [a]	31.5 [a]
	ROC	61.8	65.0	68.6	65.8
Weekly	Somers' D	19.4[a]	27.7 [a]	36.5 [a]	30.4 [a]
	ROC	59.7	63.9	68.3	65.2
Daily	Somers' D	18.7 [a]	22.6 [a]	31.1 [a]	26.7 [a]
	ROC	59.4	61.3	65.6	63.3

[a] Indicates rating system is not equivalent to a random rating system

Table 4 - Probability of systemic stress episode by CFSI grade

CFSI rating grades		Range[a]	Probability of systemic stress at grade threshold
Grade 1	(expansion period)	$Z_{CFSI} \leq -0.70$	5.4%
Grade 2	(normal period)	$-0.70 < Z_{CFSI} < 0.57$	12.8%
Grade 3	(moderate stress period)	$0.57 \leq Z_{CFSI} < 1.84$	25.4%
Grade 4	(significant stress period)	$Z_{CFSI} \geq 1.84$	38.0%

[a] Range analysis is performed on CFSI standardized distances (z-scores)

Table 5 - Systemic stress episode frequency pre- and post-1998

Frequency (SSE/year)	CFSI SSE	Benchmark SSE
Pre-1998	2.49	1.64
Post-1998	2.06	1.65

Table 6 - Cross – correlations with CFSI

	Entire Period														
			t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
Alternative indexes															
St. Louis Financial Stress Index	-	-	0.51	0.54	0.58	0.62	0.64	0.67	0.69	0.66	0.60	0.57	0.53	0.48	0.45
Kansas City Financial Stress Index	-	-	0.47	0.53	0.59	0.64	0.67	0.70	0.70	0.67	0.63	0.60	0.56	0.54	0.51
Chicago Financial Conditions Index	-	-	0.47	0.49	0.51	0.55	0.59	0.62	0.66	0.67	0.64	0.62	0.58	0.54	0.49
CFSI sub-indexes															
Funding sub-index	-	-	-0.04	-0.01	0.01	0.01	0.03	0.03	0.03	0.03	0.02	0.02	0.00	-0.02	-0.04
Credit sub-index	-	-	0.27	0.28	0.30	0.34	0.37	0.39	0.40	0.35	0.27	0.21	0.12	0.07	0.05
Foreign Exchange sub-index	-	-	0.41	0.40	0.39	0.40	0.41	0.43	0.44	0.43	0.41	0.39	0.39	0.40	0.41
Equity sub-index	-	-	0.36	0.41	0.46	0.48	0.54	0.60	0.74	0.58	0.50	0.43	0.39	0.31	0.23
Real Estate sub-index	-	-	-0.30	-0.27	-0.22	-0.17	-0.12	-0.06	-0.03	-0.05	-0.07	-0.11	-0.15	-0.17	-0.17
Securitization sub-index	-	-	0.35	0.39	0.44	0.51	0.56	0.63	0.69	0.66	0.61	0.58	0.54	0.51	0.49
	Regime 1: Separation of FI activities														
	Mean	St. Dev	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
Alternative indexes															
St. Louis Financial Stress Index	-0.55	0.11	-0.13	-0.18	-0.17	-0.18	-0.21	0.02	-0.01	-0.11	-0.02	-0.04	0.01	0.17	0.18
Kansas City Financial Stress Index	-0.65	0.29	0.21	0.15	0.04	-0.01	0.06	0.21	0.23	0.17	-0.01	-0.13	-0.17	-0.16	-0.14
Chicago Financial Conditions Index	-0.76	0.15	-0.33	-0.46	-0.52	-0.54	-0.50	-0.31	-0.25	-0.30	-0.34	-0.37	-0.36	-0.31	-0.28
Cleveland Financial Stress Index	-0.83	0.39	-	-	-	-	-	-	-	-	-	-	-	-	-
CFSI sub-indexes															
Funding sub-index	0.51	0.62	0.31	0.28	0.24	0.11	0.10	0.15	0.25	0.14	0.08	0.09	-0.03	0.01	-0.05
Credit sub-index	0.06	0.91	0.19	0.17	0.21	0.22	0.23	0.35	0.37	0.23	0.12	0.10	-0.04	0.03	0.11
Foreign Exchange sub-index	-0.72	0.50	-0.04	-0.04	-0.08	0.05	0.09	0.20	0.22	0.16	0.10	0.16	0.18	0.24	0.35
Equity sub-index	-0.61	0.58	0.04	-0.07	-0.04	-0.01	0.08	0.06	0.69	0.15	0.13	0.04	0.11	0.01	0.04
Real Estate sub-index	0.73	0.82	0.17	0.22	0.27	0.24	0.23	0.29	0.24	0.22	0.19	0.14	0.07	0.06	0.06
Securitization sub-index	-0.95	0.05	-0.22	-0.23	-0.24	-0.30	-0.29	-0.22	-0.23	-0.29	-0.28	-0.35	-0.39	-0.35	-0.29
	Regime 2: Deregulation														
	Mean	St. Dev	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
Alternative indexes															
St. Louis Financial Stress Index	-0.25	0.59	0.50	0.52	0.55	0.58	0.62	0.67	0.67	0.60	0.51	0.44	0.38	0.33	0.29
Kansas City Financial Stress Index	-0.02	0.61	0.25	0.26	0.28	0.31	0.33	0.39	0.43	0.37	0.27	0.22	0.17	0.11	0.10
Chicago Financial Conditions Index	-0.53	0.26	0.16	0.19	0.23	0.28	0.33	0.39	0.37	0.28	0.19	0.11	0.06	0.04	0.03
Cleveland Financial Stress Index	0.15	0.70	-	-	-	-	-	-	-	-	-	-	-	-	-
CFSI sub-indexes															
Funding sub-index	-0.37	0.65	-0.12	-0.10	-0.10	-0.07	-0.01	0.00	0.00	-0.02	-0.01	0.00	0.00	-0.01	-0.02
Credit sub-index	-0.27	0.79	0.28	0.25	0.28	0.38	0.50	0.55	0.62	0.56	0.45	0.33	0.17	0.09	0.08
Foreign Exchange sub-index	0.09	0.81	0.04	0.08	0.12	0.15	0.18	0.22	0.23	0.16	0.09	0.02	0.03	0.06	0.10
Equity sub-index	0.18	1.03	0.18	0.24	0.28	0.27	0.39	0.52	0.71	0.49	0.36	0.25	0.23	0.13	0.01
Real Estate sub-index	-0.50	0.76	0.27	0.28	0.36	0.45	0.56	0.68	0.76	0.71	0.62	0.52	0.44	0.39	0.36
Securitization sub-index	0.30	0.66	-0.20	-0.20	-0.18	-0.17	-0.17	-0.10	-0.01	-0.02	-0.07	-0.08	-0.07	-0.02	0.02
	Regime 3: Crisis														
	Mean	St. Dev	t-6	t-5	t-4	t-3	t-2	t-1	t	t+1	t+2	t+3	t+4	t+5	t+6
Alternative indexes															
St. Louis Financial Stress Index	1.03	1.43	0.13	0.24	0.36	0.47	0.53	0.58	0.60	0.54	0.51	0.48	0.42	0.42	0.41
Kansas City Financial Stress Index	1.01	1.58	0.21	0.28	0.37	0.47	0.50	0.56	0.62	0.56	0.51	0.49	0.43	0.34	0.40
Chicago Financial Conditions Index	0.19	0.84	0.26	0.37	0.47	0.54	0.59	0.62	0.62	0.57	0.56	0.53	0.49	0.48	0.47
Cleveland Financial Stress Index	1.05	0.93	-	-	-	-	-	-	-	-	-	-	-	-	-
CFSI sub-indexes															
Funding sub-index	-0.05	1.43	0.32	0.39	0.47	0.53	0.58	0.59	0.60	0.60	0.58	0.58	0.56	0.53	0.49
Credit sub-index	0.39	1.13	0.51	0.52	0.56	0.61	0.62	0.60	0.59	0.53	0.43	0.33	0.23	0.13	0.05
Foreign Exchange sub-index	0.88	1.00	-0.02	-0.11	-0.22	-0.30	-0.32	-0.34	-0.31	-0.27	-0.24	-0.21	-0.18	-0.10	-0.07
Equity sub-index	0.53	0.59	0.01	0.13	0.31	0.43	0.51	0.64	0.75	0.60	0.45	0.31	0.17	0.04	-0.08
Real Estate sub-index	-0.12	0.92	-0.54	-0.49	-0.42	-0.30	-0.17	-0.03	0.08	0.01	-0.03	-0.11	-0.18	-0.25	-0.27
Securitization sub-index	0.79	1.08	-0.04	0.06	0.19	0.39	0.54	0.70	0.83	0.68	0.53	0.40	0.23	0.09	0.02

Appendix A. CFSI Properties

A.1. Stationarity of quarterly CFSI

Since nonstationary process may be due to a random walk, random walk with drift, or random walk with drift around a stochastic trend, we conduct several econometric tests for the three different forms under three different null hypotheses:

Case 1. Test quarterly $CFSI_t$ as a random walk:

$$CFSI_t = \delta CFSI_{t-1} + u_t$$

Case 2. Test quarterly $CFSI_t$ as a random walk with drift

$$CFSI_t = \beta_o + \delta CFSI_{t-1} + u_t$$

Case 3. Test quarterly $CFSI_t$ as a random walk with drift around a stochastic trend.

$$CFSI_t = \beta_o + \beta_1 t + \delta CFSI_{t-1} + u_t$$

In each case, the null hypothesis is that $\delta = 0$, that is there is a unit root and time series is nonstationary:

$$\begin{cases} H_0: \delta = 0 \mid time\ series\ is\ nonstationary \\ H_A: \delta < 0 \mid time\ series\ is\ stationary \end{cases}$$

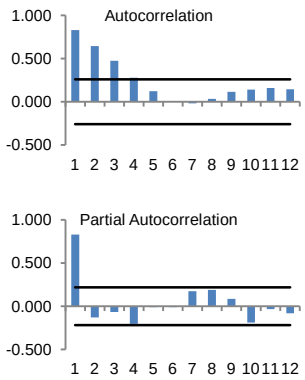
If the null hypothesis is rejected for case 1, then $CFSI_t$ is stationary with a zero mean. If the null hypothesis is rejected for case 2, then $CFSI_t$ is stationary with a nonzero mean. If the null hypothesis is rejected for case 3, then $CFSI_t$ is stationary around a deterministic trend. As Table 1A shows, quarterly $CFSI_t$ can be considered stationary around a deterministic trend at 5% critical level.

Table 1A - Unit Root tests of quarterly $CFSI_t$

	Unit Root tests:		DF[a]	ADF[b]	PP[c]	KPSS[d]	ERS[e]	NP[f]			
								MZa	MZt	MSB	MPT
$CFSI_t$ as a random walk	Test statistic			-0.62	-0.24						
	critical values τ	1% level		-2.59	-2.59						
		5% level		-1.94	-1.94						
		10% level		-1.61	-1.61						
$CFSI_t$ as a random walk with drift	Test statistic		-3.39	-3.73	-3.60	0.60	2.19	-19.06	-2.92	0.15	1.87
	critical values τ	1% level	-2.59	-3.51	-3.51	0.74	1.92	-13.80	-2.58	0.17	1.78
		5% level	-1.94	-2.90	-2.90	0.46	3.06	-8.10	-1.98	0.23	3.17
		10% level	-1.61	-2.59	-2.59	0.35	4.07	-5.70	-1.62	0.28	4.45
$CFSI_t$ as a random walk with drift around a stochastic trend	Test statistic		-4.47	-4.42	-4.39	0.05	3.60	-26.07	-3.58	0.14	3.68
	critical values τ	1% level	-3.66	-4.08	-4.08	0.22	4.24	-23.80	-3.42	0.14	4.03
		5% level	-3.10	-3.47	-3.47	0.15	5.67	-17.30	-2.91	0.17	5.48
		10% level	-2.80	-3.16	-3.16	0.12	6.78	-14.20	-2.62	0.19	6.67

[a] Dickey Fuller test
[b] Augmented Dickey Fuller test
[c] Phillips-Perron test
[d] Kwiatkowski-Phillips-Schmidt-Shin test
[e] Elliot-Rothenberg-Stock test
[f] Ng-Perron test

Figure 1A - Correlogram of quarterly FSI.



Number	AC	PAC	Q-Stat	Prob
1	0.827	0.827	42.478	0.000
2	0.643	-0.131	68.593	0.000
3	0.473	-0.066	82.956	0.000
4	0.277	-0.202	87.966	0.000
5	0.121	-0.012	88.937	0.000
6	0.008	-0.012	88.941	0.000
7	-0.020	0.172	88.968	0.000
8	0.035	0.187	89.054	0.000
9	0.115	0.086	90.008	0.000
10	0.140	-0.190	91.455	0.000
11	0.159	-0.035	93.350	0.000
12	0.145	-0.082	94.965	0.000

A.2. Regressive and Granger properties of CFSI

Table 2A - Regression results of monthly CFSI-based rating system

Variable	Coefficient	Std. Error	z-Statistic	Prob.
CFSI	0.370646	0.075077	4.936853	0
C	-1.344444	0.081267	-16.54356	0
McFadden R-squared	0.072668	Mean dependent var		0.10417
S.D. dependent var	0.305766	S.E. of regression		0.29765
Akaike info criterion	0.627299	Sum squared resid		46.6008
Schwarz criterion	0.643469	Log likelihood		-163.61
Hannan-Quinn criter.	0.633629	Deviance		327.214
Restr. deviance	352.8548	Restr. log likelihood		-176.43
LR statistic	25.64115	Avg. log likelihood		-0.3099
Prob(LR statistic)	0			
Obs with Dep=0	473	Total obs		528
Obs with Dep=1	55			

Table 3A - Granger test precedence results of CFSI versus reference volatility series

	CFSI → BBOX	CFSI → LBOX	CFSI → MOVE	CFSI → VDAX	CFSI → VIX	CFSI → ABS	CFSI → RE	BBOX → CFSI	LBOX → CFSI	MOVE → CFSI	VDAX → CFSI	VIX → CFSI	ABS → CFSI	RE → CFSI
QUARTERLY (lags=2)														
Obs	39	52	81	80	81	81	81	39	52	81	80	81	81	81
F-Statistic	3.45007	1.1284	0.06286	0.40538	1.68243	1.10551	0.83405	2.66667	0.91645	2.41796	5.63628	7.87551	2.52598	0.03274
Prob.	0.0432	0.3322	0.9393	0.6682	0.1928	0.3363	0.4382	0.0840	0.407	0.0959††	0.0052††	0.0008	0.0867	0.9678
MONTHLY (lags=2)														
Obs	114	162	231	237	243	243	243	114	162	243	237	243	243	243
F-Statistic	2.31283	1.83975	1.23157	2.87644	2.89334	1.92929	1.47364	2.31283	2.12791	2.56476	15.5048	18.3324	3.98249	0.41261
Prob.	0.1038	0.1623	0.2938†	0.0583	0.0573	0.1475	0.2312	0.1038	0.1225	0.0791	0.0000	0.0000	0.0199	0.6624
WEEKLY (lags=2)														
Obs	495	711	1056	1029	1056	1056	1056	495	711	1056	1029	1056	1056	1056
F-Statistic	1.82277	6.93859	5.08398	8.88829	0.12827	1.55808	1.14848	2.68526	0.25426	1.61575	4.88291	6.34831	5.00502	0.17261
Prob.	0.1627	0.001††	0.0063	0.0001	0.8796††	0.2110	0.3175	0.0692	0.7756††	0.1992	0.0078	0.0018††	0.0069	0.8415
DAILY (lags=2)														
Obs	3495	3567	7412	7314	7412	7412	1.54520	3495	3567	7412	7314	7412	7412	7412
F-Statistic	1.95171	2.97617	5.32891	21.1833	5.76116	35.9168	1.54520	0.90986	0.74201	0.98920	3.32653	4.10723	2.35982	0.21647
Prob.	0.1422	0.0511††	0.0049	0.0000	0.0032	0.0000	0.2133	0.4027	0.4762††	0.3719	0.0360	0.0165	0.0945	0.8054

†† – indicates one-way Granger causality with 79% or better confidence
† – indicates consistent one-way Granger precedence