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# SAFE: An Early Warning System for Systemic Banking Risk

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This paper builds on existing microprudential and macroprudential early warning systems (EWSs) to develop a new, hybrid class of models for systemic risk, incorporating the structural characteristics of the financial system and a feedback amplification mechanism. The models explain financial stress using both public and proprietary supervisory data from systemically important institutions, regressing institutional imbalances using an optimal lag method. The Systemic Assessment of Financial Environment (SAFE) EWS monitors microprudential information from the largest bank holding companies to anticipate the buildup of macroeconomic stresses in the financial markets. To mitigate inherent uncertainty, SAFE develops a set of medium-term forecasting specifications that gives policymakers enough time to take ex-ante policy action and a set of short-term forecasting specifications for verification and adjustment of supervisory actions. This paper highlights the application of these models to stress testing, scenario analysis, and policy.

Keywords: Systemic risk; early warning system; financial stress index; microprudential; macroprudential; liquidity feedback.

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## Contents


1. Introduction ........ 4

2. EWS elements ........ 9

2.1. Measuring financial stress — dependent variable data ........ 11

2.2. Drivers of risk — explanatory variables data ........ 13

3. Risk model and results ........ 14

3.1. EWS models ........ 14

3.1.1. A candidate base model ........ 16

3.1.2. Short- and long-lag base models ........ 18

3.2. Criteria for variable and lag selection ........ 18

3.3. EWS model specifications and results ........ 23

4. Discussion and implications ........ 26

4.1. Performance ........ 26

4.1.1. Competitive performance of EWS models ........ 26

4.1.2. Case study 1: Supervisory versus public EWS specifications ........ 28

4.2. Applications to supervisory policy ........ 30

4.2.1. Case study 2: Selecting action thresholds in historic stress episodes ........ 33

4.2.2. Case study 3: The financial crisis ........ 35

5. Conclusions and future work ........ 38

Acknowledgements ........ 40

References ........ 41

Tables and figures ........ 47

Appendix A. Description of explanatory data ........ 63

Appendix B. Explanatory variable construction ........ 65

Appendix C. Data sources and variable expectations ........ 76

## 1. Introduction

The objective of this study is to develop an early-warning system (EWS) for identifying systemic banking risk, which will give policymakers and supervisors time to prevent or mitigate a potential financial crisis. It is important to forecast—and perhaps to alleviate—the pressures that lead to systemic crises, which are economically and socially costly and which require significant time to reverse (Honohan et al., 2003). The current U.S. supervisory policy toolkit includes several EWSs for flagging distress in individual institutions, but it lacks a tool for identifying systemic-level banking distress.[1]

Gramlich, Miller, Oet, and Ong (2010) review the theoretical foundations of EWSs for systemic banking risk and classify the explanatory variables that appear in the systemic-risk EWS literature (see Table 1). EWS precedents typically seek the best model for the set of relationships that describe the interaction of the dependent variable and the explanatory variables. The theoretical precedents[2] typically examine the emergence of systemic risk from aggregated economic imbalances, which sometimes result in corrective shocks. The prevalent view[3] is that systemic financial risk is the possibility that a *shock event* triggers an *adverse feedback loop* in financial institutions and markets, significantly affecting their ability to *allocate*

1 Examples of current U.S. supervisory early warning systems include Canary (Office of the Comptroller of the Currency) and SR-SABR (Federal Reserve Board, 2005), which are designed to identify banks in an early stage of capital distress. An overview of EWSs for micro risk is presented by Gaytán and Johnson (2002, pp. 21–36), and King, Nuxoll, and Yeager (2006, pp. 58–65). Jagtiani et al. (2003) empirically test the validity of three supervisory micro-risk EWSs (SCOR, SEER, and Canary).

2 See particularly Borio et al. (1994); Borio and Lowe (2002, Asset; and 2002, Crises); and Borio and Drehmann (2009).

3 Group of Ten (2001).

*capital* and *serve intermediary functions*, thereby generating *spillover effects* into the real economy with *no clear self-healing mechanism*.

Illing and Liu (2003, 2006) express the useful consensus theory that the financial system's exposure generally derives from deteriorating macroeconomic conditions and, more precisely, from diverging developments in the real economic and financial sectors, shocks within the financial system, banks' idiosyncratic risks, and contagion among institutions. Thus, systemic risk is

- initiated by primary risk factors and
- propagated by markets' structural characteristics.[4]

Hanschel and Monnin (2005)[5] provide the most direct theoretical and methodological precedent for the present study by using a regression approach to estimate a model that regresses a systemic stress index on the k observed standardized past imbalances[6] of explanatory variables. In their study, only one "optimal" lag is chosen for each of the explanatory variables, which are constructed as standardized imbalances equal to the distance between a level and the mean value of the respective variables up to time t divided by the standard deviation of time t. This approach implies an assumption that the trend serves as a "proxy for the longer-term fundamental value of a variable, around which the actual series fluctuates" (Hanschel et al., 2005).

Insert Table 1 about here

4 Illing and Liu (2006, p. 244) postulate that financial stress "is the product of a vulnerable structure and some exogenous shock."

5 Construction of a continuous index is well described in Illing and Liu (2006, pp. 250–256); and Hanschel and Monnin (2005, pp. 432–438).

6 Hanschel and Monnin, following the tradition established by Borio et al., call these imbalances "gaps."

Gramlich et al. (2010) review the limitations of existing approaches to EWSs when applied to systemic risk, stating that "microprudential EWS models cannot, because of their design, provide a systemic perspective on distress; for the same reason, macroprudential EWS models cannot provide a distress warning from individual institutions that are systemically important or from the system's organizational pattern." The authors argue that the architecture of the systemic risk EWS "can overcome the fundamental limitations of traditional models, both micro and macro" and "should combine both these classes of existing supervisory models." Recent systemic financial crises show that propagation mechanisms include structural and feedback features. Thus, the proposed supervisory EWS for systemic risk incorporates both microprudential and macroprudential perspectives, as well as the structural characteristics of the financial system and a feedback-amplification mechanism.

The dependent variable for the SAFE EWS proposed here[7] is developed separately as a financial stress index.[8] The models in the SAFE EWS explain the stress index using data from the five largest U.S. bank holding companies, regressing institutional imbalances using an optimal lag method. The z-scores of institutional data are justified as explanatory imbalances. The models utilize both public and proprietary supervisory data. The paper discusses how to use the EWS and tests to see if supervisory data helps; it also investigates and suggests levels for action thresholds appropriate for this EWS.

To simulate the models, we select not only the explanatory variables but also the optimal lags, building on and extending precedent ideas from the literature with our own innovations. Most of the earlier lag selection research emphasizes the important criteria of goodness of fit, variables' statistical significance (t-statistics), causality, etc. Hanssens and Liu (1983) present

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7 Collectively, the set of models is considered to form a supervisory EWS framework called SAFE (Systemic Assessment of Financial Environment).

8 Oet et al. (2009, 2011).

methods for the preliminary specification of distributed lags in structural models in the absence of theory or information. Davies (1977) selects optimal lags by first including all possible variable lags, chosen on the basis of theoretical considerations; he further narrows the lag selection by best results in terms of t-statistics and $R^2$. Holmes and Hutton (1992) and Lee and Yang (2006) introduce techniques for selecting optimal lags by considering causality. Bahmani-Oskooee and Brooks (2003) demonstrate that when goodness of fit is used as a criterion for the choice of lag length and the cointegrating vector, the sign and size of the estimated coefficients are in line with theoretical expectations. The lag structure in the VAR models described by Jacobson (1995) is based on tests of residual autocorrelation; Winker (2000) uses information criteria, such as AIC and BIC. Murray and Papell (2001) use a lag length $k_j$ selection method for single-equation models: they start with an upper bound $k_{max}$ on $k$. If the t-statistic on the coefficient of the last lag is significant at 10 percent of the value of the asymptotic distribution (1.645), then $k_{max} = k$. If it is not significant, then $k$ is lowered by one. This procedure is repeated until the last lag becomes significant.

Recent research focuses on automatic procedures for optimal lag selection. Dueck and Scheuer (1990) apply a heuristic global optimization algorithm in the context of an automatic selection procedure for the multivariate lag structure of a VAR model. Winker (1995, 2000) develops an automatic lag selection method as a discrete optimization problem. Maringer and Winker (2005) propose a method for automatic identification of the dynamic part of VEC models of economic and financial time series and also address the non-stationary issues. They employ the modified information criterion discussed by Chao and Phillips (1999) for the case of partially non-stationary VAR models. In addition, they allow for “holes” in the lag structures, that is, lag structures are not constrained to sequences up to lag k, but might consist, for example, of only the first and fourth lag in an application to quarterly data. Using this approach, different lag structures can be used for different variables and in different equations of the system. Borbély and Meier (2003) argue that estimated forecast intervals should account for the uncertainty arising from specifying an empirical forecasting model from the sample data. To allow this uncertainty to be considered systematically, they formalize a model selection procedure that specifies a model's lag structure and accounts for aberrant observations. The procedure can be used to bootstrap the complete model selection process when estimating forecast intervals. Sharp, Jeffress, and Finnigan (2003) introduce a program that eliminates many of the difficulties associated with lag selection for multiple predictor variables in the face of uncertainty. The procedure 1) lags the predictor variables over a user-defined range; 2) runs regressions for all possible lag permutations in the predictors; and 3) allows users to restrict results according to user-defined selection criteria (for example, "face validity," significant t-tests, $R^2$, etc.). Lag-o-Matic output generally contains a list of models from which the researcher can make quick comparisons and choices.

The SAFE EWS models are based on high-quality data. The dependent data is high frequency, with over 5,000 daily observations, leading to the construction of a quarterly dependent variable series. Most dependent data is sourced from Bloomberg and the Federal Reserve Economic Data (FRED), supplemented by the Bank of England. The explanatory data comes from 77 quarterly panels from Q1:1991 to Q3:2010. We consider the 20 bank holding companies that were historically in the highest tier and aggregate the top five of them as a proxy for a group of systemically important institutions. We specify the model using 50 in-sample quarters. A large component of this data comes from public sources, mostly from the Federal Reserve System (FRS) microdata for bank holding companies and their bank subsidiaries. The public FRS data is supplemented by additional high-quality sources that are accessible to the public, such as S&P/Case Shiller[9] and MIT Real Estate Center (for the return data), Compustat databases (for some structural data), and Moody's KMV (for some risk data). We also replicate data from some publicly available models and datasets, for example, the CoVaR model[10] and the Flow of Funds data. In addition, for each of the four classes of explanatory imbalances, we depend partly on private supervisory data. Our private dataset consists of data that is not disclosed to the public or the results of proprietary models developed at the Federal Reserve. Examples of private datasets are the cross- country exposures data and supervisory surveillance models, as well as several sub-models developed specifically for this EWS.[11] Additional data descriptions are provided in Appendix A. Data sources for the explanatory variables are shown in Appendix C (Table 15).[12] The definitions, theoretical expectations, and Granger causality of the explanatory variables are summarized in Tables 16–19 (Appendix C).

The rest of this paper is structured as follows: Section 2 discusses the conceptual organization of elements of the systemic banking risk EWS. Section 3 discusses the methodology of the SAFE EWS models and their results. Section 4 discusses the research implications and case studies based on our models. Section 5 concludes with a discussion of interpretations and directions for future research.

## 2. EWS elements

The elements of an EWS are defined by a *measure of financial stress*, *drivers of risk*, and a *risk model* that combines both. As a measure of stress, the SAFE EWS uses the financial

9 Standard & Poor's (2009).
10 Adrian and Brunnermeier (2008).
11 The liquidity feedback model and the stress haircut model.
12 To conserve space, the tables show only information for the explanatory variables that ultimately enter the SAFE model.

markets' stress series by Oet et al. (2009, 2011). The present paper contributes a new typology for the drivers of risk in the EWS; its risk model applies a regression approach to explain the financial markets' stress index using optimally lagged institutional data.

Our basic conjectures are that systemic financial stress can be induced by asset imbalances and structural weakness. We can view imbalances as the deviations between asset expectations and their fundamentals. The larger the deviation, the greater is the potential shock (see Fig. 1). Therefore, systemic financial stress can be expected to increase with the rise in imbalances.

Insert Fig. 1 about here

Our second conjecture is that structural weakness in the financial system at a particular point in time increases systemic financial stress. As an illustration, consider a financial system as a network of financial intermediaries. This system is characterized by an absence of concentrations and a high degree of diversification. Individual institutions are interconnected with multiple counterparties of varying sizes across the system. This system's entities are of varying sizes, some quite large and significant, some intermediate, and some small. The failure of one institution, even a large one, will sever a chain of connections and create local stress. This failure, however, has limited potential to induce systemic stress because of the great number of network redundancies and counterparties that can take up this stress. Such a system has an inherently strong balancing ability.

By comparison, consider a financial system in which individual institutions are concentrated in particular markets and are interconnected in limited ways through a small number of intermediaries. In this system, certain financial intermediaries act as highly-interconnected gatekeepers that dominate particular markets (institutional groups). Market access for lessconnected institutions is only possible through these few significant gatekeeper institutions. As in the previous example, this system is also characterized by institutions of varying size. In the present example, however, a limited number of institutions dominate particular markets; some are interlinked with the entire network. The number of structural redundancies in this system is smaller, perhaps minimal in some markets. A failure or high-stress experience by one of the more dominant institutions in a particular market cannot be as easily sustained and therefore increases the potential for systemic risk. The failure of one of the gatekeeper institutions that interlink several markets can be catastrophic and may lead to the collapse of a market or even of the system. Therefore, this system is less tolerant of stress and failure on the part of a single significant market player.

The conjecture of the importance of structural characteristics is supported by empirical evidence, which is discussed in Gramlich and Oet (2011). Briefly, U.S. banks' loan exposures form a highly heterogeneous structure with distinct tiers. The structural heterogeneity is clearly observed in loan-type exposure (Fig. 2) and financial markets' concentrations in the top five U.S. bank holding companies (Fig. 3).

Insert Fig. 2 about here

Insert Fig. 3 about here

*2.1. Measuring financial stress — dependent variable data*

Building on the research precedent of Illing and Liu (2003, 2006), Oet et al. (2009, 2011) define systemic risk as a condition in which the observed movements of financial market components reach certain thresholds and persist. They develop the financial stress index in the U.S. (CFSI)[13] as a continuous index constructed of daily public market data. To ensure that a versatile index of stress has been identified, the researcher aims to represent a spectrum of markets from which stress may originate. As previous research in this field attests, the condition of credit, foreign exchange, equity, and interbank markets provides substantial coverage of potential stress origination. The CFSI uses a dynamic weighting method and daily data from the following 11 components: 1) financial beta, 2) bank bond spread, 3) interbank liquidity spread, 4) interbank cost of borrowing, 5) weighted dollar crashes, 6) covered interest spread, 7) corporate bond spread, 8) liquidity spread, 9) commercial paper–T-bill spread, 10) Treasury yield curve spread, and 11) stock market crashes. The data is from Bloomberg and the Federal Reserve FRED database.[14]

It is important to note that in 2008, when the SAFE EWS was developed, no public series of financial stress in the United States existed. By 2010, however, 12 alternative financial stress indexes were available. The comparison of CFSI with alternative financial stress series is discussed in Oet et al. (2009, 2011).[15]

The financial stress series $Y_t$ in the SAFE EWS is constructed separately as $CFSI_{qt}$ , a quarterly financial-markets stress index. Mathematically, the financial stress series is constructed as

$$Y_t \overset{\text{def}}{=} CFSI_{qt} \overset{\text{m}}{=} \sum_j \left[ w_{jt} * \int_{-\infty}^{z_j} f\left(z_{jt}\right) dz_{jt} \right] * 100 \tag{1}$$

Here, each of $j$ components of the index is observable in the markets with high (daily) frequency, but results in a quarterly series of financial stress in which $z_{jt}$ is the observed value of market

13 Federal Reserve Bank of Cleveland, Financial Stress Index.
14 See Oet et al. (2011) for a description of specific CSFI data sources.
15 Oet and Eiben (2009) discuss the initial CFSI construction. Oet et al. (2011) include comparisons with alternative indexes.

component $j$ at time $t$. The function $f(z_{jt})$ is the probability density function that the observed value will lie between $z_{jt}$ and $z_{jt} + dz_{jt}$. The integral expression $\int_{-\infty}^{z_j} f(z_{jt}) dz_{jt}$ is the cumulative distribution function of the component $z_{jt}$ given as a summation of the probability density function from the lowest observed value in the domain of market component $j$ to $z_j$. This function describes the precedent set by the component's value and how much that precedent matters. The $w_{jt}$ term is the weight given to indicator $j$ in the $CFSI_{qt}$ at time $t$. The key technical challenge in constructing and validating the financial stress series is the choice of weighting methodology. An inefficient choice would increase the series' potential for giving false alarms. Seeking to minimize false alarms, we were agnostic as to the choice of weighting technique and tested a number of methods, including principal component analysis. The approach we ultimately selected to minimize false alarms is the credit weights method, which is explained in Oet et al. (2009, 2011).

*2.2. Drivers of risk — explanatory variables data*

To advance from these premises, we develop a methodology that uses z-scores to express imbalances. We define an imbalance $\underline{X_t}$ as a deviation of some explanatory variable $X_t$ from its mean, constructing it as a standardized measure. That is, each $X_t$ explanatory variable is aggregated, deflated (typically by a price-based index), demeaned, and divided by its cumulative standard deviation at time $t$. The resulting z-score is designated $\underline{X_t}$. By construction, $\underline{X_t}$ describes imbalance as the distance in standard deviations from the mean of the $X_t$ explanatory variable. $\underline{X_t}$ imbalance shows potential for stress. The details of variable construction are summarized in Appendix B.

The SAFE EWS builds on existing theoretical precedents, which are described in Table 1, using the new typology of systemic-risk EWS explanatory variables (see Table 2). The definitions, theoretical expectations, and Granger causality of the explanatory variables are summarized in Table 16 - Table 19 (Appendix C).

Insert Table 2 about here

## 3. Risk model and results

There are many ways to approach a model such as this. Generally, explanatory variables do not act at a single point in time but are, in fact, distributed in time. The estimation becomes particularly difficult when the number of observations is small relative to the number of variables. In preference to the distributed estimation, an optimal lag approach is used in practice. SAFE EWS consists of a number of models, each of which is an optimal lag-linear regression model of traditional form

$$Y_t = \beta_0 + \beta_{RET}\underline{X_{RET,t-n_{RET}}} + \beta_{RSK}\underline{X_{RSK,t-n_{RSK}}} + \beta_{LIQ}\underline{X_{LIQ,t-n_{LIQ}}} + \beta_{STR}\underline{X_{STR,t-n_{STR}}} + u_t \quad (2)$$

where the dependent variable $Y_t$ is constructed separately as a series of systemic stress in U.S. financial markets, and the independent variables $\underline{X_{k,t-n_k}}$ are types of return, risk, liquidity,[16] and structural imbalances aggregated for the top five U.S. bank holding companies.

### 3.1. EWS models

Based on the premise that financial stress can be explained by imbalances in the system's assets and structural features, what imbalance stories might be proposed? At the most basic level

[16] Since we view imbalances as deviations from fundamental expectations, we choose to classify them further as return, risk, and liquidity imbalances. This classification is based on a typology of the demand for financial assets as a function of return, risk, and liquidity expectations (Mishkin 1992).

and without any other information, one can expect financial stress at a point in time to be related to past stress. Indeed, a useful finding for model development was that the financial stress index (FSI) appeared to be an autoregressive process (AR), consisting of a single lag and a seasonal lag of the financial stress series itself. To this effect, the FSI's underlying AR structure forms a benchmark model on which the researcher hopes to improve. Any model based on a credible imbalance story should outperform this naive benchmark model over time. The general strategy for constructing EWS models, then, would be to identify other explanatory variables that improve the FSI forecast over the benchmark.

From a design perspective, a hazard inherent in all ex-ante models is that their uncertainty may lead to wrong policy choices. To mitigate this risk, SAFE develops two modeling perspectives: a set of long-lag (six quarters or more) forecasting specifications to give policymakers enough time for ex-ante policy action, and a set of short-lag forecasting specifications for verification and adjustment of supervisory actions.

The two modeling perspectives have distinctly different functions and lead to different model forms. Short-lag models function dynamically, seeking to explain stress in terms of recent observations of it and of institutional imbalances that tend to produce stress relatively quickly and with a short lead. Long-lag models seek to explain the buildup of financial stress well in advance, in terms of institutional imbalances that tend to anticipate stress with a long lead. Because they focus on information lagged at least six quarters, the long-lag models cannot include the AR(1) and AR(4) benchmark components. The researcher must construct a reasonable set of variables to form a long-lag base model without the aid of a benchmark model.

To proceed, we first establish parsimonious base models for the short- and long-lag horizons that outperform the naive benchmarking model and roughly explain financial stress in-sample.

These base models tell the core imbalance story relevant to each time horizon. We then seek to establish specific EWS models that may tell additional stories of imbalances in risk, return, liquidity, and structure and further outperform the base models for each of the two forecasting horizons; these stories may differ across models. In the present study, we form eight specifications that represent a mix of explanatory variables for each horizon. Each model represents a different extension of the core story.[17]

*3.1.1. A candidate base model*

We can proceed to a parsimonious, candidate base model by forming a core story composed of a set of imbalances that have a strong, consistent relationship with financial stress. Considering the institutional and structural data, which candidate variables possess the desirable explanatory powers? In fact, the series considered in Fig. 1 show four good candidates. Among the imbalances, one good candidate is equity, which we would expect to have a positive relationship with systemic financial stress. Among the risk imbalances, a strong hedging (negative) relationship should arise through imbalances in credit risk. On the liquidity side, an

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[17] The EWS design principles laid out in Gramlich, Miller, Oet, and Ong (2010) include flexibility under multiple horizons and stress scenarios. A regression-based EWS is, at best, essentially a monitoring system highlighting important associations. Because no two crises are exactly alike, an EWS should be sensitive to a rich set of possible theoretical associations, rather than seeking an optimum fit using historic data. The reason for investigating a set of eight models is combinatory: There are four types of explanatory variables and two methods of imbalance construction: price-based and total-assets based. However, the two present sets of eight models are revisions of the sets developed in the 2009 version of SAFE EWS. In its early development, the model population was the product of a more general iterative process that used a variety of regression-specification methods: forward regression, backward regression, stepwise regression, MAXR regression, and MINR regression. We found that backward regression did not lead to theoretically meaningful specifications; that the forward, MAXR, and MINR methods produced very similar, variable-rich, theoretically meaningful specifications; and that a stepwise method produced concise, technically efficient, theoretically meaningful regressions. Accordingly, in the final selection stage for the 2009 version of SAFE, we applied only two specification methods (stepwise and MAXR) to four classes of models defined as follows: Class A models used constant-mean, price-based imbalances; class B models used rolling-mean, price-based imbalances; class C models used constant-mean, total-assets-based imbalances; and class D models used rolling-mean, total-assets-based imbalances.

asset liability mismatch should exert a positive influence. And among the structural imbalances, leverage should provide a standard positive relationship.

The logic for the sign expectations of these sample choices of candidate imbalances may go as follows: For return imbalances, equity for individual institutions acts as a buffer against potential credit losses but also increases downside risk. Considering the series' z-scores in real terms (that is, deflated by the CPI), the size of the change varies with the difference between the CPI and long-term expectations for equity return. This reflects greater downside risk. Thus, an increase in real equity should be positively related to systemic financial stress.

Among the risk imbalances, credit risk should be the standard negative variable. Measured as the distance between normal and stressed required credit capital, this imbalance reflects the hedging function of capital. The less the distance at a particular point in time, the greater the potential for systemic stress. Thus, an increase in this distance measure should relate negatively to systemic financial stress.

Among liquidity imbalances, we expect that an asset liability mismatch will positively reflect greater systemic risk. Such a mismatch describes a simple gap difference between assets and liabilities in a particular maturity segment. Thus, an increased mismatch in itself indicates increased imbalance in repricing at a particular maturity and reflects increased exposure to interest-rate risk. Thus, the larger the mismatch, the larger the potential for systemic stress.

Defined in the standard manner, leverage is the ratio of debt to equity. An institution that increases leverage takes on risky debt in order to increase gains on its inherent equity position. Thus leverage, as a magnifier of returns, increases both potential gains and potential losses. Greater leverage means higher levels of risky debt relative to safer equity; it is widely thought to fuel many financial crises. Thus, our theoretical expectation for leverage is positive.

*3.1.2. Short- and long-lag base models*

Clearly, the candidate base model described above is only one of the possible parsimonious models and is formed without particular consideration of the variable lag structure. A more rigorous procedure for forming short- and long-lag models is as follows: To help identify a set of key variables for constructing a base model, we first utilize Granger causality to find the set of variables whose Granger lags are appropriate for each modeling perspective, that is, exclusively from lag 6 to lag 12 for long-lag models, and inclusively from lag 1 to lag 12 for short-lag models. We then examine the correlations for all our variables and separate those that show a considerable correlation (more than 60 percent). For each group of potential variables with Granger lags, we use stepwise and max-R-square procedures to simulate the base models and to identify the key impact variables, high-rate-of-occurrence variables, and variables with large coefficients and high explanatory power. Finally, in each potential base model, we select the key variables using Granger lags from each category of return, liquidity, structure, and risk imbalance. If any key variable loses significance after it is entered into the base model,[18] we reiterate the variable's optimal lag to get the desired significance and expected sign. Because we intend to test the models on an out-of-sample period that includes the financial crisis of 2007, we examine only the relationship between the FSI and our X's through the first quarter of 2007.

*3.2. Criteria for variable and lag selection*

Starting from the short- and long-lag base models, we form additional short- and long-lag EWS models by extending the base models with other explanatory variables. We use the criteria below to determine whether a new variable should be included.

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[18] For example, as a result of variable multicollinearity and "holes" in the lag structure.

1) Theoretical review: Consider whether including the variable in the equation is unambiguous and theoretically sound. All variables in the model should meet the expected sign (see Appendix C, Table 16–Table 19 for theoretical sign).

2) Hypothesis testing (t-statistics): Consider whether the coefficient of the variable to be included is significant in the expected direction. We generally accept variables that are significant at the 10 percent confidence level. To avoid the heteroskedasticity problem, we report t-statistics in the variable and lag selection procedure.

3) Stationarity: Consideration of stationarity is important for time series data. We conduct stationarity tests for the entire model and each variable. The individual series' stationary quality is verified using augmented Dickey Fuller (ADF) unit root tests. If the dependent variable is found to be nonstationary, we check for cointegration before making further adjustments. Cointegration of the trial OLS specifications is verified by running ADF unit root tests on the residuals. The tests show that the null hypothesis of unit root in the residuals is strongly rejected in all three random-walk cases: random walk (RW1), random walk with drift (RW2), and random walk with drift and trend (RW3). The reason is that ADF test statistics in each case are more critical than the test critical values, even at the 1 percent level. For nonstationary variables, we apply first differencing and re-verify the above criteria.

4) Granger causality: Consider whether the variable to be included changes consistently and predictably before the dependent variable. A variable that Granger causes financial stress one way at 20 percent significance can be retained for further testing. Thus far, we seek to retain the variables with significant Granger lags, expected signs, and significant coefficients. However, if the variable coefficient loses significance or changes sign when it is included in the model, we

reiterate the variable's optimal lag, seeking to re-establish all three criteria: theoretical expectation, significant coefficient, and Granger causality.

5) Multicollinearity: Although multicollinearity is not a serious forecasting issue, to ensure that our t-statistics are not inflated and to improve model stability over time, we try to minimize potential multicollinearity issues by considering the variance inflation factor (VIF). We seek to replace the variables with VIFs higher than 10.

6) Optimal lag selection: We utilize SAS for automatic lag selection and model simulation. Starting from the base models, we enter new candidate variables that pass the above tests, one at a time, from the return, risk, liquidity, and structure imbalance classes. For each new variable, we test and select the optimal lag among variable lags from one to twelve inclusive for short-lag and from six to twelve inclusive for long-lag models. The optimality criteria include sign expectations, t-statistics, Granger causality, VIF, $R^2$, and number of observations.[19] If none of the lags for a variable show significance in the theoretically expected direction, we exclude the variable from the model. If more than one lag meets our selection requirements, we narrow the selection of the optimal lag to the one with Granger causality and the most adjusted $R^2$ increases. In summary, the variables listed in the Granger causality tables form the principal regressors in the EWS models (see Appendix C, Table 16–Table 19). The variables with Granger lags that are significant at the 10 percent level are considered first because they demonstrate a stronger Granger relationship with FSI than those that are significant at the 20 percent level.

7) Forecasting accuracy review: Consider and compare forecasting metrics. When the variable is added to the equation,

- does adjusted $\bar{R}^2$ increase?

[19] The innovation of our optimal-lag selection procedure consists of including Granger causality and multicollinearity criteria. In addition, the number of observations serves as an operational threshold: Variables with less than 50 in-sample observations are rejected.

- does MAPE decrease?
- does RMSE decrease?
- do the information criteria (AIC and SC) decrease?
- does Theil U decrease?

8) Review of bias: Do other variables' coefficients change significantly when the variable is added to the equation?

- Functional form bias: This issue generally manifests itself in biased estimates, poor fit, and difficulties reconciling theoretical expectations with empirical results. For several variables in the model, the transformation from level relationship to changes in the independent variable is found to improve the functional form.
- Omitted variable bias: This bias typically results in significant signs of the regression variables that contradict theoretical expectations. When misspecification by omitted variables is detected in a trial model, we further adjust the model by seeking to include the omitted variable (or its proxy) or we replace the misspecified variables.
- Redundant variable: Typically, this issue results in "decreased precision in the form of higher standard errors and lower t-scores."[20] Irrelevant variables in the model generally fail most of the following criteria: theoretical expectations, lack of Granger causality, statistical insignificance, deteriorating forecasting performance (for example, RMSE, MAPE, and Theil U bias), and lack of additional explanatory power to determine the dependent variable (for example, $R^2$, AIC, and SC). When a strong theoretical case exists for including an independent variable that is not otherwise proxied by another related

[20] Studenmund (2006), p. 394.

variable, we try to find a proxy variable that is theoretically sound and is not redundant to the trial specification.

9) Robustness testing: To the extent that violations of classical linear regression model (CLRM) assumptions arise, certain adjustments in the model specification need to be made.

- Treatment of serial correlation: The results of the Breusch–Godfrey LM tests for short-lag dynamic models show evidence of serial correlation in three of the seven dynamic specifications (models 1, 5, and 8 in Table 6). Since all of these equations are in theory correctly specified, the serial correlation is pure and does not cause bias in the coefficients. Thus, we can apply Newey–West standard errors to these specifications while keeping the estimated coefficients intact. Durbin–Watson statistics of the long-lag models show inconclusive evidence of positive serial correlation, and many reject negative serial correlation at a 5 percent significance level for the estimation period of Q4:1991–Q1:2007. An expanded estimation period that includes the financial crisis (Q4:1991–Q4:2010) yields Durbin–Watson statistics that confirm serial correlation of the forecast errors. Adding AR, MA, or both terms as explanatory variables in these models can potentially remedy serial correlation. Models estimated with an autoregressive term as an explanatory variable successfully eliminate serial correlation for short-lag models. Since we aim to estimate models that have longer forecasting horizons without autoregressive variables, we include MA terms as explanatory variables to remove serial correlation and improve our forecasts.
- Heteroskedasticity: This can be an additional penalty associated with bad data and inherent measurement errors in the financial time series data. We conduct modified White and Breusch–Godfrey tests to ensure that the variance of the residual is constant

(homoskedasticity CLRM assumption). The tests fail to reject the null hypothesis of homoskedasticity in all cases, a welcome finding.

- Other specification problems: The Ramsey RESET (Regression Specification Error Test)[21] is commonly used as a general catch-all test for misspecification that may be caused by the following: omitted variables, incorrect functional form, correlation between the residual and some explanatory variable, measurement error in some explanatory variable, simultaneity, and serial correlation. The very generality of the test makes it a useful bottom-line check for any unrecognized misspecification errors. While the residual follows a multivariate normal distribution in a correctly specified OLS regression, Ramsey shows that the above conditions can lead to a nonzero mean vector of the residual. The Ramsey RESET test is set up as a version of a general-specification F-test that determines the likelihood that some variable is omitted by measuring whether the fit of a given equation can be improved by adding some powers of $\widehat{Y}$. All the Ramsey RESET tests show welcome results, with a similar fit for the original and the respective test equation and the F-statistic less than the critical F-value. Provided no other specification problems are highlighted by earlier tests, Ramsey RESET tests further support the research claim that there are no specification problems.

### *3.3. EWS model specifications and results*

In-sample results of the benchmark (panel A), candidate base model (panel B), short-lag base model (panel C), and long-lag base model (panel D) are detailed in Table 3. In forming a base model, we seek a core story of theoretically consistent, long-term relationships between systemic stress $Yt$ and institutional imbalances $Xt$. The candidate model in panel B is formed by selecting

[21] Ramsey (1969).

representative imbalances, one per explanatory variable class, as discussed in the introduction. In this candidate model, real equity, asset-liability mismatch, and leverage increase the potential for systemic stress, offset by credit risk imbalances. The candidate model in panel B improves on the benchmark model in-sample, as demonstrated by the adjusted coefficient of determination and the Akaike and Schwarz information criteria. The short-lag base model in panel C is formed by establishing a core story that features positive influences of structural imbalances and negative influences of risk imbalances. The causes of increasing the potential for systemic stress (imbalances in FX concentration, leverage, and equity markets concentration) are offset by imbalances in interest-rate risk capital and credit risk distance to systemic stress. The short-lag base model further improves on the benchmark and candidate models. The long-lag base model shown in panel D is formed by modifying the core story for the longer run: positive influences of structural and risk imbalances and negative influences of risk and liquidity imbalances. Increasing the potential for systemic stress are imbalances in interbank concentration, leverage, and expected default frequency. They are offset by imbalances in fire-sale liquidity and credit risk distance to systemic stress. The long-lag base model provides a useful performance target for the long-lag EWS models.

All of the base models' variables are statistically significant in the expected direction and show significant Granger causality with the dependent financial stress series. Statistical significance at 10 percent, 5 percent and 1 percent levels is indicated by *, **, and ***, respectively. The significance of causal relationships at 20 percent and 10 percent is indicated by † and ††, respectively. The sample period is October 1991–March 2007.

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Insert Table 3 about here

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Out-of-sample results for the benchmark and base models are shown in Table 4. Viewed out-of-sample, the candidate base model fails to outperform the benchmarking model in root mean square error (RMSE) and bias (Theil U) measures, but offers modest improvement in mean absolute percentage error. The short-lag base model, however, consistently improves on the benchmarking model in all three statistical measures.

Insert Table 4 about here

Table 5 summarizes the short-lag model stories that further improve on the core story of the corresponding base model in explaining financial stress in-sample. Clearly, the positive and negative relationships with financial stress, color-coded as they are, fit two stories—a positive story of structure and a negative story of risk[22]—supplemented and enhanced by additional types of return and liquidity imbalances, both positive and negative.[23]

Insert Table 5 about here

For example, consider model 7 in Table 5. One can see that the core story, as in the other models, includes positive structure and negative risk influence. We supplement the story for this model by certain positive return imbalances and additional negative impact of risk imbalances, beyond those included in the core model. In model 7, the most significant variable for increasing the potential for systemic risk is the interest-rate risk distance to stress. This measure is related to the book value of equity that expresses the equity susceptibility to stress and is constructed through a proprietary stress-discounting model, so this is not an observable measure. The story of

[22] The reason that risk imbalances describe a negative relationship with stress is that they are, by construction, predominantly defensive functions of capital and solvency.

[23] The long-lag models tell fundamentally similar stories of positive structural imbalances and negative risk imbalances. The corresponding table is omitted for brevity.

susceptible equity is supplemented in this model by the story of total credit discounted by CPI, discussed above, and by the story of change in foreign-exchange concentrations. Decreasing the potential for systemic stress are the risk measures: solvency distance to systemic stress, credit risk distance to systemic stress, and the change in the credit risk distance to stress, all of them constructed for the SAFE EWS and not directly observable.

In-sample results of the eight competing EWS specifications for each forecasting horizon are detailed in the four-part Table 6 (short-lag) and Table 7 (long-lag) below. Out-of-sample results are given in Table 8 (short-lag) and Table 9 (long-lag).

Insert Table 6 about here

Insert Table 7 about here

Insert Table 8 about here

Insert Table 9 about here

## 4. Discussion and implications

*4.1. Performance*

*4.1.1. Competitive performance of EWS models*

The stories told by the various short- and long-lag EWS models differ, so we expect that some will do better over time, while others are more suited to particular types of crises. In general, the stories might have different performance levels. It is instructive to look at the statistical performance of these models in-sample (Tables 6 and 7) and their out-of-sample forecasting ability (Tables 8 and 9). The forecasting parameters are defined through the window ending in 2010. Some interesting observations arise, such as that some models tend to be more stable than others over time. This is an important consideration, since financial conditions and regulatory regimes change, and products come and go. Therefore, it is important for the EWS researcher to seek a stable model or to recognize the dynamics and adjust accordingly. From this work, it appears that models 2, 4, and 7 may be expected to be stable and to possess attractive explanatory powers.

We compare the relative performance of the eight short-lag specifications by running a forecasting horse race, in which we look at four known stress episodes: the LTCM crisis, the dot-com crisis, the stock market downturn of 2002, and the subprime crisis. We then rank-order the models' performance based on the RMSE (see Table 10). Some models consistently do better in this horse race, but others with less shining statistics also, somewhat surprisingly, provide powerful insights.

Insert Table 10 about here

It is tempting to think that one should seek "the winner," but we would argue against this. It is very important for a policymaker using this EWS framework to resist the temptation to find the "best" model because no two crises are exactly alike! SAFE models represent distinct stories that most consistently explain financial stress in the markets. Future stress may evolve in ways never seen before or be driven by rare imbalance combinations that differ from the best historic model. To study a possible buildup of financial stress using this EWS, one should therefore consider a variety of plausible stories that may be realized over time.

*4.1.2. Case study 1: Supervisory versus public EWS specifications*

SAFE EWS incorporates both public and supervisory data. One assumption of the researcher is that non-public data provides a more accurate and actionable EWS. To test this assumption, we remove all supervisory FRS variables from the model suggestion stage[24] and re-specify SAFE models.

There are three broad categories of explanatory data: 1) confidential, institution-specific data internal to the Federal Reserve System, 2) undisclosed Federal Reserve models and their output, and 3) data from the public domain. Category 1 consists of confidential institutional data not otherwise available to the public; category 2, which includes the undisclosed FRS models, may use either publicly available or Federal Reserve data. Category 3 comprises raw data from the public domain as well as output from publicly available models that utilize data from the public domain. We classify private supervisory data as FRS internal data (category 1) or the undisclosed output of FRS models (category 2).

We expect to see a qualitative difference between category 1 and category 2 supervisory data. The confidential data (1), although opaque to the public, is generally of high quality. The constructed data (2) is prone to a number of measurement errors and is inherently much more unstable. Many of the public series from the original specifications are preserved. Removing private supervisory series most severely affects the risk variables and, to a lesser extent, the liquidity variables. Thus, we can expect those variables to be most affected when we take the private data out to see only the public formulations of the EWS models. Table 11 shows the

[24] See Section 3.2.

distribution of category 1 data (marked †) and category 2 data (marked ††) among the imbalance classes. Table 12 shows the proportion of supervisory variables among the specified independent variables.

Insert Table 11 about here

Insert Table 12 about here

Comparing the public-data-only versions of SAFE models with those using supervisory data (Table 13 and Fig. 4), we find that models using supervisory data outperform the public formulations in goodness of fit as well as forecasting ability, as seen in the RMSE, MAPE, and bias statistics. When applied to the out-of-sample 2007–09 period, both private and public specifications capture the increase in stress during Q2:2007. However, whereas two of the private models succeed in projecting explanations into Q4:2007, the public models completely fail to explain the latter episode. Thus, we find evidence of the importance and usefulness of private data in creating a systemic risk EWS.

Insert Table 13 about here

It is clear that even public-data-based, systemic risk EWS models would allow financial institutions to study the correlations and sensitivities of their exposure and structural positions within the financial system and to use the framework to enhance systemic-risk stress testing and scenario analysis.

This case study considers only the relative out-of-sample performance of public and private SAFE models. Many interesting questions lie ahead in this line of investigation. For example, future work can address additional analytical questions, such as what factors mattered most in the recent crisis; what would be the results of likelihood tests for the three structural C's (concentration, connectivity, contagion); and what results would be produced by likelihood tests for blocks of data triggered by behavioral effects.

Insert Fig. 4 about here

*4.2. Applications to supervisory policy*

How can SAFE facilitate the work of policymakers? One of its key benefits is focusing their attention on imbalances that have strong positive and negative associations with financial stress. SAFE EWS models help explain financial market stress in terms of several imbalances, some escalating stress and others offsetting it.

From an efficient-market perspective, financial crises are shock events and therefore cannot be predicted. Efficient-markets theory tells us that it is impossible to know the timing of these shocks. Even if it were possible, this perspective tells us that bubble-pricing policy would be problematic because "it presumes that you know more than the market."[25] The theory also highlights a serious technical challenge for monitoring asset bubbles, claiming absolutely that since embedded pricing factors are unobservable in the market, it is empirically impossible to verify asset-price bubbles.[26] Furthermore, the divergence may result either from embedded price factors or from underlying economic fundamentals (state variables), and it is impossible to determine which is responsible.[27] Economists who believe that markets are fundamentally

[25] Alan Greenspan, quoted in the *New York Times*, November 15, 1998.

[26] A feature shared by asset bubbles is that prices increase at a higher rate than any that could be explained by underlying fundamentals (Kindleberger, 1992).

[27] Cogley (1999).

efficient argue that it is therefore better to focus on crisis resolution mechanisms after crises occur.

From an empirical perspective, however, crises are not only about the timing of asset price bubbles, but also about a variety of factors that evolve slowly over time. These factors are observable[28] and tend to have common features:

- Asset prices that are excessive relative to a central tendency or trend, which implicitly represent a longer-term equilibrium based on a stable set of expectations, financial technology, etc.;
- Lots of leverage, which fuels excessive asset prices. Because financial institutions' balance sheets and certain asset classes (such as real estate) are highly leveraged, they tend to play a major part in financial crises;
- A networked financial system which, combined with leveraged financial firms, can "spill" asset losses and funding problems from one institution to another, putting the entire system at risk.[29]

One practical constraint in observing imbalances is the difficulty of relating them to the economy. Shiller measures housing imbalances by deflating them by aggregate housing value.[30] Borio et al. (1994, 2002, 2009) measure imbalances by deflating them by GDP. The SAFE EWS measures imbalances by deflating them by aggregate assets or relevant price indexes.

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[28] Robert Shiller (2008) notes that it is surprising that the experts failed to recognize the bubble as it was forming. Strictly speaking, this is not quite accurate. As Alan Greenspan testified before Congress in 2005, the buildup was observed and gave policymakers serious concern "that the protracted period of the underpricing of risk…would have dire consequences" (Greenspan, 2008).

[29] These factors are not unique to the United States and can also be observed in developing countries' financial crises. The United States possesses a reserve currency that is capable of stopping spillover effects; by contrast, a developing country may be forced to appeal to the IMF for help in stopping crisis spillovers.

[30] See discussion in Standard & Poor's (2008), p.10.

The second major difficulty lies in relating one observed imbalance to others. In normally functioning markets, institutions can efficiently estimate risk and hedge it, while sustaining the financial system's balance and growth. How can a policymaker make an informed judgment that institutions' estimates of risk are becoming biased at a particular time, and that the markets' growth is becoming "irrationally exuberant"? SAFE meets this challenge by consistently estimating fundamentals of various asset classes and the structural characteristics of the system. Thus, a measurement error in a single imbalance, caused by a biased estimate of its fundamental value, is minimized by combining a number of positive and negative imbalances within a SAFE OLS model. By looking at several offsetting imbalances together, SAFE OLS estimates are BLUE—best linear unbiased estimators.

In addition, SAFE EWS assists policymakers' decision process by allowing them to target a particular action threshold above the previous mean of the financial stress series. What should the threshold be? Should policymakers target half a standard deviation of financial stress, or one standard deviation, or some other threshold? In the absence of a more rigorous theoretical framework, the SAFE EWS can help empirically. As we show in case study 2 below, iterative review of retrospective SAFE forecasts in a series of historical stress episodes can establish the difference in standard deviations between SAFE EWS forecasts and the coincident financial stress at the time of the forecast. Policymakers could then formulate a set of stress episodes when additional supervisory involvement could be contemplated to reduce economic losses. Comparing the difference between SAFE forecasts of financial stress and the coincident stress mean for all stress episodes would enable policymakers to identify the optimal target level at which policymakers should become involved. When forecasts of stress fall short of the target action level, the historical evidence would support the case that markets can self-resolve at a particular level of stress. When a forecast of stress exceeds the target level, policymakers can weigh the economic costs of preventive regulatory action against the economic costs of a shock, bringing the aggregate imbalances back to fundamentals.

The following simplified case study illustrates the process by which the SAFE EWS can facilitate policymakers' selection of action thresholds.

*4.2.1. Case study 2: Selecting action thresholds in historic stress episodes*

In this case study, we test SAFE's hypothetical performance against three historic stress episodes: the dot-com episode (Q4:1999–Q1:2000); the stock market downturn (Q2:2002–Q4:2002); and the subprime episode (Q4:2007–Q1:2008). Considering these episodes' ex-post and economic costs, policymakers would probably agree that no regulatory action was needed during the 2002 stock market downturn. They would also be likely to agree that regulatory preventive action prior to the subprime episode might have helped to alleviate the economic costs of the crisis and perhaps even to forestall it. The decision might be less clear in the dot-com episode. Those who reject the idea of regulatory intervention could point out that the stress episode was essentially a stock-market correction of overvalued high-tech firms. Those who accept the idea could point out that the correction was far from soft and, in fact, that it gave the U.S. economy a powerful push toward the early 2000s recession.

Table 14 shows the results of the policy horse race for the models: the financial stress series z-score dropped 0.3 standard deviations from its level six quarters before the stock market downturn, supporting the notion that the episode was benign. In contrast, the stress series moved up almost 0.7 standard deviation from Q2:1998 to the dot-com crisis, and almost 2.9 standard deviations from Q2:2006 to the subprime crisis. Depending on the their belief in the cost efficiency of preventive action for the dot-com crisis, policymakers using the SAFE EWS to help establish a target threshold might set it below or above 0.7 standard deviation from the financial-stress-series mean at the time of a forecast.

The results shown in the table also support our previous argument that selecting a single "best" SAFE model is ill-advised. The policy horse race shows that the best model continually changes. It also shows that some SAFE models do consistently well. Clearly, the current set of SAFE models can be used in various ways; for example, policymakers can consider only the top model at the time of each quarterly forecast, or several of the top models.

Insert Table 14 about here

We conclude the case study 2 illustration of a policy application with a retrospective case study of the out-of-sample subprime episode (see Fig.5). Let us suppose that policymakers have the use of the SAFE EWS during Q2:2006. Observing the financial stress series at this time would give them no reason for concern. In fact, by the time the data for a fresh quarterly observation of FSI is assembled from the daily observations, they would even observe a short-term trend downward as the financial markets continue to boom. Policymakers would like to anticipate possible scenarios of future financial stress six quarters forward—in this case, during Q4:2007 and Q1:2008. To do this, as suggested by the policy-horse-race results above, they would like to consider alternative plausible imbalance stories as given by several top SAFE EWS models. Calibrated to Q2:2006, the top three short-lag models are numbers 2, 4, and 7. As the forecast is run, all three of these models show significant increases relative to the current level of stress. Moreover, they all show that the trend does not peak at the forecast horizon, but in fact originates much earlier—during Q2:2007.[31] This forecast poses two critical questions for

[31] Simulating forecasts in subsequent quarters, one can observe that, as would be expected, the models tend to converge as the forecasting window narrows.

policymakers. First, is the anticipated increase in financial stress real or illusory? Second, if the increase is real, is it critical enough to risk introducing some corrective measures early in 2006 in order to diffuse the projected buildup of stress? If the buildup is illusory and policymakers introduce prophylactic measures to reduce the imbalances, they risk cramping a healthy economy. If they do nothing, financial market stress threatens to worsen. The choice of action or inaction is critical. To provide further policymaking insight, an EWS researcher must be ready to say which channels of prophylactic action should be open to policymakers. We intend to address both of these questions within a more rigorous theoretical foundation in a follow-up study.

Insert Fig. 5 about here

*4.2.2. Case study 3: The financial crisis*

The financial crisis of 2008 tests the forecasting accuracy of both the short- and long-lag models. Although the pinnacle of the crisis may have been marked by the failure of Lehman Brothers and the subsequent quantitative easing, there may also have been signs of stress as early as Q1:2007. Reading the signs then would have provided more time to consider monetary and/or supervisory policy actions to help mitigate developing stress *before* the crisis. We next consider forecasts from short- and long-lag models.

*Short-lag forecasts*

Several short-lag models predicted the advent of stress starting in Q2:2007 and, in some cases, continuing throughout that year (see Fig. 2). In particular, six of eight short-lag models predicted stress, significantly more than in the comparatively quiet years leading up to the crisis (see Fig. 6). In particular, models 2 and 8 predicted early stress in Q2:2007, while other models, such as number 4, predicted stress with a lag.

Although the majority of short-lag models contain an autoregressive explanatory variable, several additional key explanatory variables may be valuable for predicting financial stress. The extent of the contribution to early financial stress depends on the chosen lag of the explanatory variables and on the actual variables included in the forecast. For example, model 2 predicted a rapid increase in stress, beginning in Q2:2007. The observed shrinking value of Liq_5 (liquidity) and the increasing value of Str_4 (the FX currency-market concentration) in this model were the leading contributors to the rising stress level in the forecast period. This forecast indicates that previous values of Liq_5 were decreasing, a sign that the model's top five institutions were under liquidity constraints. Moreover, a rising value of Str_4 indicates an increase in future financial stress because this value measures larger firms' exposure relative to the aggregate foreign-exchange currency markets; in other words, larger firms bear a greater share of the risk associated with this market). Specifically, Liq_5 and Str_4 added 29.1 and 22.5 units, respectively, in Q2:2007 and added 28.9 and 21.5 units, respectively, in Q3:2007.

Insert Fig. 6 about here

Other models, such as number 4, predicted that stress would be present at different horizons. Model 4 predicted that financial stress would be subdued in the first two quarters but would increase significantly in Q4:2007. Furthermore, this effect was driven mainly by slightly different variables, including Liq_6 (stress-sale liquidity) and Str_4.1 (interbank currency-market concentration). The remaining models identified other noteworthy variables, such as Ret_2cpi (capital markets), Rsk_8a (expected default frequency), and Rsk_L (solvency-stress distance from systemic stress).

*Long-lag forecasts*

Long-lag models allow us to forecast stress at longer horizons, which is an advantage for ex-ante policy actions. The value of a forecast with a longer horizon is that it highlights factors that tend to contribute to stress in the longer term (at least six quarters).

As in the shorter-horizon forecasts, we can analyze which variables were important in signaling financial stress. Several long-lag forecasts predicted a notable increase in stress through Q3:2008 (see Fig. 7). Two significant drivers of stress throughout the forecast period were Liq_6 (three-month forward sale) and Liq_7 (fire sale). Like Liq_5 in short-lag model 2, a decreasing value of Liq_6 and Liq_7 signals an increase in future financial stress because the value is a sign that these firms lack liquidity relative to the past. These variables added as much as 18 units of stress in the first two quarters of the forecast period.

Insert Fig. 7 about here

Another important driver of stress was Rsk_8a (the expected default frequency), which added as much as 21 units of stress in the first quarter of the forecast (LL4), and as much as 21 units toward the end of the forecast period (LL3). The expected default frequency (EDF) measures the probability of institutional default, as described by Moody's KMV; an increase in the EDF value signals future financial stress. The growing likelihood of default has several cause-and-effect connections. For example, an increase in EDF could lead to an increase in counterparty risk, which in turn could create difficulties in raising liquidity, thus accentuating the likelihood of stress. We see similar examples of these types of connections when we analyze the long-lag forecasts further. As EDF and liquidity variables lead to financial stress, we observe an increase in Str_9 (leverage), which becomes an important driver of stress only toward the end of the forecast period. This implies that firms have a higher amount of risky debt relative to safer capital, which historically has been a critical driver of financial stress during crises. The increase in leverage may itself have been caused indirectly by previous increases in Liq_6, Liq_7, and Rsk_8a.

### 5. Conclusions and future work

This paper's main contribution has been to demonstrate the existence of a significant association between institutional imbalances, system structure, and financial market stress and to explain this association. The paper also shows significant results in terms of statistical significance, expected direction, and Granger causality.

The results of the EWS developed here focus attention on imbalances that have strong positive and negative associations with financial stress. The SAFE EWS tests the theoretical expectations of positive and negative impacts on financial stress simultaneously, which allows a consistent approach to evaluating systemic banking risk. By comparing the performance of models that use public data with those that use private (supervisory) information, the paper finds evidence of the value of supervisory data. In addition, it discusses the use and relative performance of the SAFE EWS calibrated using only the data publicly available to U.S. financial institutions.

Compared with the preceding EWSs, the SAFE EWS adds a number of innovative features. It is a hybrid EWS framework, which combines macroeconomic variables with institution-specific data. It benefits from a very rich dataset of public and private supervisory data, integrating a number of previously stand-alone supervisory tools and surveillance models. From the methodological viewpoint, the SAFE EWS extends the optimal lag approach and clarifies model selection criteria. In addition, it provides a toolkit of alternative imbalance stories to suit a variety of possible propagation mechanisms in a given systemic stress episode.

In terms of its architecture and typology, SAFE extends the theoretical precedents in EWS variables by suggesting that they fall into four classes of imbalances: return, risk, liquidity, and structure. Although researchers have long recognized structural effects, until now they have not incorporated them into an EWS of systemic risk. Moreover, the SAFE EWS incorporates a feedback amplification mechanism. Feedback mechanisms are particularly prone to measurement error and should be treated cautiously by the EWS researcher. Nevertheless, as SAFE shows in the analysis of public and private data blocks, the amplification mechanism can add significant explanatory power and deserves further consideration. In particular, the liquidity feedback mechanism appears in most SAFE models through a liquidity-independent variable and serves as a critical valuation engine for some of the more dominant risk-imbalance variables. From the financial supervisor's point of view, an EWS involves an ex-ante approach to regulation that is designed to predict and prevent crises. A hazard inherent in all ex-ante models is that their uncertainty may lead to wrong policy choices. To mitigate this risk, SAFE develops two modeling perspectives: a set of long-lag (six or more quarters) forecasting specifications that give policymakers enough time for ex-ante policy action, and a set of short-lag forecasting specifications for verification and adjustment of supervisory actions.

This paper only begins to address the important analytical question of how various specifications performed in historic periods of financial stress. It could be extended in several ways. For example, it would be useful to discuss further the important variables selected by the model, their applicability to supervisory policy and their marginal impacts, and to verify whether the variables indeed mattered and, if not, why not. Particular attention should be focused on the time pattern of evolving financial stress, that is, the speed and amplification dynamic of upcoming financial crises. It is also vital to devote close attention to analyzing the model's performance, considering the economic interpretation of the results. This may also extend to testing the model for different scenarios and to including new variables. To provide further policymaking insights, the EWS researcher should be ready to support the channels of prophylactic action that may open in response to a particular set of imbalances, and should be able to evaluate the impact of regulatory changes on financial stress in "real time." Finally, it is important to extend the EWS model to financial intermediaries other than bank holding companies.

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## Tables and figures

### Table 1

Systemic risk explanatory variables in literature.

| | Demirgüç-Kunt and Detragiache 1998 | Kaminsky and Reinhart 1999 | Borio and Lowe 2002, Asset | Borio and Lowe 2002, Crises | Edison 2003 | Hanschel and Monnin 2005 | King, Nuxoll, and Yeager 2006 | Hendricks, Kambhu, and Mosser 2007 | Borio and Drehmann 2009 | Moshirian and Wu 2009 | IMF, 2009 | Reinhart and Rogoff 2009 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| National economic | | | | | | | | | | | | |
| a) GDP national | X | X | | | X | X | | | | X | | |
| b) Credit/GDP national | X | X | X | X | X | X | | | X | (X) | | |
| c) Equity | | X | X | X | X | X | (X) | X | X | X | (X) | X |
| d) Property | | | | | | X | X | (X) | X | | | X |
| e) Investments | | | X | | | X | | | | | | |
| International economic | | | | | | | | | | | | |
| a) GDP international | | | | | | X | | | | | | |
| b) Credit/GDP international | | | | | | | | | | | | |
| c) Equity | | | | | | | (X) | X | (X) | | (X) | X |
| d) Foreign exchange rate | (X) | X | | X | X | | | (X) | | | | X |
| e) Exports/Imports | (X) | X | | | X | | | | | | | X |
| Financial system | | | | | | | | | | | | |
| a) Interbank lending | | X | | | (X) | (X) | | | | | (X) | |
| b) Leverage | | (X) | | | | | | X | | | | |
| c) Interest rate | X | X | | | X | | X | | | X | X | |
| d) Competition, concentration | | | | | | | X | X | | | | |
| e) Risk appetite, discipline | | | | | | | | X | | (X) | X | |
| f) Complexity | | | | | | | X | X | | | | |
| g) Dynamics, volatility | | | | | | | | X | | X | X | |

*Note*: This table is taken from Gramlich, Miller, Oet, and Ong (2010, p. 205).

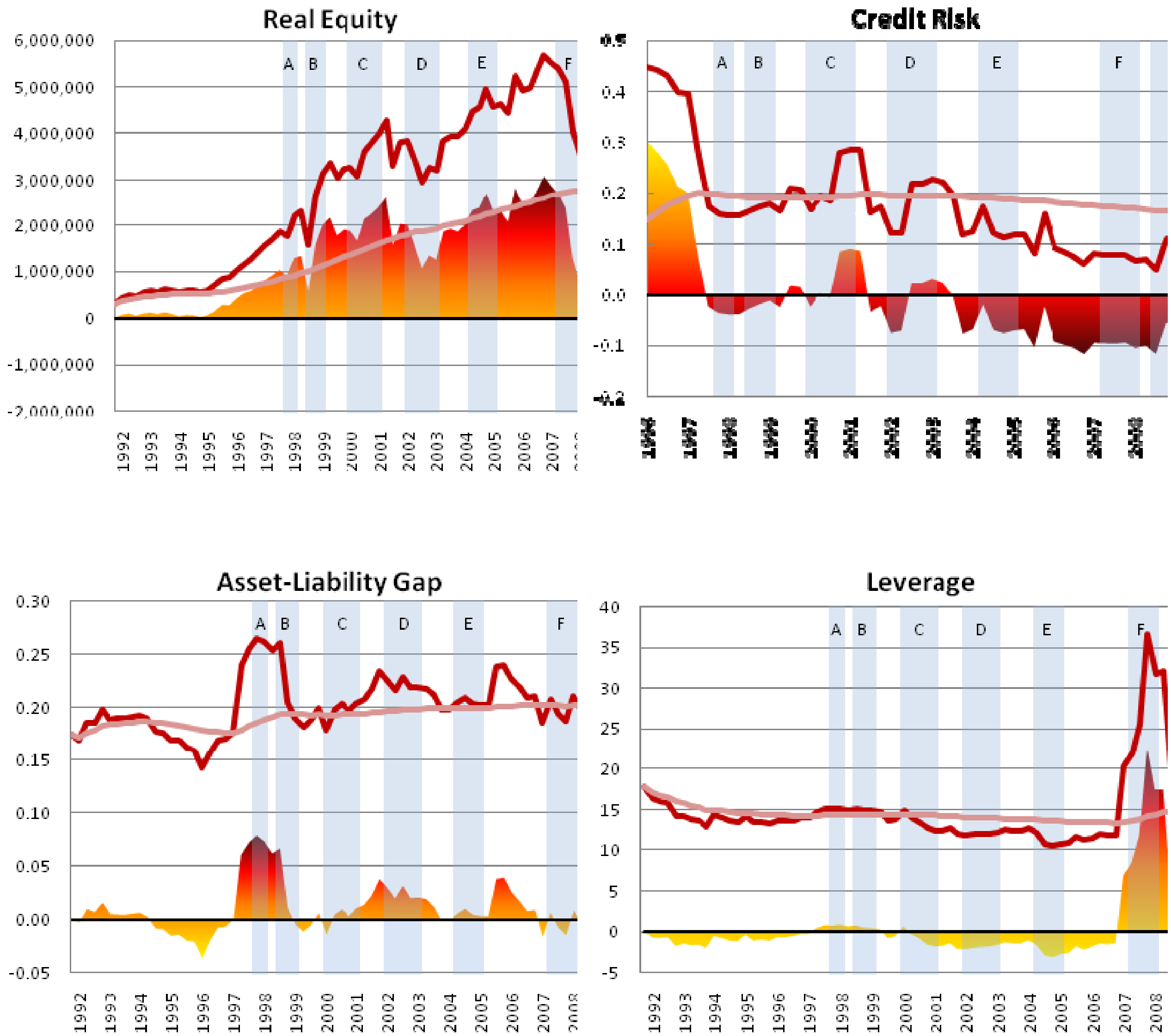



**Fig. 1.** Imbalances as deviations from fundamentals reflect potential shocks.

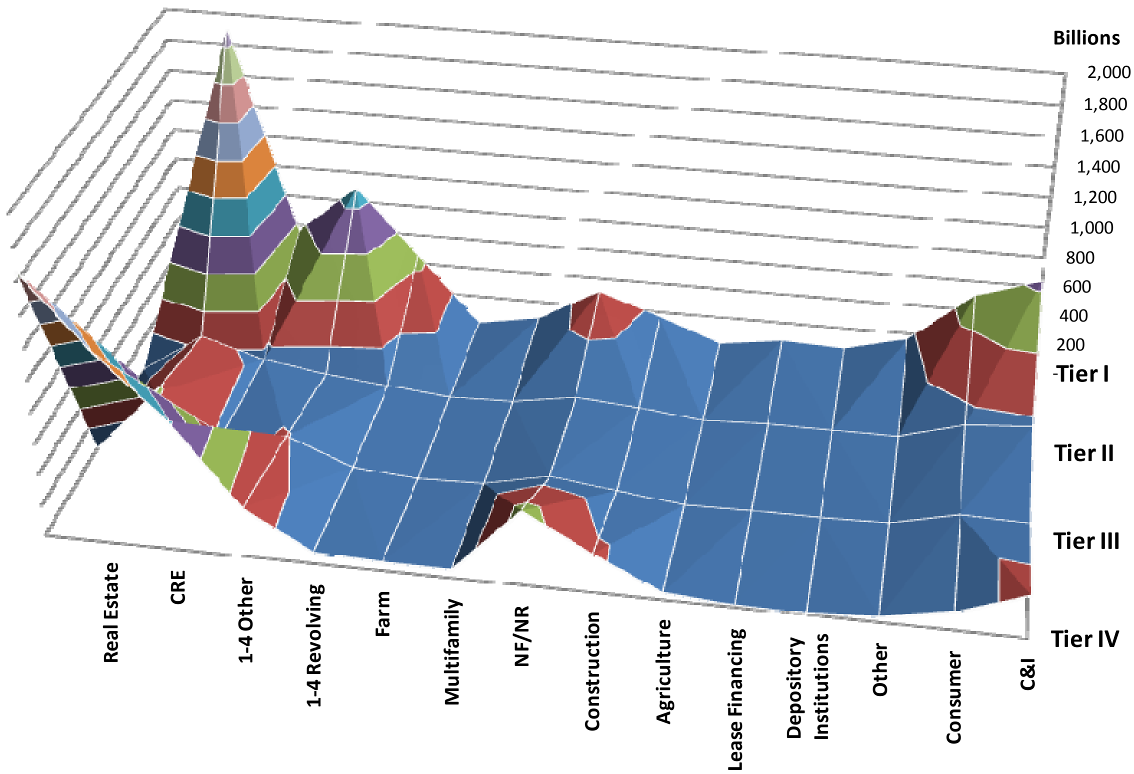



**Fig. 2.** Topology of loan USD concentrations across bank holding company tiers and loan types**.**

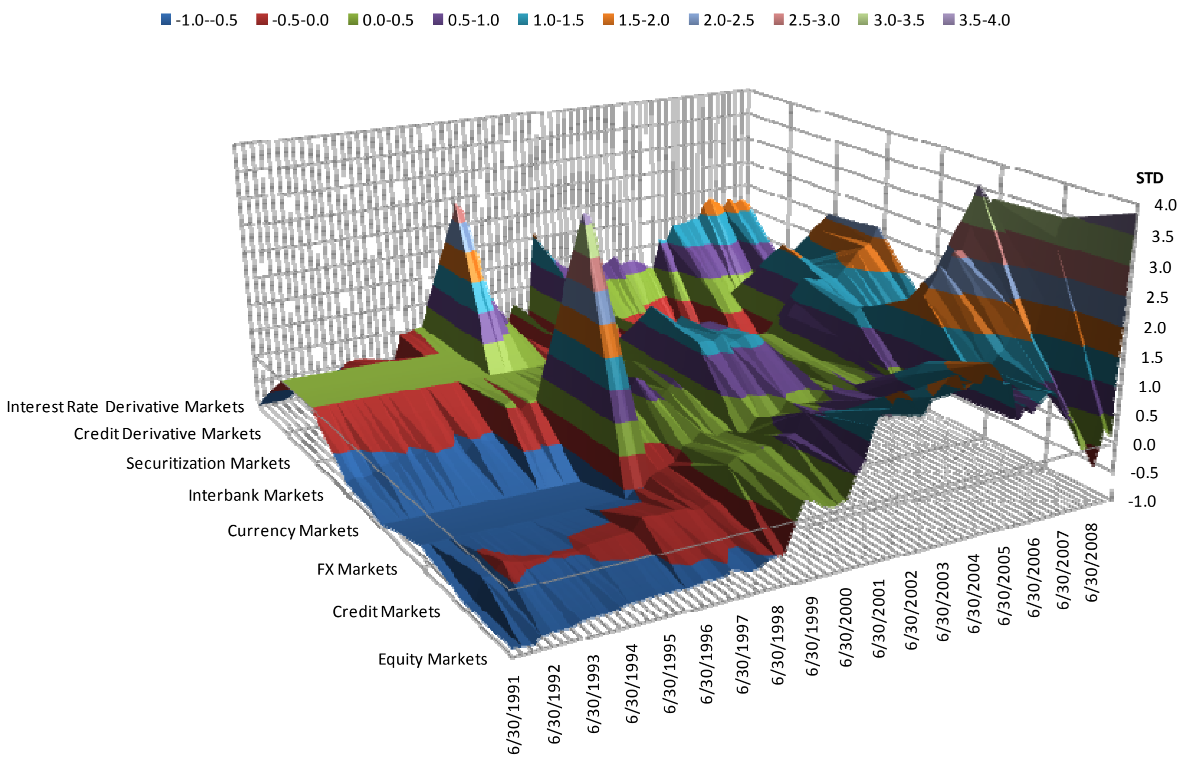



**Fig. 3.** Topology of financial market concentrations of top five US BHCs across markets and time**.**

**Table 2**

Explanatory variable classes in the SAFE model.

| Explanatory Variable Classes | Construction classes |
|---|---|
| ❖Return imbalances | ➔Through asset price boom/bust<br>\| By markets / products in: |
| | CAPITAL MARKETS<br>\|\| Equity markets<br>\|\| Credit markets<br>\|\| Property markets: residential / commercial) |
| | CURRENCY MARKETS<br>\|\| FX<br>\|\| Interbank |
| | RISK TRANSFER / DERIVATIVES MARKETS<br>\|\| Securitizations markets<br>\|\| Credit Derivatives markets<br>\|\| Interest Rate Derivatives markets |
| ❖Risk imbalances | ➔Credit<br>➔Interest rate<br>➔Market<br>➔Solvency |
| ❖Liquidity imbalances | ➔Though Funding Liquidity channels<br>➔Though Asset Liquidity channels |
| ❖Structural imbalances | ➔Connectivity<br>➔Concentration<br>➔Contagion |

## Table 3

Benchmark and base models in-sample.

**Panel A: Benchmark FSI model**

$$\widehat{FSI} = 7.85 + 0.60FSI_{-1} + 0.24FSI_{-4}$$

DF=58 K=2

| | Constant | Lagged FSI | Seasonal FSI | Adjusted R-squared | Akaike info criterion | Schwarz criterion |
|---|---|---|---|---|---|---|
| Estimates | 7.85 | 0.60 | 0.24 | | | |
| t-value | (1.44) | (5.86) | (2.31) | 0.49 | 6.72 | 6.82 |
| Granger | | | | | | |

**Panel B: Candidate Base Model**

$$\widehat{FSI} = 36.58 + 0.35FSI_{-1} + 1.70GT\_AL3_{-5} + 7.04GT\_LEVN_{-9} + 2.34\Delta PMKTCP_{-5} - 12.62\Delta CRCAP\_NV_{-11}$$

DF=61 K=5

| | Constant | Lagged FSI | AL mismatch | Leverage | Real Equity | Credit Risk | Adjusted R-squared | Akaike info criterion | Schwarz criterion |
|---|---|---|---|---|---|---|---|---|---|
| Estimates | 36.58 | 0.35 | 1.70 | 7.04 | 2.34 | -12.62 | 0.60 | 6.51 | 6.71 |
| t-value | (5.72) | (3.24) | (3.65) | (2.97) | (1.89) | (2.29) | | | |
| Granger | | | † | †† | | † | | | |

**Panel C: Short Lag Base Model**

$$\widehat{FSI} = 38.77 + 0.40FSI_{-1} + 2.06\Delta HFX4_{-6} + 8.65\Delta HEQ5_{-8} + 8.15GT\_LEVN_{-5} - 2.94\Delta EQLGDW3_{-7} - 4.55CR\_EVSV_{-8}$$

DF=61 K=6

| | Constant | Lagged FSI | Δ FX concentr. | Δ Equity Market concentr. | Leverage | Δ Interest Rate Risk capital | Credit Risk | Adjusted R-squared | Akaike info criterion | Schwarz criterion |
|---|---|---|---|---|---|---|---|---|---|---|
| Estimates | 38.77 | 0.40 | 2.06 | 8.65 | 8.15 | -2.94 | -4.55 | | | |
| t-value | (5.65) | (3.93) | (2.78) | (3.14) | (3.38) | (1.03) | (3.16) | 0.63 | 6.49 | 6.74 |
| Granger | | | †† | | †† | | †† | | | |

**Panel D: Long Lag Base Model**

$$\widehat{FSI} = 37.85 - 9.88GT\_ALG3_{-9} + 2.29EDF_{-11} - 2.24CR\_EVNV_{-6} + 4.55GT\_HIB_{-8} + 11.20GT\_LEVN_{-7}$$

DF=57 K=5

| | Constant | AL mismatch | Expected Default Frequency | Credit Risk | Currency Market concentr. | Leverage | Adjusted R-squared | Akaike info criterion | Schwarz criterion |
|---|---|---|---|---|---|---|---|---|---|
| Estimates | 37.85 | -9.88 | 2.29 | -2.24 | 4.55 | 11.20 | | | |
| t-value | (6.20) | (3.05) | (2.06) | (1.85) | (2.13) | (3.68) | 0.51 | 6.75 | 6.96 |
| Granger | | | †† | | | †† | | | |

**Table 4**

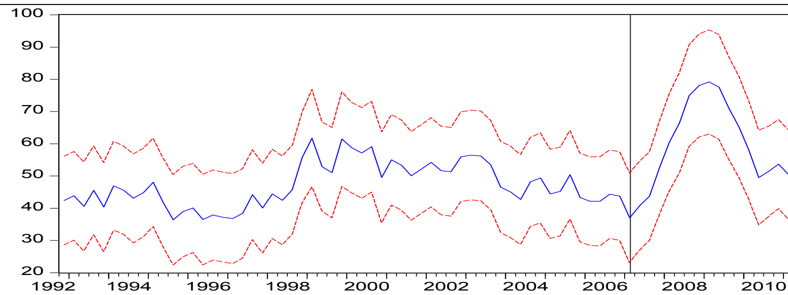
Benchmark and base models out-of-sample static forecasts.

**Panel A: Benchmark FSI model**

$$\widehat{FSI} = 7.85 + 0.60FSI_{-1} + 0.24FSI_{-4}$$

DF=58 K=2

| RMSE | MAPE | Theil U |
|---|---|---|
| 8.35 | 12.42 | 0.081 |

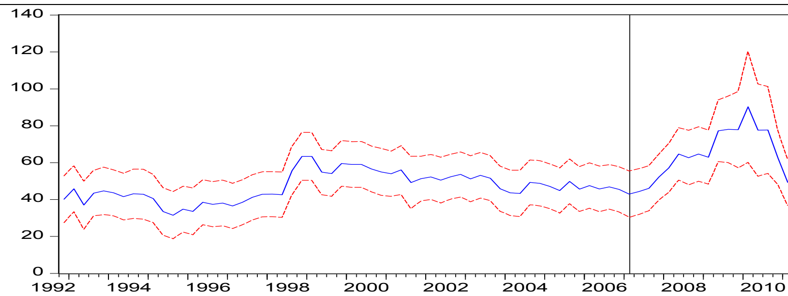



**Panel B: Candidate base Model**

$$\widehat{FSI} = 36.58 + 0.35FSI_{-1} + 1.70GT\_AL3_{-5} + 7.04GT\_LEVN_{-9} + 2.34\Delta PMKTCP_{-5} - 12.62\Delta CRCAP\_NV_{-11}$$

DF=61 K=5

| RMSE | MAPE | Theil U |
|---|---|---|
| 11.70 | 15.24 | 0.112 |

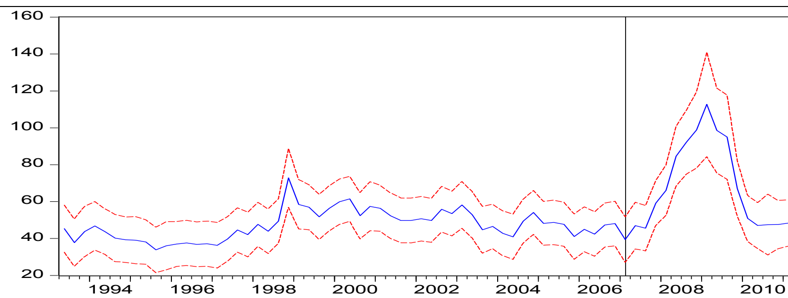



**Panel C: Short-lag base model**

$$\widehat{FSI} = 38.77 + 0.40FSI_{-1} + 2.06\Delta HFX4_{-6} + 8.65\Delta HEQ5_{-8} + 8.15GT\_LEVN_{-5} - 2.94\Delta EQLGDW3_{-7} - 4.55CR\_EVSV_{-8}$$

DF=61 K=6

| RMSE | MAPE | Theil U |
|---|---|---|
| 9.04 | 11.83 | 0.084 |

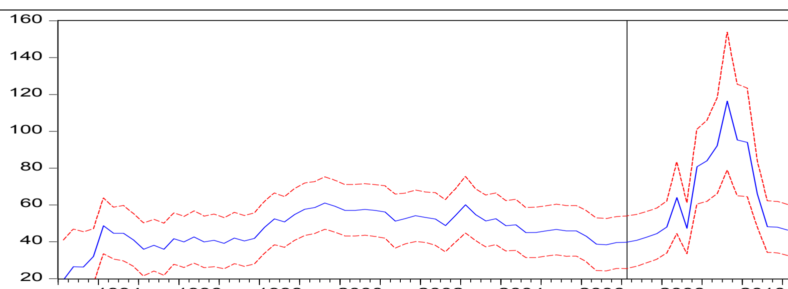



**Panel D: Long-lag base model**

$$\widehat{FSI} = 37.85 - 9.88GT\_ALG3_{-9} + 2.29EDF_{-11} - 2.24CR\_EVNV_{-6} + 4.55GT\_HIB_{-8} + 11.20GT\_LEVN_{-7}$$

DF=57 K=5

| RMSE | MAPE | Theil U |
|---|---|---|
| 15.14 | 18.75 | 0.143 |



## Table 5

Summary of short-lag model stories.

| Model | Story | Positive | Negative |
|---|---|---|---|
| | Structure$^{+}$ | Leverage | Δ Credit risk capital |
| (1) ASLS adj FSI | Risk$^{-}$ | Δ FX concentration | Δ Interest rate risk capital |
| | Return$^{+/-}$ | Δ Market capitalization | Commercial prop credit |
| | Structure$^{+}$ | Δ FX concentration | Δ Interest rate risk capital |
| (2) ASLMR adj | Risk$^{-}$ | Δ Equity market concentration | Shock liquidity |
| | Liquidity$^{-}$ | Leverage | Solvency |
| | Structure$^{+}$ | Δ FX concentration | Shock liquidity |
| (3) BSLS adj | Risk$^{-}$ | Leverage | Credit risk dist to syst stress |
| | Return$^{+}$ Liquidity$^{-}$ | Δ Market capitalization | Solvency |
| | Structure$^{+}$ | Δ FX concentration | Δ Interest rate risk capital |
| (4) BSLMR adj | Risk$^{-}$ | Δ Equity market concentration | Δ Credit risk capital |
| | Risk$^{+}$ Return$^{-}$ | Expected default frequency | Commercial property credit |
| | Structure$^{+}$ | ΔEquity market concentration | ΔCredit risk dist to syst stress |
| (5) CSLS adj | Risk$^{-}$ | Connectivity | ΔSolvency dist to syst stress |
| | | ΔConnectivity | |
| | Structure$^{+}$ | ΔEquity market concentration | ΔCredit risk dist to syst stress |
| (6) CSLMR adj | Risk$^{+}$ | Leverage | Δ Interest rate risk capital |
| | Liquidity$^{+}$ Return$^{-}$ | AL mismatch | Interest risk derivatives |
| | Structure$^{+}$ | Int rate risk dist to stress | Solvency dist to syst stress |
| (7) rev DSLS adj2 | Risk- | Total credit cpi | Credit risk dist to syst stress |
| | Risk$^{+}$ Return$^{+}$ | ΔFX concentration | ΔCredit risk dist to stress |
| | Structure$^{+}$ | ΔFX concentration | ΔCommercial property credit |
| (8) DSLMR adj | Risk$^{-}$ | FX concentration | Solvency dist to syst stress |
| | Return$^{-}$ | Interbank concentration | Credit risk dist to syst stress |

Legend:

| | |
|---|---|
| Structure | Risk |
| Return | Liquidity |

**Table 6**

In-sample regression results for SAFE EWS short-lag models.

| VARIABLE | SERIES | EXPOSURE | (1)$^{cpi}$ ASL Sadj § | (2)$^{cpi}$ ASL MRadj | (3)$^{ta}$ BSL Sadj | (4)$^{ta}$ BSL MRadj | (5)$^{cpi}$ CSL Sadj § | (6)$^{cpi}$ CSL MRadj | (7)$^{ta}$ DSL Sadj | (8)$^{ta}$ DSL MRadj § |
|---|---|---|---|---|---|---|---|---|---|---|
| **RETURN VARIABLES** | | | | | | | | | | |
| RET_1.1cpi | $\Delta PMKTCP5^{+}$ | Capital Markets – Equity (price-based) | 11.810 (4.56)*** | | | | | | | |
| RET_2cpi | $LNSTG\_t^{+}$ | Capital Markets - Bonds (price-based) | | | | | | | 7.723 (4.16)*** | |
| RET_4ta | $LNSCTAGt^{-}$ | Capital Markets - Commercial Property (total assets-based) | -7.958 (-6.93)*** | | | -5.195 (-2.74)*** | | | | |
| RET_4ta | $\Delta LNSCAT5^{-}$ | Capital Markets - Commercial Property (total assets-based | | | | | | | | -10.673 (-5.06)*** |
| RET_5.2ta | $IXDRTAGt^{-}$ | Interbank Derivative Exposure | | -1.192† (-1.78)*** | | | | | | |
| RET_6cpi | $ITRBNKG\_t^{-}$ | Currency Markets - Interbank Exposures (price-based) | | | | | | | -3.076 (-2.86)*** | |
| RET_6ta | $ITBKTAGt^{+}$ | Currency Markets - Interbank Exposures (total assets-based) | 2.193† (3.43)*** | | 3.686 (3.46)*** | 1.023 (1.23) | 3.686 (4.52)*** | 2.600 (2.28)** | | |
| RET_9ta | $IRDETAGt^{-}$ | Risk Transfer Markets - IR Derivatives (total assets-based) | | | | | | -4.298†† (-2.48)** | | |
| **RISK VARIABLES** | | | | | | | | | | |
| RSK_2 | $\Delta EQLGDW3^{-}$ | IRR Indicators - through-the-cycle function | -11.536†† (-7.59)*** | | | | | | | |
| RSK_2.1 | $IRCAP\_NV^{+}$ | IRR Indicators - through-the-cycle function | | 3.344 (4.93)*** | 1.655† (2.68)** | | | 4.859† (5.40)*** | | 2.319† (9.07)*** |
| RSK_4 | $IRCAP\_SV^{+}$ | IRR Indicators - point-in-time/stress function | | | | | | | 13.243† (4.33)*** | |
| RSK_6 | $\Delta IRCEV5^{-}$ $\Delta IRCAP\_EV^{-}$ | IRR Indicators - extreme stress/crisis function | | -13.443†† (-4.63)*** | | -9.156†† (-2.66)** | | -5.095†† (-3.15)*** | | |
| RSK_7.1 | $\Delta CRCAP\_NV^{-}$ | Credit Risk Indicators - through the cycle function | -13.191† (-5.81)*** | | | -7.290† (-2.02)** | | | | |
| RSK_8a | $EDF^{+}$ | Credit Risk Indicators - point-in-time/stress function | 3.281 (4.38)*** | 2.252 (2.81)*** | | 2.081 (2.66) ** | | 1.301 (1.17) | 2.588 (2.80)*** | 2.809 (8.02)*** |
| RSK_9 | $LNS\_EV^{-}$ | Economic Value : 12 call report loan portfolios - 99.5% BankCaR | | | | | | -2.588 (-2.16)*** | | |
| RSK_14 | $SOLV\_NV^{-}$ | Solvency - through the cycle function | | -2.378† (-3.42)*** | | | | | | |
| RSK_15 | $SOLV\_SV^{-}$ | Solvency - point-in-time/stress function | | | | | | -3.514 (-1.74)* | | |
| RSK_16 | $SOLV\_EV^{-}$ | Solvency - extreme stress/crisis function | | | | | | | | -4.554 (-3.90)*** |
| RSK_F | $IR\_EVNV^{-}$ | Interest Rate Risk - normal distance-to-systemic stress | | | | -2.421 (-3.30)*** | | | | |
| RSK_G | $IR\_SVNV^{+}$ | Interest Rate Risk - normal distance-to-stress | | | 2.811†† (2.66)** | | 2.811†† (10.32)*** | 2.637†† (2.73)*** | | |
| RSK_H | $CR\_EVSV^{-}$ | Credit Risk - stress distance-to-systemic stress | -4.997† (-3.86)*** | | -2.291 (-1.46)*** | | -2.291 (-1.78)* | | -53.223† (-6.09) *** | |
| RSK_H | $\Delta CR\_EVSV^{-}$ | Credit Risk - stress distance-to-systemic stress | | | -8.422 (-1.70) * | | -8.422 -1.86* | -12.133† (-4.68)*** | | |
| RSK_I | $CR\_EVNV^{-}$ | Credit Risk - normal distance-to-systemic stress | | | | | | | | -4.036† (-3.60)*** |
| RSK_I | $\Delta TCEVNV5^{-}$ | Credit Risk - normal distance-to-systemic stress | | | -9.465 (-4.15)*** | | -9.465 (-7.50)*** | | -5.924 (-3.44)*** | |
| RSK_K | $\Delta tCRSVNV4^{+}$ | Credit Risk - normal distance-to-stress | | | | | | | | 4.731 (4.22) *** |
| RSK_L | $SLV\_EVSV^{-}$ | Solvency - stress distance-to-systemic stress | | | | | | | -72.690†† (-5.63) *** | |
| RSK_L | $\Delta TSEVSV5^{-}$ | Solvency - stress distance-to-systemic stress | | | -5.251 (-2.53)** | | -5.251†† (-6.88)*** | | | |
| RSK_M | $SLV\_EVNV^{-}$ | Solvency - normal distance-to-systemic stress | -2.531†† (-4.71)*** | | | -2.183†† (-2.17)*** | †† | -3.662† (-3.73)*** | | |
| **LIQUIDITY VARIABLES** | | | | | | | | | | |
| LIQ_1 | $Gt\_AL03^{+}$ | AL Gap Indicators - '0 to 3 months' maturity band | | | | 1.491 (2.04) ** | | | | |
| LIQ_2 | $Gt\_AL312^{+}$ | AL Gap Indicators - '3 to 12 months' maturity band | 1.556† (2.17)** | | | | | | | |
| LIQ_2 | $\Delta tAL3122^{+}$ | AL Gap Indicators - '3 to 12 months' maturity band | | | | | | | 2.453 (2.43)* | |
| LIQ_4 | $Gt\_ALG3^{+}$ | AL Gap Indicators - 'greater than 3 years' maturity band | | | 3.007 (5.84)*** | | 3.007 (7.64)*** | 5.665 (6.14)*** | | |
| LIQ_5 | $Gt\_LX\_NV^{-}$ | Liquidity Index Indicators - 1-year forward sale | -5.027 (-3.49)*** | -4.009 (-3.43) | | | | | -3.751 (-2.75)*** | |
| LIQ_6 | $Gt\_LX\_SV^{-}$ | Liquidity Index Indicators - 3-month forward sale | | | -1.702 (-2.37)** | -1.740 (-3.18) *** | -1.702 (-6.11)*** | -0.962 (-1.24) | | |
| **STRUCTURE VARIABLES** | | | | | | | | | | |
| STR_1.2 | $Gt\_P5PCV^{+}$ | Connectivity Indicators – CoVaR at 5% | 3.667 (6.69)*** | | | | | | | 1.596 (2.90) *** |
| STR_1.3 | $\Delta TD1PCV3^{+}$ | Connectivity Indicators – Delta CoVaR at 1% | | | 6.278 (1.69) * | | 6.278 (2.51)** | | | |
| STR_1.4 | $Gt\_D5PCV^{+}$ | Connectivity Indicators – Delta CoVaR at 5% | | | 6.586 (4.08)*** | 1.479 (2.22) ** | 6.586 (5.52)*** | 4.421 (2.91)*** | 1.565 (2.29)** | |
| STR_2 | $\Delta HEQ5^{+}$ | Concentration Indicators - Capital Markets (Equity) | | 14.322† (4.07)*** | | 13.369† (3.93)*** | 10.320† (7.35)*** | 10.274† (4.27)*** | 3.952† (2.17)** | |
| STR_4 | $Gt\_HFX^{+}$ | Concentration Indicators - Currency Markets (FX) | | 21.051†† (3.14)*** | | | | | 3.873†† (5.50)*** | 4.128† (5.67)*** |
| STR_4 | $\Delta HFX4^{+}$ | ΔConcentration Indicators - Currency Markets (FX) | 54.066†† (10.08)*** | | 1.579†† (2.24)** | 31.770†† (4.48)*** | 1.579†† (3.60)*** | 3.891†† (4.84)*** | 5.318†† (4.24)*** | 5.584†† (6.86)*** |
| STR_4.1 | $Gt\_HIXP^{+}$ | Concentration Indicators - Currency Markets (FX) | 2.778 (7.43)*** | | 10.320†† (4.33)*** | | | | | 1.436† (2.73)*** |
| STR_5 | $Gt\_HIB^{+}$ | Concentration Indicators - Currency Markets (Interbank) | | | | | | | 3.686† (2.17)** | 3.368† (2.53)** |
| STR_8 | $\Delta tHIRD5^{+}$ | Concentration Indicators - Risk Transfer Markets (IR Derivatives) | | | | | | | | 3.310†† (5.41)*** |
| STR_9 | $Gt\_LEVN^{+}$ | Contagion (normal leverage) | 9.463† (6.689)*** | 6.488†† (2.85)*** | | 13.065†† (4.69)*** | | 7.071 (2.36)** | 4.717†† (1.39) | |
| DYNAMIC | $FSI_{t-1}^{+}$ | Lagged Financial Stress Index | 0.289 (3.9)*** | 0.327 (4.43)*** | 0.308 (3.37)*** | 0.242 (2.75)*** | 0.308 (4.59)*** | 0.239 (2.77)*** | | 0.134 (2.07)** |
| CONSTANT | | | 21.440 | 39.182 | 28.388 | 40.873 | 28.388 | 52.213 | 22.284 | 26.935 |
| OBSERVATIONS | | | 56 | 54 | 56 | 55 | 53 | 55 | 56 | 58 |
| R-squared | | | 0.84 | 0.83 | 0.78 | 0.85 | 0.78 | 0.80 | 0.87 | 0.81 |
| AIC (OLS) | | | 5.90 | 5.88 | 6.19 | 5.83 | 6.19 | 6.11 | 5.66 | 6.00 |
| SC (OLS) | | | 6.48 | 6.28 | 6.72 | 6.42 | 6.72 | 6.77 | 6.23 | 6.49 |

*Note:* Absolute value of t statistics is shown in parentheses. Theoretical expectations are noted by +/-/≠0. Statistical significance at 10%, 5% and 1% levels is indicated by *, **, and ***, respectively. The significance of Granger causality at 20% and 10% is shown by † and ††, respectively. § denotes Newey-West errors.

## Table 7
In-sample regression results for SAFE EWS long-lag models.

| VARIABLE | SERIES | EXPOSURE | (1) long Lag | (2) long Lag | (3) long Lag | (4) long Lag | (5) long Lag | (6) long Lag | (7) long Lag | (8) long Lag |
|---|---|---|---|---|---|---|---|---|---|---|
| **RETURN VARIABLES** | | | | | | | | | | |
| RET_1.1cpi | $\Delta PMKTCP5^{+}$ | Capital Markets – Equity (price-based) | | | -2.535 (1.663)* | 4.293 (2.236)** | | | | |
| RET_2cpi | $LNSTG\_t^{+}$ | Capital Markets - Bonds (price-based) | | | | | | | 10.025 (4.300)*** | 6.763 (3.031)*** |
| RET_2ta | $LNSTTAGt^{-}$ | Capital Markets - Bonds(total assets based | -11.549 (2.442)** | | | | | | | |
| RET_4ta | $\Delta LNSCAT5^{-}$ | Capital Markets - Commercial Property (total assets-based | -4.819 (1.902) | | | | | -4.941 (2.458) | | |
| RET_6cpi | $ITRBNKG\_t^{-}$ | Currency Markets - Interbank Exposures (price-based) | -4.077† (3.149)*** | | | | | -2.298†† (2.599)*** | -3.855† (3.769)*** | -3.153† (3.609)*** |
| RET_6ta | $ITBKTAGt^{+}$ | Currency Markets - Interbank Exposures (total assets-based) | 2.112†† (2.251)** | | -4.426†† (5.245)*** | | | | | |
| RET_7cpi | $SECEG\_t^{+}$ | Risk Transfer Markets - Securitizations (price-based) | | 2.555†† (1.592)** | 3.209†† (4.254)*** | 3.250†† (1.847)* | 4.992†† (3.055)*** | 3.225†† (2.250)*** | | 4.016†† (2.962)*** |
| RET_7ta | $SECETAGt^{-}$ | Risk Transfer Markets - Securitizations (total assets-based) | -3.409†† (1.693)* | | 4.183†† (3.111)*** | | | | -2.843† (1.449) | |
| RET_9ta | $IRDETAGt^{-}$ | Risk Transfer Markets - IR Derivatives (total assets-based) | | -4.525 (3.601)*** | | | -5.577 (3.641)*** | | | |
| **RISK VARIABLES** | | | | | | | | | | |
| RSK_2 | $\Delta EQLGDW3^{-}$ | IRR Indicators - through-the-cycle function | -6.019†† (2.142)** | | | | -7.970† (2.341)** | | -7.284†† (2.285)** | |
| RSK_7.1 | $\Delta CRCAP\_NV^{-}$ | Credit Risk Indicators - through the cycle function | | | -21.638 (4.947)*** | | | -8.138†† (1.799)* | | |
| RSK_8a | $EDF^{+}$ | Credit Risk Indicators - point-in-time/stress function | 3.066†† (2.929)*** | | 3.743†† (4.298)** | 3.450†† (4.298)*** | | | | 2.955†† (3.214)*** |
| RSK_81 | $LNS\_MVEDF^{-}$ | Market Value : 12 call report loan portfolios (w. EDF uncertainty) | | | | | -21.451 (2.615)** | | | |
| RSK_11 | $SABRDPR^{+}$ | Supervisory Rating Indicators - point-in-time/stress function | | 30.093 (3.427)*** | | | | | | |
| RSK_14 | $SOLV\_NV^{-}$ | Solvency - through the cycle function | | | | -7.377 (2.835)** | | | | |
| RSK_15 | $SOLV\_SV^{-}$ | Solvency - point-in-time/stress function | -6.120 (3.152)*** | | | | | | | |
| RSK_16 | $SOLV\_EV^{-}$ | Solvency - extreme stress/crisis function | | | | | | | | -2.416† (2.464)** |
| RSK_E | $IR\_EVSV^{-}$ | Interest Rate Risk - stress distance-to-systemic stress | | | -1.620 (2.485)** | | | | | |
| RSK_G | $IR\_SVNV^{+}$ | Interest Rate Risk - normal distance-to-stress | 3.268 (2.673)*** | | | | | | | |
| RSK_H | $\Delta CR\_EVSV^{-}$ | Credit Risk - stress distance-to-systemic stress | | -18.655 (3.230)*** | | | | -12.476 (3.169)*** | | |
| RSK_I | $CR\_EVNV^{-}$ | Credit Risk - normal distance-to-systemic stress | | -6.921†† (3.07)*** | -2.320 (2.207)** | -2.914†† (2.013)** | | | | -3.549†† (3.292)*** |
| RSK_K | $\Delta tCRSVNV4^{+}$ | Credit Risk - normal distance-to-stress | | | 4.086 (2.269)** | | | | | |
| RSK_L | $SLV\_EVSV^{-}$ | Solvency - stress distance-to-systemic stress | | | | | -3.602†† (1.938)* | | | |
| RSK_L | $\Delta TSEVSV5^{-}$ | Solvency - stress distance-to-systemic stress | | | | | | | -8.851†† (2.103)** | -16.239 (4.197)*** |
| RSK_M | $SLV\_EVNV^{-}$ | Solvency - normal distance-to-systemic stress | | -5.910†† (3.422)*** | | -3.437† (2.732)*** | | | | |
| RSK_N | $SLV\_SVNV^{-}$ | Solvency - normal distance-to-stress | | | | | | -7.423 (3.416)*** | | |
| **LIQUIDITY VARIABLES** | | | | | | | | | | |
| LIQ_2 | $\Delta tAL3122^{+}$ | AL Gap Indicators - '3 to 12 months' maturity band | | | | | 5.645 (2.883)*** | 4.893 (2.458)** | 5.528 (2.998)*** | 4.098†† (2.642)*** |
| LIQ_5 | $Gt\_LX\_NV^{-}$ | Liquidity Index Indicators - 1-year forward sale | | | -16.240 (4.875)** | -7.697 (1.849)** | | | | |
| LIQ_6 | $Gt\_LX\_SV^{-}$ | Liquidity Index Indicators - 3-month forward sale | | -16.240 (4.875)*** | | | -12.930 (3.118)** | -13.718 (3.793)*** | | |
| LIQ_7 | $Gt\_LX\_EV^{-}$ | Liquidity Index Indicators - immediate fire sale | | -8.159 (2.076)** | -4.799 (1.687)* | -9.308 (2.131)*** | -15.098 (3.350)*** | | | -6.974 (1.795)* |
| **STRUCTURE VARIABLES** | | | | | | | | | | |
| STR_1.2 | $Gt\_P5PCV^{+}$ | Connectivity Indicators – CoVaR at 5% | | | | 2.406†† (2.001)* | | 3.853†† (3.666)*** | | 4.851†† (4.999)*** |
| STR_1.3 | $\Delta TD1PCV3^{+}$ | Connectivity Indicators – Delta CoVaR at 1% | | | | | | | 3.912 (2.883)*** | |
| STR_1.4 | $Gt\_D5PCV^{+}$ | Connectivity Indicators – Delta CoVaR at 5% | | 3.393 (2.310)** | | | | | 2.610 (1.660)* | |
| STR_2 | $\Delta HEQ5^{+}$ | Concentration Indicators - Capital Markets (Equity) | 9.118 (3.565)*** | | | | 7.778 (3.047)*** | | | |
| STR_4 | $\Delta HFX4^{+}$ | ΔConcentration Indicators - Currency Markets (FX) | 1.843†† (2.622)*** | | | | | | | |
| STR_4.1 | $Gt\_HIXP^{+}$ | Concentration Indicators - Currency Markets (FX) | | | | | | | 2.953 (3.193)*** | 2.090 (2.294)** |
| STR_5 | $Gt\_HIB^{+}$ | Concentration Indicators - Currency Markets (Interbank) | 7.928 (3.732)*** | 7.379 (4.225)*** | 7.191 (4.783)*** | 4.777 (2.414)** | | 5.510 (3.082)*** | | |
| STR_8 | $\Delta tHIRD5^{+}$ | Concentration Indicators - Risk Transfer Markets (IR Derivatives) | | | | 2.834 (1.732)* | 3.562 (2.179)** | 4.633 (3.083)*** | | |
| STR_9 | $Gt\_LEVN^{+}$ | Contagion (normal leverage) | 15.449†† (4.461)*** | 9.755 (3.276)*** | 14.244 (5.161)*** | 16.239) †† (4.938)*** | 11.616 (4.466)*** | 19.400 (9.857)*** | 20.221 (8.920)*** | 20.269 (5.898)*** |
| CONSTANT | | | 68.430 | 20.321 | 26.290 | 43.936 | 28.670 | 49.921 | 59.861 | 55.316 |
| OBSERVATIONS | | | 56 | 50 | 53 | 52 | 52 | 53 | 50 | 52 |
| R-squared | | | 0.708 | 0.778 | 0.834 | 0.703 | 0.707 | 0.766 | 0.754 | 0.815 |
| AIC (OLS) | | | 6.354 | 6.156 | 5.891 | 6.423 | 6.381 | 6.162 | 6.246 | 5.947 |
| SC (OLS) | | | 6.860 | 6.615 | 6.411 | 6.911 | 6.8312 | 6.646 | 6.667 | 6.434 |

*Note:* Absolute value of t statistics is shown in parentheses. Theoretical expectations are noted by +/-/≠0. Statistical significance at 10%, 5% and 1% levels is indicated by *, **, and ***, respectively. The significance of Granger causality at 20% and 10% is shown by † and ††, respectively.

**Table 8**

Out-of-sample statistics for SAFE EWS short-lag models.

| | (1)cpi ASL Sadj | (2)cpi ASL MRadj | (3)ta BSL Sadj | (4)ta BSL MRadj | (5)cpi CSL Sadj | (6)cpi CSL MRadj | (7)ta DSL Sadj | (8)ta DSL MRadj |
|---|---|---|---|---|---|---|---|---|
| RMSE | 9.54 | 5.40 | 4.93 | 6.18 | 5.08 | 8.10 | 4.77 | 5.21 |
| MAPE | 8.34 | 7.59 | 8.00 | 7.38 | 7.84 | 7.80 | 6.41 | 7.56 |
| Theil U | 0.093 | 0.050 | 0.050 | 0.060 | 0.051 | 0.081 | 0.048 | 0.052 |

**Table 9**

Out-of-sample statistics for SAFE EWS long-lag models.

| | (1) LL1 | (2) LL2 | (3) LL3 | (4) LL4 | (5) LL5 | (6) LL6 | (7) LL7 | (8) LL8 |
|---|---|---|---|---|---|---|---|---|
| RMSE | 7.736 | 10.264 | 11.031 | 11.82 | 15.38 | 12.444 | 13.53 | 11.694 |
| MAPE | 13.168 | 14.351 | 14.507 | 15.645 | 15.542 | 18.541 | 21.701 | 17.409 |
| Theil U | 0.0736 | 0.0973 | 0.105 | 0.1123 | 0.116 | 0.119 | 0.127 | 0.112 |

**Table 10**

Short-lag horse race results ranked by RMSE.

| LTCM Crisis Q3 1998 | Dot-Com Crisis Q4 1999 | Stock Market Downturn Q2 2002 | Subprime Crisis Q4 2007 | Horse Race |
|---|---|---|---|---|
| (5) | (6) | (6) | (4) | (4) |
| (7) | (4) | (7) | (2) | (7) |
| (4) | (5) | (4) | (7) | (6) |
| (3) | (7) | (1) | (8) | (5) |

**Table 11**

Distribution of supervisory data among imbalance classes.

| Return Imbalances | Liquidity Imbalances | Risk Imbalances | Structure Imbalances |
|---|---|---|---|
| - FRS – FDR micro data<br>- CRSP<br>- S&P Case-Shiller data<br>- MIT CRE data | - FRS – FDR micro data<br>- Moody's | - FRS – FDR micro data<br>- Moody's | - FRS – FDR micro data<br>- CRSP<br>- FRS - CoVaR model<br>- FRS - Flow of Funds |
| † FRS – X-Country data | †† FRS - IRR FOCUS<br>†† FRS - BankCaR<br>†† FRS – SABR/SEER<br>†† FRBC –SCAP-haircut<br>†† FRBC – LFM | †† FRS - IRR FOCUS<br>†† FRS - BankCaR<br>†† FRS –CAMELS<br>†† FRS-SABR/SEER<br>†† FRBC –SCAP-haircut<br>†† FRBC – LFM | † FRS – X-Country data |

*Note:* Clear row indicates public data. Shaded row indicates supervisory data. Confidential supervisory data (category 1) is shown by †, constructed supervisory data (category 2) is shown by ††.

**Table 12**

Proportion of supervisory variables among imbalance classes.

| Imbalance Class | Supervisory series | Proportion FRS |
|---|---|---|
| Total | 33 | 50.0 percent |
| Return Imbalances | 1 | 10.0 percent |
| Liquidity Imbalances | 3 | 42.9 percent |
| Risk Imbalances | 28 | 82.4 percent |
| Structure Imbalances | 1 | 7.1 percent |

## Table 13

Comparative statistics of supervisory and public specifications.

| Panel A: short-lag comparison | | Bench mark | SL Base | SL(1) | SL(2) | SL(3) | SL(4) | SL(5) | SL(6) | SL(7) | SL(8) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| PUBLIC in-sample | Obs | 59 | 62 | 59 | 54 | 62 | 55 | 59 | 58 | 56 | 59 |
| | R-squared | 0.51 | 0.59 | 0.75 | 0.71 | 0.59 | 0.69 | 0.64 | 0.63 | 0.76 | 0.77 |
| | AIC (OLS) | 6.78 | 6.6 | 6.27 | 6.38 | 6.6 | 6.49 | 6.55 | 6.63 | 6.23 | 6.15 |
| | SC (OLS) | 6.89 | 6.81 | 6.72 | 6.71 | 6.81 | 6.9 | 6.84 | 7.02 | 6.63 | 6.53 |
| PUBLIC out-of-sample | RMSE | 8.48 | 7.68 | 9.34 | 8.49 | 8.66 | 6.97 | 6.13 | 8.18 | 6.38 | 5.73 |
| | MAPE | 12.32 | 5.68 | 9.39 | 10.37 | 12.35 | 9.69 | 10.54 | 10.85 | 8.59 | 8.44 |
| | Theil U | 0.082 | 0.073 | 0.093 | 0.077 | 0.082 | 0.07 | 0.063 | 0.082 | 0.064 | 0.058 |
| PRIVATE in-sample | Obs | | 53 | 56 | 54 | 56 | 55 | 53 | 55 | 56 | 58 |
| | R-squared | | 0.61 | 0.84 | 0.83 | 0.78 | 0.85 | 0.78 | 0.8 | 0.87 | 0.81 |
| | AIC (OLS) | | 6.59 | 5.9 | 5.88 | 6.19 | 5.83 | 6.19 | 6.11 | 5.66 | 6 |
| | SC (OLS) | | 6.84 | 6.48 | 6.28 | 6.72 | 6.42 | 6.72 | 6.77 | 6.23 | 6.49 |
| PRIVATE out-of-sample | RMSE | | 7.88 | 9.54 | 5.4 | 4.93 | 6.18 | 5.08 | 8.1 | 4.77 | 5.21 |
| | MAPE | | 10.94 | 8.34 | 7.59 | 8 | 7.38 | 7.84 | 7.8 | 6.41 | 7.56 |
| | Theil U | | 0.074 | 0.093 | 0.05 | 0.05 | 0.06 | 0.051 | 0.081 | 0.048 | 0.052 |

| Panel B: long-lag comparison | | LL Base | LL1 | LL2 | LL3 | LL4 | LL5 | LL6 | LL7 | LL8 |
|---|---|---|---|---|---|---|---|---|---|---|
| PUBLIC in-sample | Obs | 57 | 56 | 50 | 57 | 56 | 60 | 53 | 50 | 56 |
| | R-squared | 0.36 | 0.50 | 0.55 | 0.53 | 0.50 | 0.39 | 0.66 | 0.67 | 0.39 |
| | AIC (OLS) | 6.99 | 6.84 | 6.78 | 6.76 | 6.82 | 6.99 | 6.49 | 6.51 | 7.02 |
| | SC (OLS) | 7.13 | 7.24 | 7.01 | 7.08 | 7.11 | 7.30 | 6.87 | 6.85 | 7.31 |
| PUBLIC out-of-sample | RMSE | 17.85 | 15.07 | 21.15 | 25.21 | 17.86 | 16.45 | 28.70 | 26.48 | 19.47 |
| | MAPE | 20.49 | 18.15 | 21.08 | 24.17 | 20.11 | 19.16 | 26.19 | 25.08 | 20.63 |
| | Theil U | 0.164 | 0.138 | 0.184 | 0.221 | 0.159 | 0.154 | 0.248 | 0.235 | 0.178 |
| PRIVATE in-sample | Obs | 57 | 56 | 50 | 53 | 52 | 52 | 53 | 50 | 52 |
| | R-squared | 0.52 | 0.71 | 0.78 | 0.82 | 0.70 | 0.71 | 0.77 | 0.75 | 0.82 |
| | AIC (OLS) | 6.75 | 6.35 | 6.16 | 5.89 | 6.42 | 6.38 | 6.16 | 6.25 | 5.95 |
| | SC (OLS) | 6.96 | 6.86 | 6.61 | 6.41 | 6.91 | 6.83 | 6.65 | 6.67 | 6.43 |
| PRIVATE out-of-sample | RMSE | 14.62 | 18.82 | 12.64 | 19.95 | 18.91 | 15.38 | 27.56 | 27.01 | 26.29 |
| | MAPE | 16.72 | 17.86 | 13.79 | 18.40 | 19.13 | 15.54 | 24.53 | 23.78 | 21.93 |
| | Theil U | 0.138 | 0.167 | 0.118 | 0.179 | 0.166 | 0.144 | 0.241 | 0.241 | 0.228 |

**Table 14**

Policy horse race results ranked by SAFE to FSI variance.

| Episode | Δ FSI | Ave | Best | Top 2 | Top 3 | Top 4 | SL(1) | SL(2) | SL(3) | SL(4) | SL(5) | SL(6) | SL(7) | SL(8) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dot-com crisis | 0.68 | -1.41 | 2.08 | -0.61 | -1.61 | -1.46 | 2.08 | -1.01 | -0.13 | -0.31 | -2.17 | -3.30 | -3.61 | -2.86 |
| Stock Market downturn | -0.32 | -0.18 | -0.64 | -0.17 | -0.30 | -0.33 | -0.34 | 0.35 | -0.36 | -0.57 | -0.42 | -0.64 | 0.21 | 0.30 |
| Subprime crisis | 2.86 | 1.71 | 3.44 | 2.16 | 1.84 | 1.74 | 1.43 | 2.51 | 0.88 | 3.44 | 1.13 | 1.23 | 1.20 | 1.85 |

| Legend: | Best | 2nd | 3rd | 4th |
|---|---|---|---|---|

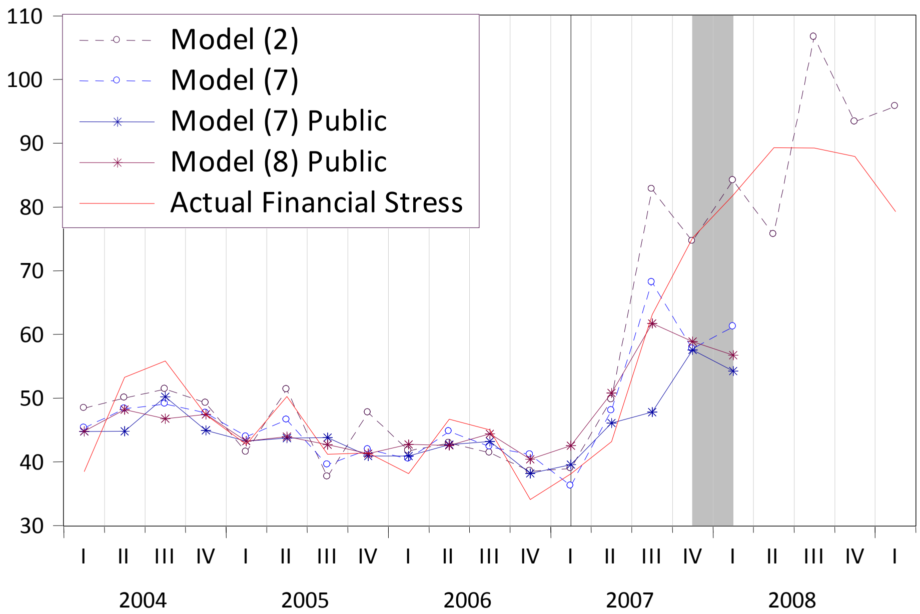



**Fig. 4.** Out-of-sample performance of private and public models.

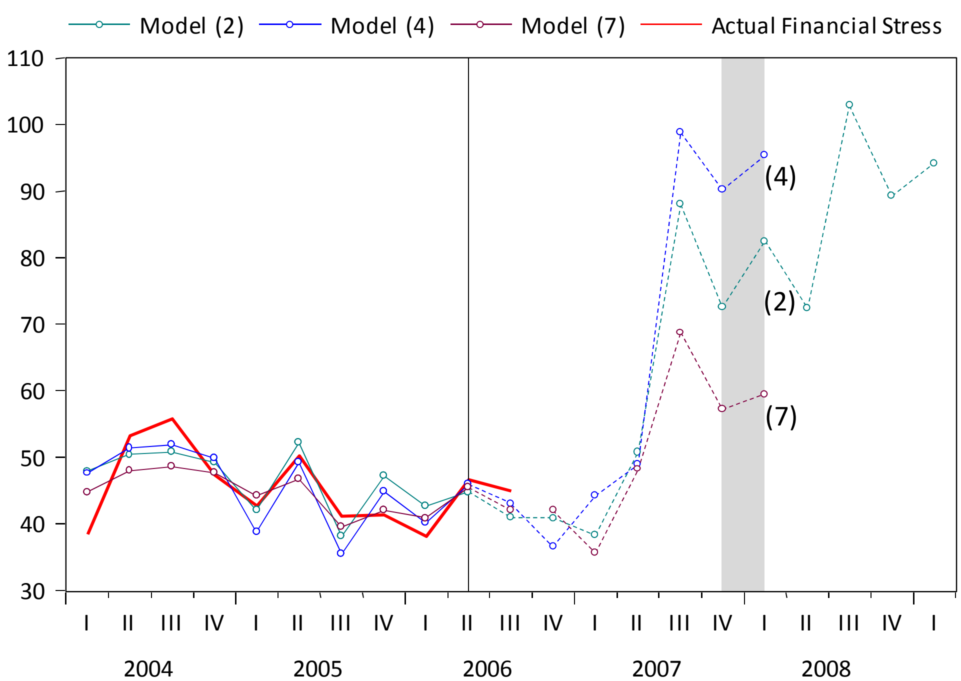



**Fig. 5.** SAFE EWS out-of-sample forecasts (case study 2).

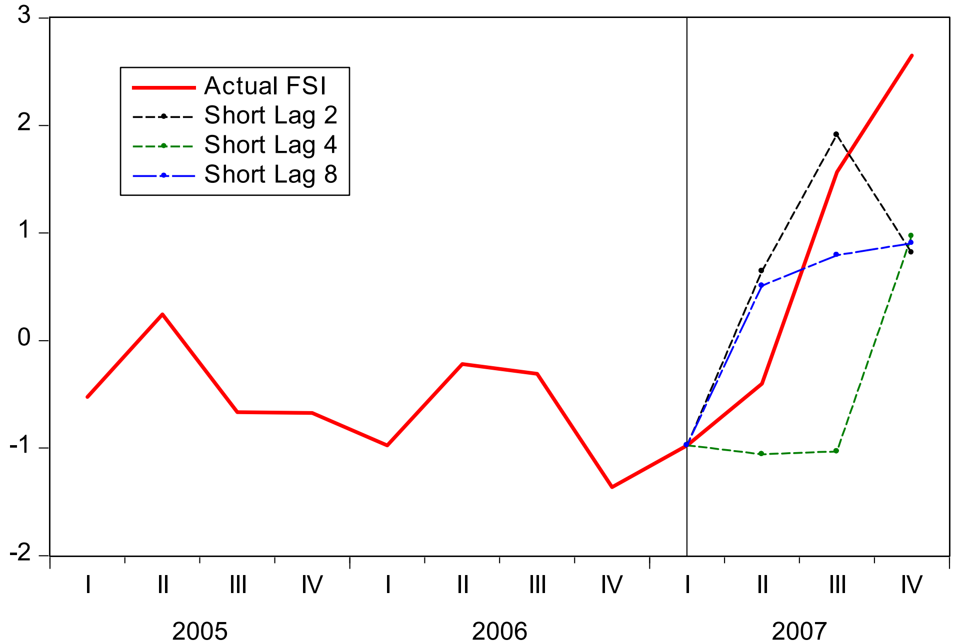


**Fig. 6.** Short-lag forecast on Q1:2007.

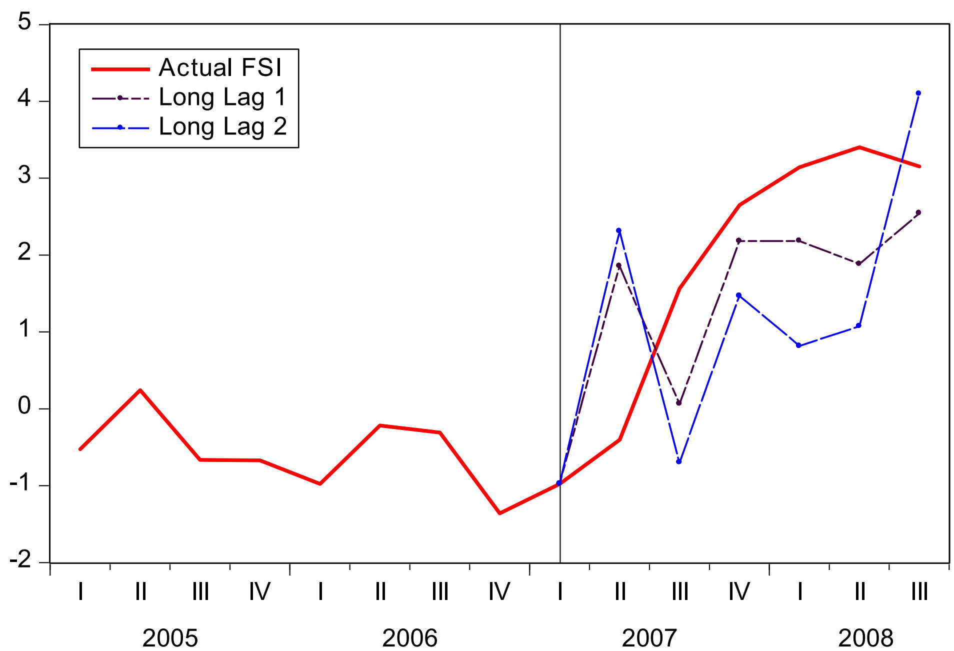


**Fig. 7.** Long-lag forecast on Q1:2007.

**Appendix A. Description of explanatory data**

Four classes of explanatory variables are tested: return, risk, liquidity, and structure. Financial stress is frequently associated with shocks from deflating asset bubbles that characterize irrational expectations of returns. Accordingly, ***return indicators*** consist of data useful in monitoring the formation of expectation bubbles in returns. The indicators are designed to capture imbalances in various asset markets, a key aspect of expectation bubbles. The methodology extends the work of Borio et al. (1994). Borio analyzes three separate asset classes (equities, residential property, and commercial property). The EWS model expands this approach to include additional asset classes: equities; bonds; residential and commercial property in the capital markets; international and interbank exposure in the currency markets; securitizations, credit derivatives, and interest-rate derivatives in the risk-transfer markets.

***Risk indicators*** consist of data useful for monitoring unsustainable or irrational risk-taking, which can lead to institutional and aggregate accumulation of risk beyond a rational equilibrium value. The risk data is based both on publicly available financial information and on private supervisory EWS of individual institutions' risk. Public information is used in risk indicators for two components, market and credit, and can be observed over time by comparing three distinct time series for each risk: the book value, market value, and economic value of the corresponding assets. The economic-value time series is obtained through private supervisory FRB-IRR Focus and FRB-Bank CaR (Frye and Pelz, 2008) models. Private supervisory risk data is based on application of the FRB-SABR model to historic data.

***Liquidity indicators*** consist of time-series data incorporating both funding- and asset-liquidity data through a maturity-band-differentiated net liquidity time series. Each time point is represented by two sets of liquidity components: a set of asset-liability mismatch measures by each maturity band; and a set of liquidity index measures based on the valuations of all assets and liabilities relative to three time-horizon points: immediate fire sale; three-month forward sale; and 1-year forward sale. The data applies asset-liability classification and assumptions from the FRB-IRR Focus model. The following four maturity bands are used for both assets and liabilities: 0–3 months, 3–12 months, 1–3 years, and more than 3 years. Available funding liquidity for each maturity band is tracked through two sets of data: components of total large and small time deposits and components of other borrowed money, including FHLB advances). Available asset liquidity for each maturity band is tracked through four sets of data: components of first-lien, 1–4-family mortgages loans and pass-throughs; components of CMOs and mortgage derivatives; all other loans; and all other securities.

***Structural indicators*** consist of time-series data describing organizational features of the financial system. The model tests three distinct types of structural data: connectivity, concentration, and contagion.[a] *Connectivity data* describes structural fragility through a measure of individual institutions' interconnectedness and marginal impact on the aggregate financial system. The data is obtained by means of a sub-model using a correlation approach. The model applies Adrian and Brunnermeier's (2008) CoVaR technique measuring the relative contribution of firms to systemic risk (CoVaR), which is measured as "the value at risk (VaR) of financial institutions conditional on other institutions being in distress. The increase of CoVaR relative to VaR measures spillover risk among institutions."[b] CoVar, as a connectivity indicator, is estimated using quantile regressions. *Concentration data* describes structural fragility due to

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[a] The model evolved independently through the concurrent work of James Thomson (2009) on the identification of systemic institutions. Thomson proposed the "4C's" (correlation, concentration, contagion, and conditions) as a basis for selecting systemically important institutions. The conditions component is akin to expectations in the SAFE model. Thus, there is a conceptual parallel between the 4C's and SAFE architecture when correlation, concentration, and contagion are considered as forms of structural variables and conditions as a form of expectations variables.

concentrations in the exposure profile, both on- and off-balance sheets. A higher concentration indicates increased susceptibility to stress due to expectation shocks. Concentration is measured through the market share for institutions and the aggregate Herfindahl index measured for the capital, currency, and risk-transfer markets. Separate market-share and Herfindahl measures are obtained in each of these markets. An institution's concentration in a particular market, expressed through the corresponding market share, is a useful explanatory indicator of structural fragility because it measures the relative position of significant institutions in the financial system. Aggregate concentration, expressed through the Herfindahl index, is a useful explanatory indicator of structural fragility for the same reason. *Contagion data* describes the structural fragility of individual institutions and the aggregate financial system by the transmission of some shock from one entity to other, dependent entities. The economic literature describes financial contagion through a variety of these transmission channels, for example, direct transmission via interbank credit and liquidity markets and indirect transmission resulting from the general deterioration of financial-market conditions. This study considers leverage-based ratios to be a useful basis for describing financial contagion as a measure of the "financial immunity" of an individual institution or cluster of institutions against a variety of shocks.

## Appendix B. Explanatory variable construction

### *B.1. Construction of aggregate imbalances*

All explanatory time-series indicators (that is, indicators of return expectations, risk expectations, and liquidity expectations, as well as structural indicators) are aggregated as rolling standardized imbalances, an approach developed by Borio and Lowe (2002), and expanded by Borio et al. (2009) and Hanschel et al. (2005). This transformation shows the researcher the degree of deviation from long-term, historical trends in behavior. Implicit in this approach is the

[b] Adrian and Brunnermeier (2008).

assumption that the historical trend serves as a "proxy for the longer-term fundamental value of a variable, around which the actual series fluctuates" (Hanschel, et al., 2005). In a sense, the gap between the original series and its trend reflects an economic imbalance. To obtain imbalance measures for each indicator, data for the five largest bank holding companies (according to total asset size by quarter) are aggregated through simple addition. The equation below articulates this logic for an arbitrary indicator X:

$$\mathrm{X_t} = \mathrm{X_{1,t}} + \mathrm{X_{2,t}} + \mathrm{X_{3,t}} + \mathrm{X_{4,t}} + \mathrm{X_{5,t}} \tag{3}$$

Once $X_t$ is generated, imbalance transformations are performed using the following equation:

$$\underline{X_t} \stackrel{\mathrm{def}}{=} \text{Standardized Imbalance of } \mathrm{X_t} = {(\mathrm{X_t} - \mu_t^X)}\big/{\sigma_t^X} \tag{4}$$

where $X_t$ is the observed value of the reference variable in quarter t, $\mu_t^X$ is the historical mean of this variable up to quarter t, and $\sigma_t^X$ is the historical standard deviation of the variable up to quarter t.

Because dollars are the units of aggregations in this category of variables, our imbalance measures are likely to increase simply because of inflation. Thus, we control for inflationary effects using two separate methods before applying imbalance transformations. One method is to deflate aggregate dollar values by a price index. We chose to deflate the majority of series with the Consumer Price Index less food and energy. Residential and commercial real estate values were more appropriately deflated using more closely-targeted indexes (the Case-Shiller price index and the MIT transactions-based commercial real estate price index, respectively). To the extent that consumer prices move at a different pace than financial-asset prices, this method enables the researcher to examine value imbalances within asset classes rather than real imbalances, because relative prices are not constant.

We use another method to deflate dollar values: dividing each variable by the aggregate value of total assets for the five largest institutions. This method resembles the first; however, because it deflates with total assets, relative prices should be much closer to constant, so any increase in the imbalance measure in an asset class can be attributed to changes in the level of firm activity. Hence, this method will produce measures of what can be called quantity imbalances.

*B.2. Construction of return variables*

Accumulated return imbalances are specific to each asset based on its individual characteristics. Returns of many asset classes can be observed within different financial markets. Because money flows across these various asset markets, disturbances in one market can affect the others. Capital markets (equity and credit markets) provide financing through issuance in primary markets and trading stocks and bonds in secondary markets. Currency markets support short-term financing and investment through both dollar-based interbank markets and foreign-exchange markets. Returns of risk transfer instruments (securitizations, credit derivatives, and interest-rate derivatives) can be observed in the risk-transfer markets, which provide opportunities to manage risk by hedging and balance-sheet transformations.

Return indicators consist of data useful in monitoring the formation of expectation bubbles in returns. Financial stress is frequently associated with expectation shocks from deflating assets bubbles. The indicators are designed to capture imbalances in various asset markets, a key aspect of expectation bubbles. The EWS model utilizes the following asset classes: equities, bonds, residential property, and commercial property in the capital markets; international exposure and interbank exposure in the currency markets; and securitizations, credit derivatives, and interest-rate derivatives in the risk-transfer markets. Most data for return variables is publicly available.

*B.3. Construction of risk variables*

SAFE collects and monitors risk-indicator data along four dimensions: market risk, interest-rate risk, credit risk, and solvency.[c] Accumulated imbalances in market risk exposure cause shocks to institutions' mark-to-market portfolios. Accumulated imbalances in interest-rate risk exposure cause interest-rate shocks to institutions' assets and liabilities. Accumulated imbalances in credit risk exposure give rise to shocks associated with failure to meet contractual payment obligations. Market, interest-rate, and credit risks can cause significant financial stress in institutions and the financial system. In general, unsustainable or irrational risk-taking can cause institutional and aggregate accumulation of risk beyond a rational equilibrium value.

Market risk indicators are constructed on securities to capture the impacts of market risk shocks to mark-to-market securities portfolios. SAFE monitors the distance between the hypothetical normal, stress, and crisis-scenario valuations of the market risk of on-balance-sheet securities, using the following data: for the normal (through-the-cycle) scenario, securities' book value; for the stress (point-in-time) scenario, securities' market value; and for the crisis scenario, change in securities' economic value.

Interest-risk indicators are constructed on equity to capture the impact of interest-rate shocks on the balance sheets of financial institutions. SAFE monitors the distance between the hypothetical normal, stress, and crisis-scenario valuations of interest rates' on-balance-sheet

[c] Solvency may also be considered a useful indicator of structural fragility. A good argument for this view can be made on the grounds that insolvency, like systemic risk itself, may arise through a variety of mechanisms, for example, failed expectations of return, risk, or liquidity. Capital for a single financial institution is the institution's structural buffer against risk. The aggregate capital of the financial system at large represents a measure of collective safeguard against *disjointed* failures. The capital level should also be considered in assessing the safety and soundness of individual and aggregate financial institutions. For the SAFE modeling approach, the choice of where to include solvency indicators (as components of risk or as components of structure) is not relevant. We chose to include solvency in the set of risk indicators because the construction and use of this indicator parallels risk indicators more closely than structural indicators.

exposure, using the following data: for the normal (through-the-cycle) scenario, the book value of equity less goodwill; for the stress (point-in-time) scenario, the corporate value of equity at market value; and for the crisis scenario, the change in the economic value of equity.

Credit risk indicators capture credit portfolios' book value, market value, and economic value. The book value of the credit portfolios is modeled as the difference between the combined value of the 12 call-report loan portfolios and reported allowances for loan and lease losses. The market value of credit portfolios is modeled as the difference between expected loss and the combined value of the 12 call-report loan portfolios. The economic value of credit portfolios is modeled as the difference between the combined value of the 12 call-report loan portfolios and their simulated 99.5 percent stress loss from the supervisory Bank CaR model (Frye and Pelz, 2008).

Solvency directly reflects the capacity of capital to absorb losses and of funds to repay debts. The insolvency of one or more significant institutions creates shocks to the financial system that may be either absorbed or amplified, depending on the other structural-fragility factors: connectivity, concentration, and leverage. Solvency indicators are constructed to capture the difference between an aggregate risk-based capital need (defined as the sum of credit risk, market risk, interest-rate risk, and operational risk exposures)[d] and available financial resources (defined as Tier 1 capital plus ALLL). Like other risk measures, the SAFE model considers solvency indicators both as standardized imbalances constructed from interim aggregate levels of solvency (under separate book, market, and economic valuations) and as standardized imbalances constructed from differences in the respective solvency valuations.

*B.4. Construction of liquidity variables*

When the market for a particular asset breaks down for any reason, buyers and sellers are unable to reach a consensus on the price, and the asset becomes illiquid regardless of its underlying value. Managing institutional liquidity is a matter of matching the demand for liquidity, reflected through current liabilities, with the supply of liquidity, reflected through current assets. Matching involves both funding liquidity and asset liquidity. Reliance on a continuous supply of short-term financing involves funding risk that is tied to an institution's ability to match-fund with cash inflows from current assets. A mismatch exists at a particular time if incoming cash flows, such as fees, interest due, principal payments, and prepayments, are insufficient to meet current liabilities due at that time. To the extent that mismatch exists, financial institutions have funding liquidity needs for short-term financing. Because short-term financing is typically cheap, institutions are continually tempted to rely on it for meeting obligations of all maturities. This, of course, only exacerbates the mismatch across all maturities. Moreover, the availability and pricing of short-term financing is highly dependent on an institution's own creditworthiness and the valuations of assets pledged as collateral. Exogenous shocks to either current liabilities or current assets can damage creditors' and counterparties' perception of the institution and its underlying collateral. Aggregate liquidity mismatches indicate the presence of funding and asset liquidity on a systemic scale.

Liquidity risk indicators consist of time-series data incorporating both funding liquidity and asset liquidity data through a maturity-band-differentiated net liquidity time-series. Each time point is represented by two sets of liquidity components: 1) a set of standardized imbalance measures of maturity mismatch, sorted by each maturity band; and 2) a set of standardized imbalance measures of a liquidity index that is based on valuations of all assets and liabilities

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[d] Due to current data limitations in operational risk exposures, SAFE implements a measure of operational risk exposure similar to the Basel II basic indicator approach. In the future, this

relative to three time horizons, namely, immediate fire sale; 3-month forward sale; and 1-year forward sale. Most but not all of the underlying asset and liability data used for the maturity mismatch measurement is publicly available. However, some coarseness in the granularity of the available data necessitates a further set of private supervisory transformations and valuation assumptions. SAFE applies the asset liability classification and assumption scheme from the Federal Reserve's private asset liability supervisory model (FRB IRR and Securities Focus Model). While the original data is all public-domain, call-report financial data, the classification, aggregation, and maturity assumption scheme is unique to the FRB Focus model. The following four maturity bands are used for both assets and liabilities: 0–3 months, 3–12 months, 1–3 years, and more than 3 years. Available funding liquidity for each maturity band is tracked through two sets of data: components of "total large and small time deposits," and components of "other borrowed money (including FHLB advances)." Available asset liquidity for each maturity band is tracked through four sets of data: components of "first-lien 1–4 family mortgages loans and pass-throughs," components of "CMOs and mortgage derivatives," "all other loans," and "all other securities."

The liquidity index is computed for three time horizons: immediate fire sale, 3-month forward sale, and 1-year forward sale, following Pierce (1966), as

$$I_i = \sum_{k=1}^{N}[(W_k)(P_{kt+i}/\overline{P_{kt}})] \tag{5}$$

Valuations for the asset and liability classes are based on a private supervisory set of liquidity haircuts developed separately as part of this study. The liquidity haircut scheme was based on the published supervisory haircuts used for the SCAP exercise and were supplemented as required

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component of risk expectations may be expanded and improved.

by public standardized sources, such as Moody's Investors Service (2001, 2002) and IOSCO (2002).[e, f]

Risk-based liquidity amplification is incorporated for the three time horizons, extending the methodology proposed by Krishnamurthy (2010), who shows that in both crisis and non-crisis conditions, the price of an asset $Ps$ at date $s$ is a function of three factors: the long-term fundamental value of the asset $\overline{P}$, the time-dependent liquidity discount $P_t(L)$, and the counterparty uncertainty function $\varphi$. In normally functioning markets, asset price may be modeled as

$$P_s = \overline{P} - P_t(L) * \varphi^2 \tag{6}$$

while in crisis-shocked markets, uncertainty gets magnified as

$$P_s = \overline{P} - P_t(L) * \varphi \tag{7}$$

We implement the model as follows:

1) Normal uncertainty $\varphi$ is quantified as a credit-rating-equivalent, long-term (through-the-cycle) default probability
2) Stress-condition uncertainty $\varphi$ is quantified as a point-in-time expected default probability, using the Merton model's expected default frequency (Moody's KMV EDF)
3) Shock-condition uncertainty $\varphi$ in extreme stress is the quantified maximum value of stress-condition uncertainty at a peer institution
4) The liquidity index is computed for the three time horizons (immediate fire sale, 3-month forward sale, and 1-year forward sale), quantifying an immediate fire sale as a shock condition, a 3-month forward sale as a stress condition, and a 1-year forward sale as a normal condition.

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e Matz (2007).

*B.5. Construction of structural variables*

The impact of a systemic institution on macroeconomic markets is conditional on various structural factors. In this paper, we consider how structural relationships affect macroeconomic conditions by examining three types of structural indicators: measures of connectivity, measures of market concentration, and measures of market contagion through leverage.

*B.5.1. Connectivity*

Connectivity describes the interconnectedness and interdependence of systemic firms. A connectivity measure is designed to capture an aspect of structural fragility by measuring the interconnectedness and marginal impact of individual institutions on the aggregate financial system. To identify connectivity, we employ Adrian and Brunnermeier's conditional value-at-risk (CoVaR) technique, estimated using quantile regressions. CoVaR measures the value at risk[g] of one financial portfolio conditional on the distress of another financial portfolio.[h] In particular, we are interested in the extent to which poor stock-market returns are correlated with weak market returns for our quarterly systemic institutions. We determine the relationship by computing the 1 percent and 5 percent CoVaR and subtracting the 1 percent and 5 percent value at risk of the stock market for each institution and aggregating through simple summation. Mathematically, we can express our connectivity indicator as

$$\sum_{j=1}^{5} CoVaR_q^{i|j} - VaR_q^i \tag{8}$$

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[f] Raffis (2007).

[g] $VaR^i$ is defined mathematically as $\Pr\left(R^i \geq VaR_q^i\right) = q$, where $R^i$ is the dollar return of portfolio i and $VaR_q^i$ is the unconditional q[th] percentile of portfolio i's historical dollar returns.

[h] $CoVaR^{i|j}$ is defined mathematically as $\Pr\left(R^i \geq CoVaR_q^{i|j} \middle| R^j = VaR_q^j\right) = q$, where $R^i$ is the dollar return of portfolio i, $VaR_q^j$ is the q[th] percentile of portfolio j's historical dollar returns, and $CoVaR_q^{i|j}$ is the q[th] percentile of portfolio i's historical dollar returns, conditional on portfolio j's returns being equal to its q[th] percentile historical dollar returns.

where i is a broad-based stock market portfolio and j refers to each of our quarterly systemic institutions. We also compute a percentage based on a connectivity measure by dividing each difference in the summation above by the corresponding VaR in order to control for sharp differences in each institution's market capitalization.

*B.5.2. Concentration*

Concentration describes the diversification of financial institutions—or its lack. Highly concentrated systemic firms create pockets that are highly susceptible to shocks through the concentration channels. Therefore, concentration indicators are designed to capture an aspect of structural fragility resulting from concentrations in the exposure profile both on and off balance sheets. Concentration in these various exposures is measured through the market share for institutions and the aggregate Herfindahl index measured for the capital, currency, and risk-transfer markets. Separate market share and Herfindahl-like measures are obtained in each of these markets.

An institution's concentration in a particular market, expressed through the corresponding market share, is a useful explanatory indicator of structural fragility, since it measures the relative position of significant institutions in the financial system. Similarly, aggregate concentration, expressed through a form of the Herfindahl index, is a useful explanatory indicator of structural fragility, since it measures the relative position of large enterprises in the economy. The rationale for including concentration as an indicator of structural fragility is that, other things being equal, higher levels of market concentration are increasingly less efficient in absorbing and diversifying the impact of small shocks on expectations. Thus, a higher concentration indicates increased susceptibility to stress as the result of expectation shocks.

We measure market concentration by computing modified Herfindahl indexes for capital (equity and credit); currency (FX and interbank); and risk transfer (securitizations, credit derivatives, and interest-rate derivatives) markets. To compute the modified Herfindahls, we first calculate market shares for each of our five systemic institutions, then aggregate the market shares as follows:

$$Herfindahl_m = \left(\sum_{j=1}^{5} S_j^2\right) + (N-5)\left[\frac{1-\sum_{j=1}^{5} S_j}{(N-5)}\right]^2 \qquad (9)$$

where $S_j$ is the market share of firm $j$ in market $m$ and $N$ is the number of bank holding companies. For markets where total size is unavailable, we calculate market shares as proportions of the total volume of the 20 largest institutions by size of total assets, and N becomes 20.

## Appendix C. Data sources and variable expectations

## Table 15

Explanatory Variables Data Sources.

| INDICATOR | DATA | SOURCE | VARIABLE | START DATE |
|---|---|---|---|---|
| RETURN VARIABLES | | | | |
| Capital Markets - Equity | Corporate value of equity at market value | CRSP | RET_1.1cpi | 3/31/1980* |
| | Residential Real Estate - National Price Index | S&P/Case-Shiller Home Price Indices | | 3/31/1987 |
| Capital Markets - Credit | Call report loan portfolios | FRS - FDR | RET_2cpi | 9/30/1990† |
| | Residential Real Estate - National Price Index | S&P/Case-Shiller Home Price Indices | | 3/31/1987 |
| Capital Markets - Commercial Property | Call Report Commercial property portfolios (Construction, Non-farm non-residential, Multifamily) | FRS - FDR | RET_4ta | 9/30/1990† |
| | Commercial Real Estate - National Price Index | MIT Transactions-Based Index | | 3/31/1984 |
| Currency Markets – International Exposures | Bank Constructed Interbank Derivative Exposure | FRS - FDR | RET_5.2ta | 3/31/1995 |
| Currency Markets – Interbank Exposures | Bank Constructed Interbank Exposure | FRS – FDR | RET_6ta<br>RET_6cpi | 3/31/2002† |
| Risk Transfer Markets - Interest Rate Derivatives | Bank Constructed IR Derivatives Exposure | FRS - FDR | RET_9ta | 3/31/1995† |
| RISK EXPECTATIONS | | | | |
| IRR Indicators - through-the-cycle function | Equity less goodwill | FRS - FDR | RSK_2 | 6/30/1986 |
| | Interest Rate Risk Capital - through-the-cycle function | ℗ Calculated | RSK_2.1 | 6/30/1986 |
| IRR Indicators - point-in-time/stress function | Interest Rate Risk Capital - stress function | ℗ Calculated | RSK_4 | 6/30/1997 |
| IRR Indicators - extreme stress/crisis function | Change in economic value of equity | ℗ FRS - IRR FOCUS | RSK_6 | 6/30/1997†Δ |
| Credit Risk Indicators - through the cycle function | Book Value: 12 call report loan portfolios - reported ALLL | FRS - FDR | RSK_7.1 | 12/31/1976 |
| | Credit Capital - through the cycle function | ℗ Calculated | | 9/31/1991* |
| Credit Risk Indicators - extreme stress/crisis function | Economic Value : 12 call report loan portfolios - 99.5 percent BankCaR | ℗ FRS - BankCaR Model | RSK_9 | 9/31/1991* |
| Solvency - through the cycle function | Solvency - normal value | ℗ Internal Model | RSK_14 | 9/31/1991* |
| | Tier 1 Capital | FRS - FDR | | 9/31/1991* |
| Solvency - point-in-time/stress function | Solvency - stress value | ℗ Internal Model | RSK_15 | 9/31/1991* |
| Solvency - extreme stress/crisis function | Solvency - extreme value | ℗ Internal Model | RSK_16 | 9/31/1991* |
| IRR stress distance function | Interest Rate Risk - normal distance-to-systemic stress | ℗ Internal Model | RSK_F | 9/31/1991* |
| IRR stress distance function | Interest Rate Risk - normal distance-to-stress | ℗ Internal Model | RSK_G | 9/31/1991* |
| Credit Risk stress distance function | Credit Risk - stress distance-to-systemic stress | ℗ Internal Model | RSK_H | 9/31/1991* |
| Credit Risk stress distance function | Credit Risk - normal distance-to-systemic stress | ℗ Internal Model | RSK_I | 9/31/1991* |
| Credit Risk stress distance function | Credit Risk - normal distance-to-stress | ℗ Internal Model | RSK_K | 9/31/1991* |
| Solvency stress distance function | Solvency - stress distance-to-systemic stress | ℗ Internal Model | RSK_L | 9/31/1991* |
| Solvency stress distance function | Solvency - normal distance-to-systemic stress | ℗ Internal Model | RSK_M | 9/31/1991* |
| LIQUIDITY EXPECTATIONS | | | | |
| AL Gap Indicators - '0 to 3 months' maturity band | AL Gap Indicators - '0 to 3 months' maturity band | ℗ Calculated<br>℗ IRR FOCUS specification | LIQ_1 | 6/30/1997†Δ |
| AL Gap Indicators - '3 to 12 months' maturity band | AL Gap Indicators \|3 to 12 Months | ℗ Calculated<br>℗ IRR FOCUS specification | LIQ_2 | 6/30/1997†Δ |
| AL Gap Indicators - 'greater than 3 years' maturity band | AL Gap Indicators \|'greater than 3 years' maturity band | ℗ Calculated | LIQ_4 | 6/30/1997†Δ |
| Liquidity Index Indicators - 1-year forward sale | Liquidity Index Indicators – 1-year forward sale | ℗ Internal Model | LIQ_5 | 9/31/1991* |
| Liquidity Index Indicators - 3-month forward sale | Liquidity Index Indicators - 3-month forward sale | ℗ Internal Model | LIQ_6 | 9/31/1991* |
| Liquidity Index Indicators - immediate fire sale | Liquidity Index Indicators - immediate fire sale | ℗ Internal Model | LIQ_7 | 9/31/1991* |
| STRUCTURE | | | | |
| Connectivity Indicators - CoVaR | Connectivity Indicators - CoVaR | ℗ CoVaR Model (FRS) | STR_1.2<br>STR_1.3<br>STR_1.4 | 9/31/1991* |
| Concentration Indicators - Capital Markets (Equity) | Concentration Indicators - Capital Markets (Equity) | ℗ Calculated<br>FRS - Flow of Funds | STR_2 | 9/31/1991* |
| Concentration Indicators - Currency Markets (FX) | Concentration Indicators - Currency Markets (FX) | ℗ Calculated<br>FRS - Flow of Funds | STR_4<br>STR_4.1 | 9/31/1991* |
| Concentration Indicators - Currency Markets (Interbank) | Concentration Indicators - Currency Markets (Interbank) | ℗ Calculated<br>FRS - Flow of Funds | STR_5 | 9/31/1991* |
| Concentration Indicators - Risk Transfer Markets (Interest Rate Derivatives) | Concentration Indicators - Risk Transfer Markets (Interest Rate Derivatives) | ℗ Calculated<br>FRS - Flow of Funds | STR_8 | 9/31/1991* |
| Leverage Indicators - normal | Leverage Indicators - normal | FRS - FDR | STR_9 | 6/30/1986 |

*Note:* ℗ denotes private supervisory data components. * indicates start date set by data request.† denotes partial availability in of earlier data. Δ indicates gap in component data.

**Table 16**

Return variables: definitions, expectations, and Granger causality.

| VARIABLE | SERIES | EXPOSURE | GRANGER LAG | THEORETICAL EXPECTATION |
|---|---|---|---|---|
| RET_1.1cpi | $\Delta MKTCP^{+}$ | Capital Markets - Bonds (total-assets based) | – | For an individual firm, a greater market capitalization provides an additional market equity buffer against potential losses, but also increases the downside risk. A larger RET_1.1cpi describes a larger difference between long-term return expectations and CPI and reflects greater downside risk to equity, positively related to the systemic financial stress. |
| RET_2cpi | $LNSTG\_T^{+}$ | Capital Markets - Bonds (total-assets based) | †: 11, 12 | For an individual firm, a larger loan portfolio provides a buffer against potential credit losses, but also increases the downside risk. Here we use time series of Z-scores of aggregate of loan portfolios deflated by CPI. A larger value describes a larger difference between long-term return expectations and CPI and reflects greater downside risk in the credit markets. |
| RET_4ta | $^{-}LNSCTAGt$ | Capital Markets - Commercial Property (total assets-based) | – | For an individual institution, an increasing commercial property indicator reflects a larger credit risk exposure in the commercial property asset class, but may also reflect an underlying organic growth in assets. The aggregated commercial property portfolios are deflated by total assets, the measure describes a natural hedge against systemic stress. |
| RET_4ta | $^{-}\Delta LNSCAT$ | Capital Markets - Commercial Property (total assets-based) | – | |
| RET_5.2ta | $^{-}IXDRTAGt$ | Interbank Derivative Exposure | ††: 11<br>†: 10, 12 | The large and standardized derivative markets involve a large number of participants, and although a firm level, an unwise, ill-informed or plainly speculative position can lead to an individual firm loss, the market overall is well diversified and well insulated from overall collapse, since the market participants losses and gains are balanced out. In the event that a major dealer or user of interbank derivates collapsed, the interbank derivatives markets are structured to self-resolve in an orderly fashion. Thus, a rise in a long-term real-time mean of the interbank derivative exposure should be negatively related to the systemic financial stress. |
| RET_6cpi | $^{-}ITRBNKG\_t$ | Currency Markets - Interbank Exposures (price-based) | ††: 2 | Of the two available series, the CPI-based series reflects growth in interbank markets relative to inflationary expectations and captures greater aggregate liquidity and economic optimism reflected in the interbank markets, thus negatively related to systemic financial stress. On the other hand, the total-assets based series of aggregate interbank exposures, reflects the growth interbank concentration relative to aggregate assets, and thus, capture the structural aspect of interbank markets that is positively related systemic financial stress.[j] |
| RET_6ta | $ITBKTAGt^{+}$ | Currency Markets - Interbank Exposures (TA-based) | ††: 2, 4<br>†: 5 | |
| RET_9ta | $^{-}IRDETAGt$ | Risk Transfer Markets - Interest Rate Derivatives | ††: 11, 12<br>†: 8, 10 | We argue that interest rate risk derivative market has an established defensive function. A rise in a long-term real-time (accumulated) mean of the interest-rate risk derivative exposure should be negatively related to the systemic financial stress. |

[j] See Blåvarg and Nimander (2002), Rajan (1996), Furfine (2003), and Degryse and Nguyen (2004).

**Table 17**

Liquidity Variables: definitions, expectations, and Granger causality.

| VARIABLE | SERIES | EXPOSURE | GRANGER LAG | THEORETICAL EXPECTATION |
|---|---|---|---|---|
| LIQ_1 | $Gt\_AL03^{+}$ | AL Gap Indicators - '0 to 3 months' maturity band | †: 3, 4 | Asset Liability mismatch describes a simple gap difference between assets and liabilities. A larger mismatch indicates a larger imbalance in re-pricing and maturity and reflects a larger interest rate risk exposure. |
| LIQ_2 | $Gt\_AL312^{+}$ | AL Gap Indicators - '3 to 12 months' maturity band | †: 4 | |
| LIQ_4 | $Gt\_ALG3^{+}$ | AL Gap Indicators - 'greater than 3 years' maturity band | – | |
| LIQ_5 | $^{-}Gt\_LX\_NV$ | Liquidity Index Indicators - 1 year forward sale | †: 8, 9, 10 | A larger value of the Liquidity Index is associated with a more liquid and therefore less risky conditions. Hence, a rise in a long-term real-time(accumulated) mean of this index should be negatively related to the systemic financial stress. |
| LIQ_6 | $^{-}Gt\_LX\_SV$ | Liquidity Index Indicators - 3-month forward sale | – | |
| LIQ_7 | $^{-}Gt\_LX\_EV$ | Liquidity Index Indicators - immediate fire sale | – | |

*Note:* Plus sign indicates positive expectation. Minus sign indicates negative expectation. †† indicates Granger causality with 90 percent or better confidence. † indicates Granger causality with 79 percent or better confidence.

## Table 18

Risk variables: definitions, expectations, and Granger causality.

| VARIABLE | SERIES | EXPOSURE | GRANGER LAG | THEORETICAL EXPECTATION |
|---|---|---|---|---|
| RSK_2 | $^{-}EQLGDW$ | IRR Indicators - through-the-cycle function | ††: 2, 3, 4, 5, 6, 7, 12<br>†: 8, 10, 11 | For an individual institution, this indicator is constructed as the institution's book value equity less goodwill. A rise in the aggregate series indicates more capacity the institution has to withstand losses and should be negatively related to the systemic financial stress. |
| RSK_2 | $^{-}\Delta EQLGDW$ | IRR Indicators - through-the-cycle function | ††: 3, 4, 5, 12<br>†: 7, 8, 10, 11 | |
| RSK_2.1 | $IRCAP\_NV^{+}$ | IRR Indicators - through-the-cycle function | ††: 2, 4, 7, 8<br>†: 3, 5, 9, 10, 11, 12 | For an individual institution, this indicator is constructed as the institution's book value equity less goodwill inflated by the supervisory probability of default (RSK_2.1) and downgrade (RSK_4). The measure proxies an economic capital view of interest rate capital that would be required through the cycle (RSK_2.1) and under stress (RSK_4). The larger the value, the more is the long-term pressure on the institution and higher the potential for default induced by interest-rate risk capital needs. |
| RSK_4 | $IRCAP\_SV^{+}$ | IRR Indicators - point-in-time/stress function | ††: 2, 7, 8, 9, 10, 11<br>†: 4, 5, 12 | |
| RSK_6 | $^{-}\Delta IRCAP\_EV$ | IRR Indicators - extreme stress/crisis function | ††: 2, 3, 4, 5, 6, 7 | This series describes aggregate economic value of the balance sheet evaluated under extreme stress. The larger the value, the better is the residual capacity to counteract stress and losses. Therefore, a rise in a long-term real-time (accumulated) mean of this series should be negatively related to the systemic financial stress. |
| RSK_7.1 | $^{-}CRCAP\_NV$ | Credit Risk Indicators - through the cycle function | ††: 2, 3, 4, 5 | For an individual institution, this series describes through-the-cycle credit capital, quantified as average positive ALLL for past 3 years. A rise in the reserves indicates greater capacity to withstand losses, therefore, a rise in a long-term real-time (accumulated) mean of this series should be negatively related to the systemic financial stress. |
| RSK_7.1 | $^{-}\Delta CRCAP\_NV$ | Credit Risk Indicators - through the cycle function | †: 3, 4, 5, 6 | |
| RSK_8a | $EDF^{+}$ | Credit Risk Indicators - point-in-time/stress function | ††: 9<br>†: 7, 8, 10 | This series measures an aggregated Z-Score for the Moody's KMV Expected Default Frequency (EDF). A rise in the series indicates greater likelihood of systemic default. Thus, a rise in a long-term real-time (accumulated) mean of this series should be positively related to the systemic financial stress. |
| RSK_9 | $^{-}LNS\_EV$ | Economic Value : 12 call report loan portfolios - 99.5 percent BankCaR | †: 2, 3, 9 | For an individual institution, this indicator measures residual economic value of the loan portfolio evaluated at extreme stress (proxied by 99.5 percent BankCaR). Rise in the series indicates greater residual capacity to withstand extreme stress and lesser potential for systemic stress. |
| RSK_14 | $^{-}SOLV\_NV$ | Solvency - through the cycle function | ††: 2, 3, 4, 5, 8<br>†: 7, 9, 10, 11 | Solvency at each point in time is measured as the difference between available financial resources and required internal capital. The series measures the safety buffer helping to alleviate potential losses and stress. A rise in the solvency series indicates more available capacity to handle stress and losses and should be negatively related to the systemic financial stress. |
| RSK_15 | $^{-}SOLV\_SV$ | Solvency - point-in-time/stress function | ††: 2, 3, 4, 5, 7, 8<br>†: 9 | |
| RSK_16 | $^{-}SOLV\_EV$ | Solvency - extreme stress/crisis function | †: 8, 9 | |
| RSK_F | $^{-}IR\_EVNV$ | Interest Rate Risk - normal distance-to-systemic stress | ††: 2, 4<br>†: 3, 5, 7, 8, 9, 10, 11 | The series measures the residual value between crisis and normal valuation of the company's balance sheet. The less the value, the greater the potential for systemic stress. |
| RSK_G | $\boldsymbol{IR\_SVNV}^{+}$ | Interest Rate Risk - normal distance-to-stress | ††: 2, 4<br>†: 3, 5, 6, 7, 8, 9 | The series measures the incremental growth in internally required interest-rate risk capital as the institutional balance sheets transition from normal to stress valuations. The less the value, the smaller is the incremental capital required and the less is the potential for systemic stress. |
| RSK_H | $^{-}CR\_EVSV$ | Credit Risk - stress distance-to-systemic stress | ††: 2, 3<br>†: 4 | The series measures the difference between internally required credit capital at extreme value and internally required credit capital at stress value. As the distance increases at a particular point in time, the potential for systemic stress decreases. |
| RSK_H | $^{-}\Delta CR\_EVSV$ | Credit Risk - stress distance-to-systemic stress | †: 3, 5 | |
| RSK_I | $^{-}CR\_EVNV$ | Credit Risk - normal distance-to-systemic stress | †: 2, 3, 4, 8, 9 | The series measures the difference between internally required credit capital at extreme value (RSK_I) or stress value (RSK_K) and internally required credit capital at normal-through-the-cycle value. As the distance increases at a particular point in time, the potential for systemic stress decreases. |
| RSK_K | $^{-}CR\_SVNV$ | Credit Risk - normal distance-to-stress | – | |
| RSK_L | $^{-}SLV\_EVSV$ | Solvency - stress distance-to-systemic stress | ††: 2, 3, 4, 5, 7, 8<br>†: 6, 9 | The time series of solvency stress distance (RSK_L) or normal distance (RSK_M) to systemic tress measures the potential deficit in the solvency buffer at each point in time. By construction, this distance series is always negative, but may approach zero. Thus, the larger is this deficit, the closer it is to zero, the less is the potential for systemic stress. |
| RSK_M | $^{-}SLV\_EVNV$ | Solvency - normal distance-to-systemic stress | ††: 3, 4, 5, 8<br>†: 6 | |

*Note:* Plus sign indicates positive expectation. Minus sign indicates negative expectation. †† indicates Granger causality with 90 percent or better confidence. † indicates Granger causality with 79 percent or better confidence.

**Table 19**

Structure variables: definitions, expectations, and Granger causality.

| VARIABLE | SERIES | EXPOSURE | GRANGER LAG | THEORETICAL EXPECTATION |
|---|---|---|---|---|
| STR_1.2 | $Gt\_P5PCV^{+}$ | Connectivity Indicators – CoVaR at 5 percent | †: 5 | For an individual institution, the conditional value at risk indicates the relative contribution of the institution to the aggregate 5 percent quantile Value at Risk. A rise in the aggregated series corresponds to greater contribution to systemic risk. |
| STR_1.3 | $Gt\_D1PCV^{+}$ | Connectivity Indicators – Delta CoVaR at 1 percent | – | For an individual institution, the marginal value at risk indicates the difference in the institution's x percent quantile CoVaR and the aggregate x percent quantile Value at Risk. A rise in the series corresponds to greater contribution to systemic risk. |
| STR_1.4 | $Gt\_D5PCV^{+}$ | Connectivity Indicators – Delta CoVaR at 5 percent | – | |
| STR_2 | $Gt\_HEQ^{+}$ | Concentration Indicators - Capital Markets (Equity) | – | This series measures the concentration time series of market capitalization of top five US BHCs relative to the total US equity market from the Flow of Funds. The rise in the series shows increasing market dominance of smaller number of firms and reflects a growing potential for market disruption due to failure of the individual participants. |
| STR_4 | $Gt\_HFX^{+}$ | Concentration Indicators - Currency Markets (FX) | ††: 2, 3, 4<br>†: 5, 8 | This series measures the concentration time series of FX exposures of top five US BHCs relative to the total FX market from the Flow of Funds. The rise in the series shows increasing market dominance of smaller number of firms and reflects a growing potential for market disruption due to failure of the individual participants. |
| STR_4.1 | $Gt\_HIXP^{+}$ | Concentration Indicators - Currency Markets (FX) | ††: 6<br>†: 2, 4, 7 | |
| STR_5 | $Gt\_HIB^{+}$ | Concentration Indicators - Currency Markets (Interbank) | ††: 6, 8, 9, 10, 11<br>†: 5, 7 | This series measures concentration in currency interbank markets assuming this market can be represented by the top twenty bank holding companies. Although this is a relative measure of market concentration as captured by the BHCs, rise in the concentration indicator shows increasing market dominance of smaller number of firms and reflects a growing potential for market disruption due to failure of the individual participants |
| STR_8 | $Gt\_HIRD^{+}$ | Concentration Indicators - Risk Transfer Markets (Interest Rate Derivatives) | – | This series measures the concentration time series in risk transfer markets for interest rate derivatives. The rise in the series shows increasing market dominance of smaller number of firms and reflects a growing potential for market disruption due to failure of the individual participants. |
| STR_9 | $Gt\_LEVN^{+}$ | Contagion (normal leverage) | ††: 2, 3, 4, 12<br>†: 5 | Normal leverage is measured as ratio of debt to equity. Use of leverage allows financial institutions to increase potential gains on its inherent equity position. Since increases in debt carries a variety of risks, typically credit, market, and interest rate risk, increased leverage is a double-edged magnifier of returns, increasing both potential gains and potential losses. The rise in the normal leverage describes higher level of "risky" debt relative to "safer" equity. |

*Note:* Plus sign indicates positive expectation. Minus sign indicates negative expectation. †† indicates Granger causality with 90 percent or better confidence. † indicates Granger causality with 79 percent or better confidence.