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SAFE: An early warning system for systemic banking risk

Mikhail V. Oet [a,b,*], Timothy Bianco [a], Dieter Gramlich [c], Stephen J. Ong [a]

[a] Federal Reserve Bank of Cleveland, United States
[b] Case Western Reserve University, United States
[c] Baden-Wuerttemberg Cooperative State University, Germany

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ABSTRACT

This paper builds on existing microprudential and macroprudential early warning systems (EWSs) to develop a new, hybrid class of models for systemic risk that incorporates 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 and policy.

1. Introduction

People view and economists study financial tsunamis as distinct and unique events. Different as they are, they all can be understood through a common lens of financial stress.[1] Armed with this lens, this study aims to understand the factors that can explain financial stress in the United States' banking system.

The notion that our lives are punctuated by these exceptional financial crises is not new. William Mitchell (1923, p. 5) observed that "Fifteen times within the past one hundred and ten years, American business has passed through a "crisis"...Further, no two crises have been precisely alike and the differences between some crises have been more conspicuous than the similarities. It is not surprising, therefore, that business men long thought of crises as "abnormal" events brought on by some foolish blunder made by the public or the government."

Some say, therefore, that financial crises are shock events and therefore cannot be predicted, and that it is impossible to know the timing of these shocks. Even if it were possible, this perspective tells us that bubble-pricking policy would be problematic because "it presumes that you know more than the market."[2] Others argue that 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[3] and tend to have common features such as excessive asset prices relative to a longer-term central tendency, lots of leverage in the banking system that fuels excessive asset prices, and a networked financial system that can "spill" asset losses and funding problems from one institution to another, putting the entire system at risk.[4]

* Corresponding author.
E-mail addresses: mikhail.v.oet@clev.frb.org (M.V. Oet), timothy.bianco@clev.frb.org (T. Bianco), gramlich@dhbw-heidenheim.de (D. Gramlich), stephen.ong@clev.frb.org (S.J. Ong).

[1] Illing and Liu (2003, 2006, p. 243) examine financial stress "as a continuous variable with a spectrum of values, where extreme values are called a crisis." This concept of financial stress extends Bordo et al. (2000) notion of "an index of financial conditions" which studies whether aggregate price shocks are useful for dating financial instability. See Oet et al. (2011) for historical review of the financial stress measures. Among the recent research contributions to financial stress are studies by Hakkio and Keeton (2009), Hatzius et al. (2010), Kliesen and Smith (2010), Oet et al. (2011), Brave and Butters (2011), Hollo et al. (2012), and Carlson et al. (2012).

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

[3] 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).

[4] 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.

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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 and Klingebiel, 2003). The current US supervisory policy toolkit includes several EWSs for flagging distress in individual institutions, but it lacks a tool for identifying systemic-level banking distress.[5] Therefore, the SAFE EWS is designed to test the association of institutional imbalances and financial stress empirically.

Gramlich et al. (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). Theoretical precedents[6] typically examine the emergence of systemic risk from aggregated economic imbalances, which sometimes result in corrective shocks. A common view[7] 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 capital and serve intermediary functions, thereby generating spillover effects into the real economy with no clear self-healing mechanism.

Illing and Liu (2003, 2006) further detail the hypothesis 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.[8]

Gramlich et al. (2010, p. 208) 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 hybrid 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." 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 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: tests of relative value of private supervisory data, analysis of possible action thresholds appropriate for this EWS, and the use of the supervisory EWS. Section 5 concludes with a discussion of interpretations and directions for future research.

2. Early warning system (EWS) conception

2.1. EWS elements

What factors in the banking system explain financial stress? How and to what extent do these factors and financial stress interact? Fig. 1 shows the conceptual model guiding the research, mapped in literature. The model suggests that financial stress can be explained by the institutional imbalances in the banking system, including its structural imbalances and the functional intermediation imbalances of return, risk, and liquidity transformation.

Financial imbalance theory is the principal theory used to explain financial stress. It was developed by Borio and Lowe (2002a, 2002b, 2004) and Borio and Drehmann (2009) for aggregate macroeconomic imbalances and extended by Oet et al. (2013) to institutional imbalances. Financial imbalances are defined as deviations of financial variables from their mean, so they represent pressures in the financial system. As a first subset of institutional imbalances, functional imbalances are defined through the intermediary functions of financial institutions and consist of return transformation, liquidity transformation, and risk transformation (Mishkin, 1992). As a second subset of institutional imbalances, structural imbalances reflect structural vulnerabilities in the morphology of the financial system (Gramlich and Oet, 2011).

The process of interaction of financial stress and the banking system factors is modeled from the perspective of feedbacks theory (Wiener, 1948; Tustin, 1953; and more recently: Krishnamurthy, 2010; Brunnermeier and Pedersen, 2009; Bijlsma et al., 2010; Kapadia et al., 2012), developed to study the dynamic behavior of complex systems. Tustin (1952) described feedback as "the fundamental principle that underlies all self-regulating systems, not only machines but also the processes of life." Systemic feedback is defined as loop system or mechanism in which the system responds to perturbation either in the same direction—positive feedback accentuating or accelerating a process—or in the opposite direction—negative feedback inhibiting or slowing down a process. Thus a positive systemic feedback is a mechanism that responds to perturbation in the same direction as the perturbation, while negative systemic feedback responds to the perturbation in the opposing direction.

Basically, 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 markets' stress series provided by the Federal Reserve Bank of Cleveland (Oet and Eiben, 2009; Oet et al., 2011). Financial stress is defined to be "observable, continuous manifestations of forces exerted on economic agents" (Oet et al., 2011, p. 12). The present paper contributes a new typology for the drivers of risk in the EWS. The risk model applies a regression approach to explain the financial markets' stress index using optimally lagged, public and private institutional data from the 25 largest US bank holding companies. The risk model extends Hanschel and Monnin (2005) who estimate a model that regresses a systemic stress index on observed standardized past imbalances.[9] In their study, only one "optimal" lag is chosen for each of the explanatory variables, which are constructed as standardized imbalances, represented by *z*-scores. This approach implies that the trend of an individual imbalance serves as a "proxy for the longer-term fundamental value of a variable, around which the actual series fluctuates" (Hanschel and Monnin, 2005, p. 439).

Our basic conjectures are that systemic financial stress can be induced by asset imbalances (Borio and Lowe, 2002a, 2002b, 2004; Borio and Drehmann, 2009) and structural weakness. We

[5] Examples of current US 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 et al. (2006, pp. 58–65). Jagtiani et al. (2003) empirically test the validity of three supervisory micro-risk EWSs (SCOR, SEER, and Canary).

[6] See particularly Borio et al. (1994), Borio and Lowe (2002a, 2002b), and Borio and Drehmann (2009).

[7] Group of Ten (2001).

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

[9] Hanschel and Monnin, following the tradition established by Borio and Lowe (2002a), call these imbalances "gaps."

Table 1
Systemic risk explanatory variables in literature.

	Demirgüç-Kunt and Detragiache (1998)	Kaminsky and Reinhart (1999)	Borio and Lowe (2002a)	Borio and Lowe (2002b)	Edison (2003)	Hanschel and Monnin (2005)	King et al. (2006)	Hendricks et al. (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 adapted from Gramlich et al. (2010, p. 205).

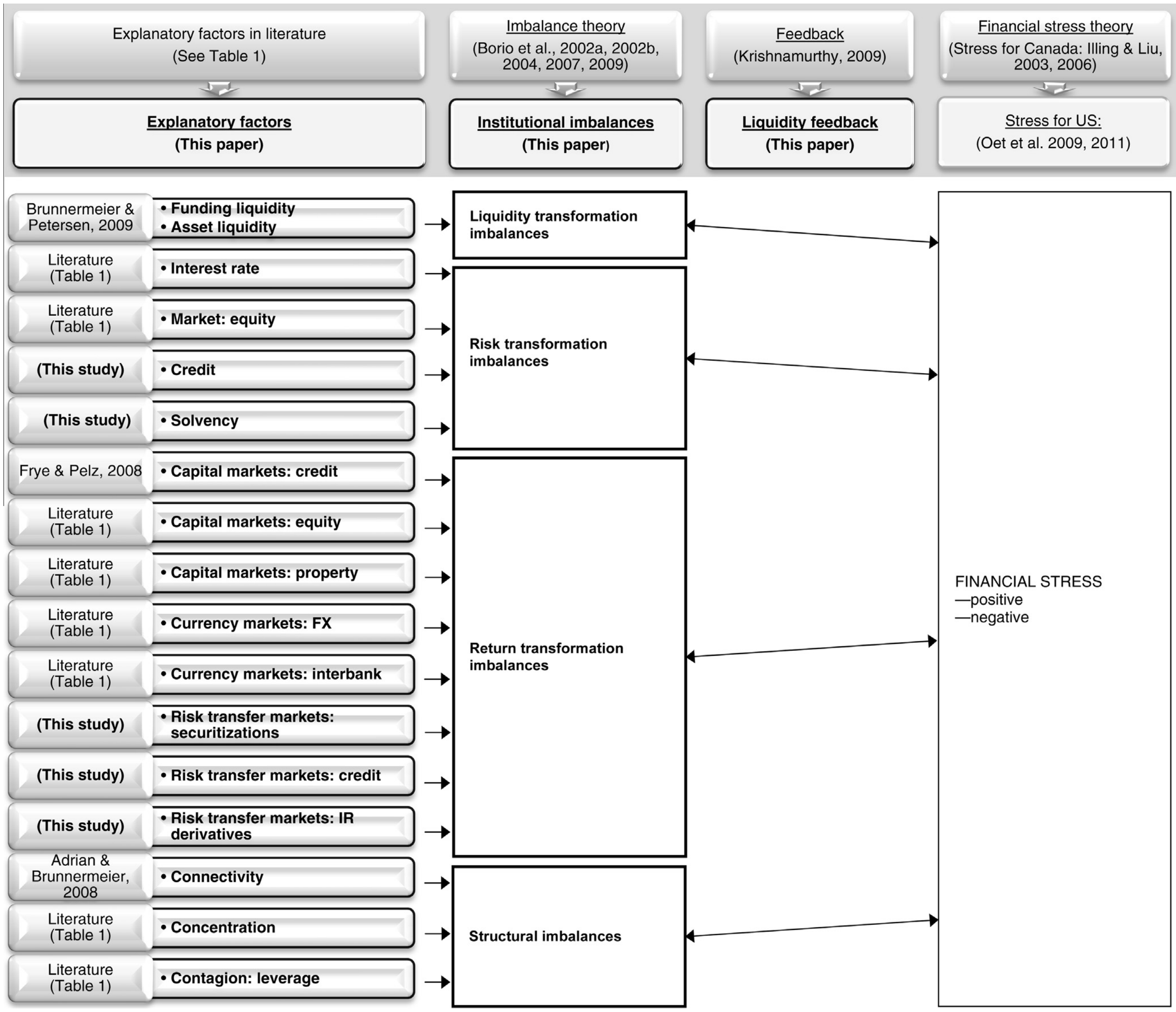

Fig. 1. Literature map and conceptual model: explanatory factors for financial stress.

can view imbalances as the deviations between asset expectations and their fundamentals. The larger the deviation, the greater is the potential shock. Therefore, systemic financial stress can be expected to increase (decrease) with the rise (fall) in positive imbalances and decrease (increase) with the rise (fall) in negative imbalances.

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 in which institutions of varying size are concentrated in particular markets and are interconnected in limited ways through a small number of highly connected intermediaries. In this system, the highly connected intermediaries dominate particular markets and control access to alternative markets for less-connected institutions. A high-stress experience by such a dominant institution is transmitted to the many smaller institutions locked out of alternative market access, cannot be easily sustained by the system, and increases the potential for systemic risk. The failure of one institution that interlinks several markets therefore may lead to a systemic damage due to the partial collapse of one or more markets. The conjecture of the importance of structural characteristics is supported by empirical evidence, which is discussed in Gramlich and Oet (2011).

Fig. 2 shows a sample of asset markets' concentrations of the US bank holding companies in 2009 across tiers of varying size. The financial markets' concentrations of the top 25 US bank holding companies are shown in Fig. 3 across time.

2.2. Measuring financial stress—dependent variable data

Building on the research precedent of Illing and Liu (2003, 2006), Oet and Eiben (2009), and Oet et al. (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 US (CFSI)[10] as a contemporaneous and continuous measure. The CFSI is created utilizing daily publicly observable data from the following components covering a wide spectrum of financial sectors: (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

[10] Federal Reserve Bank of Cleveland, Financial Stress Index.

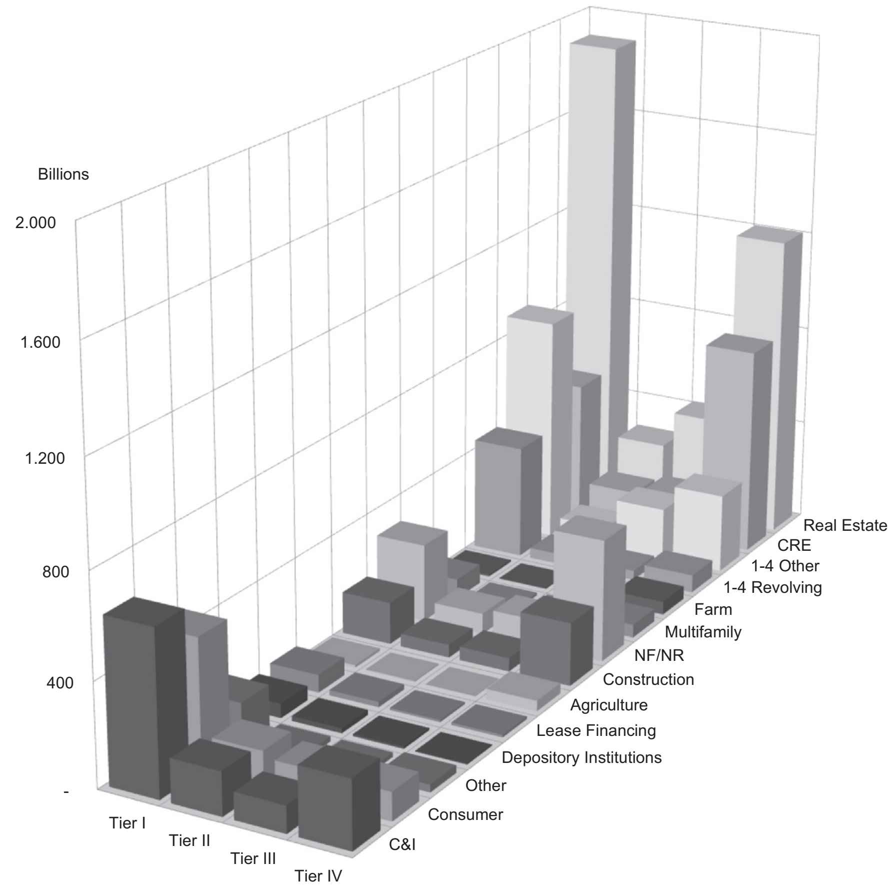

Fig. 2. Topology of loan asset USD concentrations across bank holding company tiers.

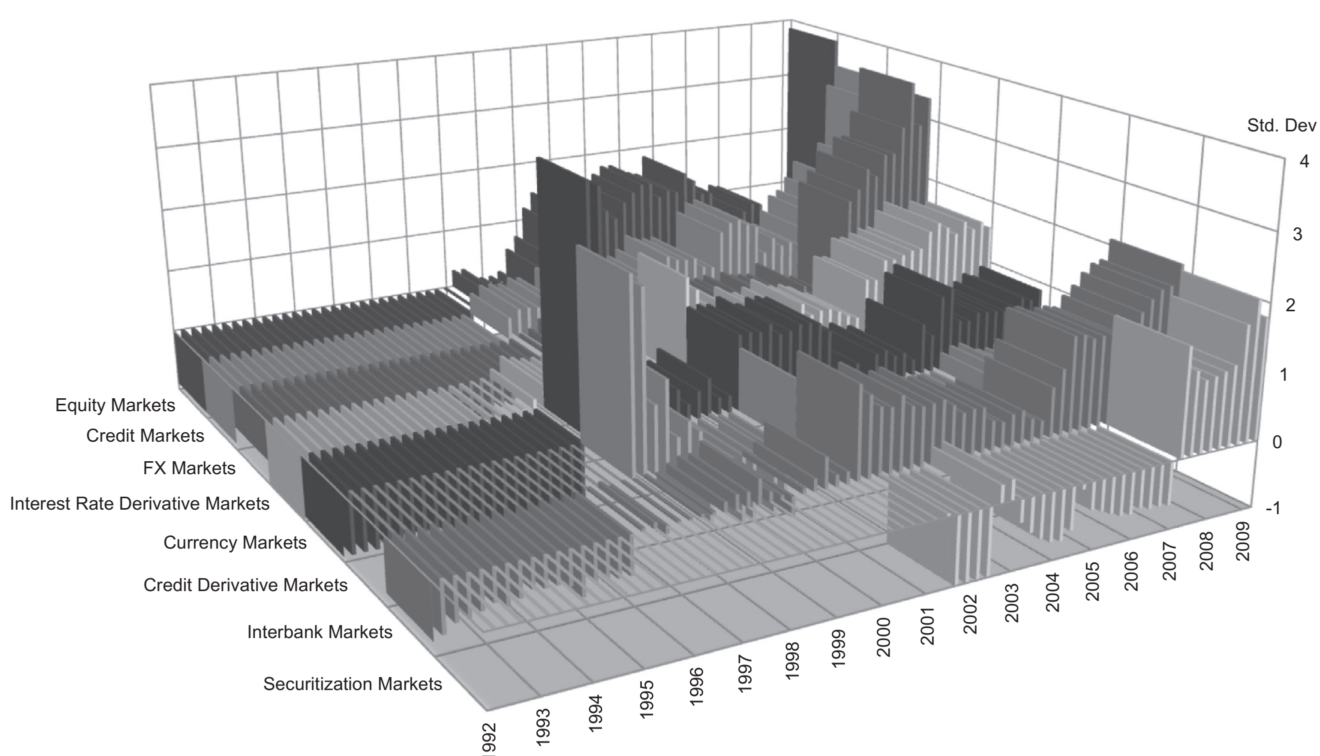

Fig. 3. Topology of financial market concentrations of top 25 US BHCs across markets and time.

crashes.[11] There are many weighting techniques available and utilized in indexing financial stress, such as equal weights, variance weights, principal component, and market size weights. Such techniques were tested in turn and the approach selected to minimize false alarms is a variation of a market size weight called the "credit weights" method. This method utilizes Flow of Funds data and measures the amount of credit outstanding in the four broad financial markets that make up the 11 components. This allows for a dynamic weighting methodology where weights change as conditions in financial markets shift (Oet and Eiben, 2009; Oet et al., 2011). Table 2 details the construction of the financial stress series.

Bianco et al. (2012, pp. 1–2) highlight that these components, mainly spreads, provide significant coverage of the US financial system markets. While stress in any of these markets could carry over into the broader financial system, the combined information contained in the stress components gains value as "systemic stress-related events are more likely to affect spreads in multiple markets. Observing conditions in a number of markets allows for the potential identification of a common factor, that is, financial stress."

In 2008, no public series of financial stress in the US existed. By 2010, however, 12 alternative financial stress indexes were available. Fig. 4 compares the CFSI with other indexes of financial stress created by Federal Reserve Banks. The CFSI tracks these analogous indexes reasonably well, which suggests that it is an appropriate measure of financial stress (Oet et al., 2011). Any observed differences in the timing and extent of stress is due to different weighting methodology or utilizing different aspects of financial markets (Gramlich et al., 2012). The further comparison of CFSI with alternative financial stress series is discussed in Oet and Eiben (2009) and Oet et al. (2011).

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

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

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

2.3. Drivers of risk—explanatory variables data

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 Fig. 1). The aim of the SAFE EWS is to explain highly significant episodes of stress as measured by CFSI. To advance from these premises, we develop a methodology that uses z-scores to express imbalances. We define an imbalance X_t as the deviation of an explanatory variable $\underline{X_t}$ 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.[12]

[11] See Oet et al. (2011) for a description of specific CFSI data sources.

[12] Oet et al. (2012) provide detailed information about variable construction.

The explanatory data comes from 81 quarterly panels from Q4:1991 to Q4:2011. A large component of explanatory 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 publicly available sources, such as S&P/Case Shiller[13] Compustat databases, Moody's KMV, and Flow of Funds, among others. Additional public data comes from research models in the public domain such as the CoVaR model (Adrian and Brunnermeier, 2008) and the BankCaR model (Frye and Pelz, 2008). Furthermore, each class of explanatory imbalances draws information from private supervisory data which is not disclosed to the public including the results of proprietary models developed by 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.[14] Table 3 reports summary statistics of the explanatory data. Additional data descriptions are provided in Appendix A. Data sources for the explanatory variables are shown in Appendix B (Table B.1).[15] The definitions, theoretical expectations, and Granger causality of the explanatory variables are summarized in Tables B.2–B.5.

3. Risk model and results

3.1. Methodology outline

As a first step, the SAFE EWS consists of a number of models, each of which is an optimal lag-linear regression model of traditional form

$$\begin{aligned} Y_t = {} & \beta_0 + \beta_{RET} \underline{X_{RET,t-n_{RET}}} + \beta_{RSK} \underline{X_{RSK,t-n_{RSK}}} + \beta_{LIQ} \underline{X_{LIQ,t-n_{LIQ}}} \\ & + \beta_{STR} \underline{X_{STR,t-n_{STR}}} + u_t, \end{aligned} \tag{2}$$

where the dependent variable Y_t is the CFSI and the independent variables $\underline{X_{k,t-n_k}}$ are types of return, risk, liquidity,[16] and structural imbalances aggregated for the top 25 US bank holding companies based on the size of total assets. Analyzing the top institutions and their significance to financial (in)stability is intuitive. It is assumed that analyzing the top 25 US bank holding companies provides substantial coverage of systemically important financial institutions. Further, the consequences of looking at *too few* institutions is greater than looking at too many. While it is likely that there are tiers of institutions that have different predictive abilities, it is beyond the scope of this study.

Whereas the SAFE EWS aims to create a set of stories that explain stress over different horizons, it is difficult to quantify these forecasts individually. To simplify interpretation for supervisory objectives, we continue by creating a set of forecast combinations. This regression based technique generates forecast weights summing to unity by regressing the stress index on the various forecasts. The short-lag forecast combination takes the form of

$$\begin{aligned} CFSI_t = {} & w_1 SL1_t + w_2 SL2_t + w_3 SL3_t + w_4 SL4_t + w_5 SL5_t \\ & + w_6 SL6_t + w_7 SL7_t + (1 - w_1 - w_2 - w_3 - w_4 - w_5 \\ & - w_6 - w_7) SL8_t + \varepsilon_t, \end{aligned} \tag{3}$$

where $SL1$ through $SL8$ refers to the series of one-step ahead forecasts from the eight short lag models since the fourth quarter of 1991 and the w parameter refers to the weights obtained for the

[13] See Standard and Poor's (2009).

[14] The liquidity feedback model and the stress haircut model.

[15] To conserve space, the tables show only information for the explanatory variables that ultimately enter the SAFE model.

[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).

Table 2
Construction components of the financial stress series (CFSI).

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

individual forecasts. Similarly, the long-lag forecast combination takes the form of

$$\begin{aligned} CFSI_t = {} & w_1LL1_t + w_2LL2_t + w_3LL3_t + w_4LL4_t + w_5LL5_t \\ & + w_6LL6_t + w_7LL7_t + (1 - w_1 - w_2 - w_3 - w_4 - w_5 \\ & - w_6 - w_7)LL8_t + \varepsilon_t, \end{aligned} \tag{4}$$

where $LL1$ through $LL8$ refers to the series of one-step ahead forecasts from the eight long lag models since the fourth quarter of 1991.

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 and without any other information, one can expect financial stress at a point in time to be related to past stress. To this effect, the FSI's underlying autoregressive (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 different specifications and therefore lead to different model forms. Short-lag models function dynamically, seeking to explain stress in terms of recent observations 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 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 do not include the autoregressive components.

3.2. EWS models

To proceed, we first establish parsimonious base models for the short- and long-lag horizons that outperform the benchmark and

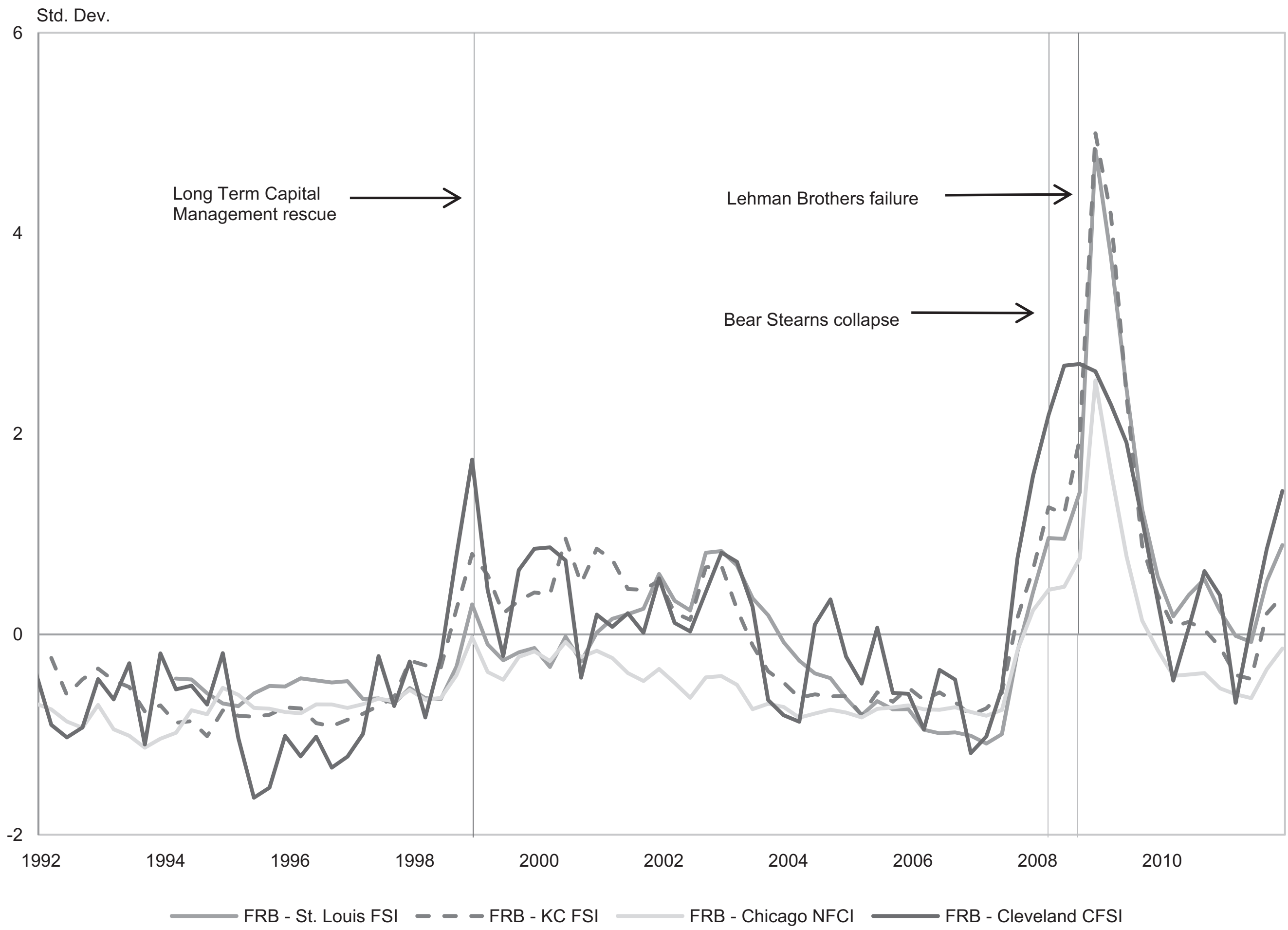

Fig. 4. Comparison of financial stress indices. *Note:* Values are quarterly averages, represented as z-scores. *Source*: Federal Reserve Bank of Cleveland; Federal Reserve Bank of Chicago; Federal Reserve Bank of Kansas City; Federal Reserve Bank of St. Louis

approximate financial stress in-sample. 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.

3.2.1. 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 relationship with financial stress. Considering the institutional and structural data, which candidate variables possess the desirable explanatory powers? Among several of 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 asset-liability (AL) mismatch should exert a positive influence. And among the structural imbalances, leverage should provide a standard positive relationship. These imbalances are shown in Fig. 5.

The logic for the sign expectations of these sample choices of candidate imbalances goes 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.

Table 3
Summary statistics and correlations for select explanatory variables.

Variables	ΔRET_1.1CPI$_{-7}$	RET_6TA$_{-12}$	RET_7TA$_{-8}$	RSK_2$_{-11}$	RSK_7.1$_{-7}$	RSK_E$_{-11}$	LIQ_1$_{-8}$	LIQ_4$_{-8}$	LIQ_7$_{-8}$	STR_1.2$_{-6}$	STR_1.4$_{-2}$	STR_1.4$_{-8}$	STR_2$_{-7}$	STR_4$_{-3}$	ΔSTR_4$_{-5}$	ΔSTR_4$_{-9}$	ΔSTR_4$_{-11}$	STR_4.1$_{-8}$	STR_4.1$_{-12}$	STR_5$_{-10}$	STR_8$_{-6}$	STR_9$_{-12}$
Summary statistics																						
Average	−0.06	1.36	−0.21	0.02	0.00	0.05	0.72	0.45	−0.88	−0.64	−0.01	−0.01	0.00	1.22	0.01	0.01	0.01	1.44	1.44	1.37	−0.01	−0.37
Standard deviation	0.36	1.23	0.95	0.46	0.14	0.71	1.55	1.80	1.02	0.53	0.84	0.84	0.44	1.81	0.99	0.99	0.99	1.41	1.41	1.13	0.69	1.30
Median	−0.01	1.52	0.00	0.01	−0.01	0.00	1.05	0.96	−1.26	−0.51	0.00	0.00	−0.06	0.75	0.01	0.01	0.01	1.52	1.52	1.48	−0.08	−0.67
Maximum	0.95	4.46	2.88	1.53	0.45	4.47	6.10	7.24	0.90	0.60	2.74	2.74	1.75	6.33	6.92	6.92	6.92	4.33	4.33	5.77	2.81	4.71
Minimum	−1.35	−1.88	−3.13	−3.06	−0.36	−4.18	−3.85	−2.27	−2.22	−2.26	−2.61	−2.61	−1.14	−1.66	−2.85	−2.85	−2.85	−1.21	−1.21	−1.38	−2.03	−3.32
Correlation matrix																						
ΔRET_1.1CPI$_{-7}$	1.00																					
RET_6TA$_{-12}$	0.25	1.00																				
RET_7TA$_{-8}$	−0.01	−0.51	1.00																			
RSK_2$_{-11}$	0.27	−0.18	0.05	1.00																		
RSK_7.1$_{-7}$	0.35	0.08	0.08	0.11	1.00																	
RSK_E$_{-11}$	−0.06	0.00	0.03	0.06	0.03	1.00																
LIQ_1$_{-8}$	−0.08	0.00	−0.08	0.00	0.16	−0.04	1.00															
LIQ_4$_{-8}$	0.01	0.31	−0.17	−0.19	0.38	−0.08	0.74	1.00														
LIQ_7$_{-8}$	−0.17	−0.38	−0.03	0.25	−0.36	0.00	0.10	−0.34	1.00													
STR_1.2$_{-6}$	−0.14	−0.16	−0.11	0.11	−0.12	0.05	−0.32	−0.50	0.42	1.00												
STR_1.4$_{-2}$	0.09	0.13	0.00	0.05	−0.08	−0.27	0.00	0.02	0.01	−0.07	1.00											
STR_1.4$_{-8}$	0.01	0.02	−0.03	0.02	0.24	−0.02	−0.09	0.05	−0.14	0.03	0.16	1.00										
STR_2$_{-7}$	0.69	−0.15	0.08	0.25	0.27	0.12	−0.03	−0.08	0.04	−0.04	0.04	−0.06	1.00									
STR_4$_{-3}$	0.07	0.21	−0.07	−0.09	0.27	−0.15	0.34	0.58	−0.40	−0.42	−0.03	−0.05	−0.08	1.00								
ΔSTR_4$_{-5}$	0.09	0.03	0.06	0.03	0.05	0.01	−0.21	−0.18	−0.01	0.38	0.05	0.18	0.08	0.17	1.00							
ΔSTR_4$_{-9}$	0.05	0.06	0.04	−0.07	−0.01	0.04	0.10	0.15	−0.01	−0.18	−0.20	0.04	−0.07	0.12	−0.03	1.00						
ΔSTR_4$_{-11}$	0.01	−0.06	0.07	−0.17	0.03	−0.04	0.08	0.09	0.04	0.18	−0.16	0.04	0.07	0.10	0.11	0.12	1.00					
STR_4.1$_{-8}$	−0.10	−0.30	0.25	−0.26	0.13	−0.07	0.25	0.38	−0.40	−0.33	0.02	0.08	−0.04	0.47	0.00	−0.02	0.19	1.00				
STR_4.1$_{-12}$	0.16	0.31	−0.02	−0.14	0.34	−0.14	0.28	0.48	−0.50	−0.52	−0.01	−0.01	0.00	0.39	−0.12	−0.05	−0.13	0.30	1.00			
STR_5$_{-10}$	0.17	0.19	0.12	−0.12	−0.16	−0.12	−0.16	−0.04	−0.40	−0.27	−0.05	0.02	−0.10	0.29	0.14	0.11	0.01	0.14	0.19	1.00		
STR_8$_{-6}$	0.31	0.12	0.03	0.34	−0.03	0.22	0.03	−0.13	0.07	0.04	−0.10	0.05	0.32	−0.12	0.06	−0.12	0.00	−0.25	0.18	0.21	1.00	
STR_9$_{-12}$	0.05	−0.14	−0.22	0.30	0.25	−0.10	0.49	0.33	0.43	0.09	−0.04	−0.04	0.20	0.13	−0.06	−0.07	−0.11	−0.11	0.05	−0.44	0.07	1.00

Note: Due to space limitations, the summary statistics and the correlation matrix are shown for select explanatory variables. The complete tables are available from the authors upon request.

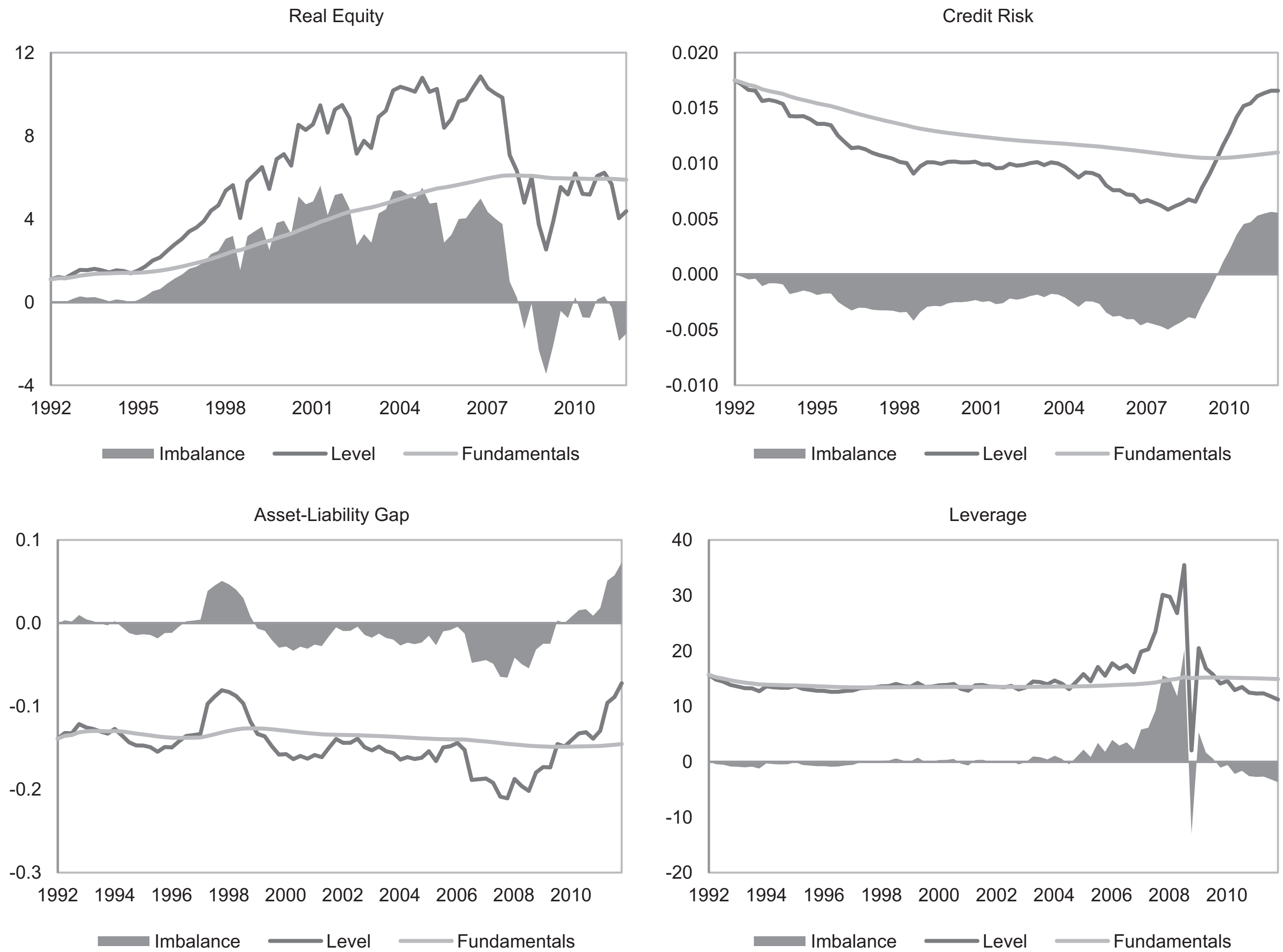

Fig. 5. Imbalances as deviations from fundamentals reflect potential shocks. *Note:* Imbalances as deviations from fundamentals reflect potential shocks. Level refers to the raw data, fundamentals refer to the accumulated average, and the imbalance refers to the difference between these.

3.2.2. Criteria for variable and lag selection

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. We can improve on this by utilizing a more rigorous technique by testing less obvious explanatory variables effectiveness at forecasting stress using the optimal lag approach. We use straightforward techniques to the criteria below to determine whether a new variable should be included. 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.

(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 B, Tables B.2–B.5 for theoretical sign).

(2) *Hypothesis testing:* Consider whether the coefficient of the variable to be included is significant in the expected direction. To avoid heteroskedasticity, we report *t*-statistics in the variable and lag selection procedure.

(3) *Granger causality:* Consider whether the variable to be included changes consistently and predictably before the dependent variable. 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.

(4) *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. This is especially significant not for forecasting but rather for model interpretation. The usefulness of an EWS where several explanatory variables are highly collinear is not clear. While the individual forecasts that are used to create the forecast combination will clearly be highly collinear, the explanatory variables that make these forecasts are not. As a result, this allows the supervisor to narrow in on the significant variables affecting financial stress. Naturally, during the financial crisis, many seemingly uncorrelated variables may have become collinear or the relationships may become unstable. As a result, we examine only the relationship between the FSI and our *X*'s through the first quarter of 2007.

(5) *Optimal lag selection*: Starting from the base models, candidate variables from the return, risk, liquidity, and structure imbalance classes are tested by an optimal lag selection algorithm (Oet et al., 2013). The optimality criteria include sign expectations, *t*-statistics, Granger causality, and VIF among others. For each new candidate variable, we select its optimal lag for the appropriate short-lag and long-lag models.

Table 4
Benchmark and base models in-sample.

Panel A: Benchmark FSI model

$$\widehat{FSI} = 45.65 + 0.59FSI_{-1} + 0.25FSI_{-4}$$
DF=58 K=2

	Constant	Lagged FSI	Seasonal FSI	Adjusted R-squared	Akaike info criterion	Schwarz criterion
Estimates	45.65	0.59	0.25	0.49	6.74	6.85
t-value	(7.76)	(5.93)	(2.52)			

Panel B: Candidate Base Model

$$\widehat{FSI} = 9.30 + 0.52FSI_{-1} + 0.63GT\_AL312_{-3} + 2.99GT\_LEVN_{-11} + 7.35\Delta PMKTCP_{-2} - 0.35\Delta CRCAP\_NV_{-11}$$
DF=61 K=5

	Constant	Lagged FSI	AL mismatch	Leverage	Real Equity	Credit Risk	Adjusted R-squared	Akaike info criterion	Schwarz criterion
Estimates	9.30	0.52	0.63	2.99	7.35	-0.35	0.56	6.68	6.89
t-value	(1.76)	(5.22)	(0.52)	(1.54)	(3.44)	(0.03)			
Granger				†	††				

Panel C: Short Lag Base Model

$$\widehat{FSI} = 22.17 + 0.44FSI_{-1} + 2.28Gt\_D5PCV_{-2} + 4.55\Delta tAL3122_{-5} + 2.31HFX4_{-3} + 4.88\Delta PMKTCP5_{-7} - 6.55\Delta EQLGDW3_{-11}$$
DF=61 K=6

	Constant	Lagged FSI	Connectivity	AL mismatch	Concentration	Capital Markets - Equity	IRR Indicator – through-the-cycle function	Adjusted R-squared	Akaike info criterion	Schwarz criterion
Estimates	22.17	0.44	2.28	4.55	2.31	4.88	-6.55			
t-value	(5.36)	(4.37)	(2.35)	(1.81)	(4.24)	(2.31)	(1.89)	0.67	6.41	6.65
Granger			††		††		††			

Panel D: Long Lag Base Model

$$\widehat{FSI} = 37.14 \mp 4.06Gt\_HIB_{-12} + 1.70Gt\_AL03_{-6} \mp 5.69\Delta HEQ5_{-7} + 12.66BCAR\_995_{-12} - 7.94Gt\_LX\_EV_{-10} - 3.48IR\_EVSV_{-11} - 2.05SECEG\_t_{-10}$$
DF=62 K=7

	Constant	Currency Market concentr.	A-L Gap	Capital Market concentr.	Bank Capital at Risk	Liquidity Index	Interest Rate Risk	Currency Markets – interbank exposure	Adjusted R-squared	Akaike info criterion	Schwarz criterion
Estimates	37.14	4.06	1.70	5.69	12.66 (3.58)	-7.94	-3.48 (3.09)	-2.05	0.54	6.75	7.02
t-value	(15.71)	(4.53)	(3.54)	(3.13)		(3.30)		(1.95)			
Granger			††		††		††	††			

† - Granger causality at 20%
†† - Granger causality at 10%

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 4. The candidate model in panel B improves on the benchmark model in-sample. The short-lag base model in panel C is formed by establishing a core story that features positive influences of structural, liquidity, and return imbalances and negative influences of risk imbalances. The causes of increasing the potential for systemic stress (imbalances in connectivity, asset-liability gap, foreign exchange concentration, and capital markets – equity) are offset by imbalances in interest-rate risk capital and credit risk distance to systemic stress. The short-lag base model 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, risk, and liquidity imbalances as well as negative influences of risk, liquidity, and return imbalances. Increasing the potential for systemic stress are imbalances in interbank market concentration, asset-liability gap, equity market concentration, and bank capital-at-risk. They are offset by imbalances in fire-sale liquidity, interest rate risk, and currency markets – interbank exposures. The long-lag base model provides a useful performance target for the long-lag EWS models.

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, coded as they are, fit two stories—a positive story of structure and a negative story of risk[17]—supplemented and enhanced by additional types of return and liquidity imbalances.[18]

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). Note that the out of sample forecast metrics for the short-lag and long-lag models are not directly comparable. The forecast horizon for the short-lag suite of models is two quarters compared to the long-lag suite which has a forecast horizon of six quarters. Rather these metrics are useful for comparison within the short-lag and long-lag sets of models.

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 of two quarters for short-lag models and six quarters for long-lag models, including their forecast combination. 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.

4. Discussion and implications

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 scenarios. In general, the stories might have different performance levels. Therefore, it is important for the EWS researcher to seek a stable model or to recognize the dynamics and adjust accordingly.

4.1. Supervisory versus public EWS specifications

SAFE EWS incorporates both public and supervisory data based on the assumption that non-public data provides a more accurate

[17] The reason that risk imbalances describe a negative relationship with stress is that they are, by construction, predominantly defensive functions of capital and solvency.
[18] The long-lag models tell fundamentally similar stories of positive structural imbalances and negative risk imbalances.

Table 5
Summary of short-lag model stories.

Model	Story	Positive	Negative
(1)	Structure^{+}	FX concentration	
	Liquidity^{+}	AL gap indicator	
	Return^{+}	Currency markets – interbank exposures	
(2)	Structure^{+}	FX concentration	Loan portfolio
	Risk^{+-}	IR derivatives concentration	IRR indicator – through-the-cycle function
	Return^{-}	Expected default frequency	Risk transfer – securitization
(3)	Structure^{+}	FX concentration	Risk transfer – securitization
	Risk^{-}	FX concentration	Interbank derivative exposure
	Return^{-} Liquidity^{+}	AL gap – 3-to-12 months maturity band	Solvency
(4)	Structure^{+}	FX concentration	Solvency
	Risk^{-}	Equity concentration	Risk transfer - securitization
	Return^{-}	Connectivity – CoVaR	
(5)	Structure^{+}	FX concentration	Loan portfolio
	Risk^{-}	FX concentration	Credit risk – distance to stress
		Equity concentration	IRR indicator – through-the-cycle function
(6)	Structure^{+}	Capital markets - equity	Interest rate risk
	Risk^{+-}	IR derivatives concentration	Credit risk – distance to stress
	Return^{+}	Expected default frequency	IRR indicator – through-the-cycle function
(7)	Structure^{+}	FX concentration	Currency market – interbank exposure
	Risk-	Equity concentration	Credit risk – distance to stress
	Return^{-} Liquidity^{+}	AL gap indicator	Loan portfolio
(8)	Structure^{+}	FX concentration	Credit risk – distance to stress
	Risk^{-}	FX concentration	IRR indicator – through-the-cycle function
		Equity concentration	Solvency

Legend: Structure, Risk, Return, Liquidity

and actionable EWS. To test this assumption, we remove all supervisory FRS variables from the model suggestion stage[19] 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). Table 10 shows the distribution of category 1 data (marked †) and category 2 data (marked ††) among the imbalance classes. Table 11 shows the proportion of supervisory variables among the specified independent variables.

Comparing the public-data-only versions of SAFE models with those using supervisory data (Table 12 and Fig. 6), we find that models using supervisory data significantly outperform models with only public data for long-lag models while the results are mixed for the short-lag models when applied to the out-of-sample period. Both private and public short-lag specifications capture the increase in stress during the second quarter of 2007. More significantly however, is the increase in stress predicted by the private long-lag forecast combination. While the private forecast does predict an increase in stress throughout the period ending in the third quarter of 2008, the degree of predicted stress is significantly lacking. Thus, we find evidence of the importance and usefulness of private data in creating a systemic risk EWS.

4.2. The financial crisis

The financial crisis of 2008 tests the model 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.

4.2.1. Short-lag forecasts

Several short-lag models predicted the advent of stress starting in Q2:2007 and, in some cases, continuing throughout that year. In particular, many short-lag models predicted stress, significantly

[19] See Table 10.

Table 6
In-sample regression results for SAFE EWS short-lag models.

Variable	Series	Exposure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return Variables										
RET_1.1CPI	$\Delta PMKTCP5^{+}$	Capital markets – equity (price–based)	4.689 † (2.307)**	5.466 † (3.274)***	4.712 † (2.754)***			6.805 † (3.630)***		
RET_5.2TA	$IXDRTAGt^{-}$	Interbank derivative exposure			−1.635 (2.425)**					
RET_6CPI	$ITRBNKG\_t^{-}$	Currency markets *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. interbank exposures (price–based)							−3.359 † (4.264)***	
RET_6TA	$ITBBKTAGt^{+}$	Currency markets – interbank exposures (total assets–based)	1.902 †† (2.996)***						2.213 (3.119)***	
RET_7CPI	$SECEG\_t^{\#0}$	Risk transfer markets – securitizations (price–based)			−3.895 †† (5.507)***					
RET_7TA	$SECETAGt^{\#}$	Risk transfer markets – securitizations (total assets–based)		−3.612 (2.919)***	−2.611 (2.147)**	−2.384 † (1.828)*				
Risk Variables										
RSK_2	$\Delta EQLGDW3^{-}$	IRR imbalance - through-the-cycle function		−7.341 †† (2.635)**	−6.411 †† (2.380)**		−9.290 †† (3.087)***	−6.231 †† (2.058)**		−5.721 †† (2.065)**
RSK_7.1	$\Delta CRCAP\_NV^{-}$	Credit risk imbalance - through the cycle function		−18.891 (2.676)**			−14.092 (1.833)*		−24.865 (3.007)***	−16.849 (2.247)**
RSK_8A	EDF^{+}	Credit risk imbalance - point-in-time/ stress function		2.276 (4.348)***			1.325 (2.510)**	1.506 (3.093)***		
RSK_81	LNS_MVEDFP^{-}	Market value : 12 call report loan portfolios (w. EDF uncertainty)		−8.938 (2.154)**	−8.119 (2.269)**				−9.698 †† (1.974)*	
RSK_9A	$BCAR\_995^{+}$	Bank Capital-At-Risk		4.931 †† (2.166)**						
RSK_E	IR_EVSV^{+}	Interest rate risk - stress distance-to-systemic stress		−2.678 †† (3.694)***			−1.845 (2.231)**	−2.256 (2.997)***		
RSK_I	$\Delta TCEVNV^{-5}$	Credit risk - normal distance-to-systemic stress		−6.834 (2.554)**	−4.770 (1.923)*		−9.392 (3.276)***	−6.484 (2.343)**		
RSK_N	SLV_SVNV^{-}	Solvency - normal distance-to-stress			−5.001 (3.197)***	−4.868 (2.807)***				−2.928 (1.799)*
Liquidity Variables										
LIQ_1	Gt_P5PCV^{+}	AL imbalance - '0 to 3 months' maturity	1.597 †† (3.967)***			0.808 †† (2.234)**	1.610 †† (3.921)***			
LIQ_2	$\Delta\ tAL3122^{+}$	AL imbalance - '3 to 12 months' maturity		2.191 (2.456)**	6.930 (2.998)***	2.479 (2.543)**		2.852 (2.594)**		
LIQ_4	Gt_ALG3^{+}	AL imbalance - 'greater than 3 years' maturity		1.004 †† (2.929)***	0.944 †† (2.401)**			1.100 †† (2.157)**	2.997 †† (4.719)***	
Structure Variables										
STR_1.2	Gt_P5PCV^{+}	Connectivity imbalance – CoVaR at 5%				5.674 †† (4.159)***				5.933 †† (4.242)***
STR_1.3	$\Delta TD1PCV3^{+}$	Connectivity imbalance – delta CoVaR at 1%					3.516 (2.516)**			
STR_1.4	Gt_D5PCV^{+}	Connectivity imbalance – delta CoVaR at 5%		2.425 †† (3.071)***		2.606 †† (3.166)***	1.717 (2.030)**		1.957 †† (2.430)**	2.729 †† (3.223)***
STR_2	$\Delta HEQ5^{+}$	Concentration imbalance - capital markets (equity)	3.030 (2.127)**			5.276 (4.158)***	4.960 (3.683)***	2.804 (2.130)**	4.535 (3.312)***	6.083 (4.397)***
STR_4	$HFX4^{+}$	ΔConcentration imbalance - currency markets (FX)			2.859 †† (5.062)***	1.872 †† (3.923)***		1.414 †† (2.457)**	1.201 †† (1.793)*	2.522 †† (5.255)***
STR_4	$\Delta HFX4^{+}$	ΔConcentration imbalance - currency markets (FX)	1.615 †† (2.386)**	1.968 †† (3.425)***	1.288 †† (1.891)*	1.199 † (1.935)*	1.518 †† (2.354)**	1.610 †† (2.452)**	1.035 † (1.718)*	1.491 † (2.465)**
STR_4.1	Gt_HIXP^{+}	Concentration imbalance – cross-country exposure	3.340 (4.211)***		2.931 † (4.283)***	3.780 † (5.270)***	2.300 † (3.137)***	1.830 (2.512)**	3.835 † (5.222)***	3.774 † (5.082)***
STR_5	Gt_HIB^{+}	Concentration imbalance - currency markets (interbank)		4.101 (6.705)***		1.692 (2.556)**	3.481 (5.353)***		1.903 (3.068)***	
STR_8	$\Delta tHIRD5^{+}$	Concentration imbalance - risk transfer markets (IR derivatives)	2.078 (1.688)*	4.941 (4.049)***				3.715 (3.122)***		
DYNAMIC	FSI^{+}_{t-1}	Lagged Financial Stress Index	0.401 (4.698)***	0.475 (7.058)***	0.345 (4.417)***	0.445 (5.269)***	0.392 (4.496)***	0.274 (3.190)***		0.434 (5.169)***
CONSTANT			15.440	15.205	25.027	12.667	17.290	23.891	30.863	16.533
OBSERVATIONS			61	61	61	61	61	61	61	61
R-SQUARED			0.733	0.824	0.817	0.803	0.784	0.783	0.774	0.780
AIC (OLS)			6.224	5.901	5.921	5.973	6.076	6.082	6.080	6.057
SC (OLS)			6.536	6.489	6.441	6.423	6.560	6.566	6.492	6.438

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.

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

Variable	Series	Exposure	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Return Variables										
RET_1.1CPI	*PMKTCP5*$^{+}$	Capital markets – equity (price-based)								2.394 †† (2.021)**
RET_1.1CPI	*ΔPMKTCP5*$^{+}$	Capital markets – equity (price-based)			4.902 † (6.553)***	4.028 † (8.441)***		4.417 † (6.834)***		3.165 † (4.273)***
RET_2CPI	*LNSTG_t*	Capital markets - vonds (price-based)					2.087 (1.590)			
RET_4TA	*ΔLNSCAT5*$^{-}$	Capital markets - commercial property (total assets-based		−7.733 (6.011)***		−7.413 (7.166)***			−9.698 (5.631)***	
RET_6CPI	*ITRBNKG_t*$^{-}$	Currency markets - interbank exposures (price-based)			−1.387 †† (2.004)*	−5.086 (7.676)***				−3.511 †† (4.132)***
RET_6TA	*ITBKTAGt*$^{+}$	Currency markets - interbank exposures (total assets-based)	4.102 †† (9.428)***	3.257 †† (6.690)***	4.445 †† (8.064)***	4.400 †† (8.931)***	2.627 †† (4.778)***	2.293 †† (4.134)***	3.474 †† (5.482)***	
RET_7CPI	*SECEG_t*$^{\#0}$	Risk transfer markets - securitizations (price-based)			4.079 (3.442)***	2.340 (2.778)***		2.736 (3.317)***		
RET_7TA	*SECETAG_t*$^{\#0}$	Risk transfer markets - securitizations (total assets-based)		1.141 (1.462)				−4.309 (3.819)***		−3.613 (3.617)***
RET_9TA	*IRDETAGt*$^{-}$	Risk transfer markets - IR derivatives (total assets-based)		−2.706 (3.221)***			−2.264 (2.911)***			
Risk Variables										
RSK_7.1	*ΔCRCAP_NV*$^{-}$	Credit risk imbalance - through the cycle function	−16.671 (6.142)***		−9.838 (2.805)***			−15.961 (3.500)***		
RSK_81	*LNS_MVEDF*$^{-}$	Market value : 12 call report loan portfolios (w. EDF uncertainty)						−13.431 (3.741)***		
RSK_9A	*BCAR_995*$^{+}$	Bank Capital-At-Risk							11.237 †† (4.475)***	
RSK_9	*LNS_EV*$^{-}$	Economic value : 12 call report loan portfolios - 99.5% BankCaR		−5.157 (2.129)**						
RSK_E	*IR_EVSV*$^{-}$	Interest rate risk - stress distance-to-systemic stress	−1.632 †† (5.347)***	−1.486 †† (3.149)***	−2.180 †† (5.274)***				−3.929 (4.697)***	−2.607 (3.396)***
RSK_I	*ΔTCEVNV5*$^{-}$	Credit risk - normal distance-to-systemic stress				−9.448 (4.731)***				−5.833 (2.725)***
RSK_N	*SLV_SVNV*$^{-}$	Solvency - normal distance-to-stress					−3.112 (4.556)***	−1.757 (3.405)***	−6.556 (7.987)***	−3.550 (3.220)***
Liquidity Variables										
LIQ_1	*Gt_AL03*$^{+}$	AL imbalance - '0 to 3 months' maturity		2.084 †† (5.135)***		1.461 †† (4.458)***			1.732 †† (3.624)***	
LIQ_2	*tAL3122*$^{+}$	AL imbalance - '3 to 12 months' maturity		4.257 † (3.225)***	4.081 †† (2.084)**		3.668 (2.677)**			
LIQ_2	*ΔtAL3122*$^{+}$	AL imbalance - '3 to 12 months' maturity	5.117 (4.073)***				5.311 (3.735)***			
LIQ_4	*Gt_ALG3*$^{+}$	AL imbalance - 'greater than 3 years' maturity	1.840 †† (3.635)***		0.756 †† (1.843)*		1.853 †† (3.993)***			2.421 †† (6.702)***
LIQ_7	*Gt_LX_EV*$^{-}$	Liquidity index imbalance - immediate fire sale		−8.855 † (3.533)***	−7.634 † (3.186)***	−17.489 † (9.049)***	−8.563 † (3.351)***	1.949 †† (5.836)***		
Structure Variables										
STR_1.2	*Gt_P5PCV*$^{+}$	Connectivity imbalance – CoVaR at 5%			4.589 †† (6.714)***	3.078 †† (4.768)***				3.380 †† (4.074)***
STR_1.3	*ΔTD1PCV*$^{+}$	Connectivity imbalance – delta CoVaR at 1%	1.785 (2.156)**							
STR_1.4	*Gt_D5PCV*$^{+}$	Connectivity imbalance – delta CoVaR at 5%		1.084 (2.754)***					1.009 (3.100)***	
STR_2	*ΔHEQ5*$^{+}$	Concentration imbalance - capital markets (equity)	1.493 † (3.294)***	4.000 (6.555)***			1.880 (2.647)**			2.448 (2.572)**
STR_4	*HFX4*$^{+}$	Concentration imbalance - currency Markets (FX)			0.750 †† (1.837)*					
STR_4	*ΔHFX4*$^{+}$	Concentration imbalance - currency markets (FX)	1.302 † (7.037)***			0.905 †† (5.486)***	1.222 † (5.077)***			
STR_4.1	*Gt_HIXP*$^{+}$	Concentration imbalance – cross-country exposure	3.160 (3.135)***			1.834 † (2.124)**			3.421 (3.223)***	1.647 (1.912)*
STR_5	*Gt_HIB*$^{+}$	Concentration imbalance - currency markets (interbank)	1.995 (4.628)***	2.748 (4.530)***	1.473 (2.755)***			3.616 (7.779)***	3.602 (5.443)***	1.824 (2.454)**
STR_8	*ΔtHIRD5*$^{+}$	Concentration imbalance - risk transfer markets (IR derivatives)		0.728 (1.652)					1.782 (3.040)***	
STR_9	*Gt_LEVN*$^{+}$	Contagion (normal leverage)			7.405 † (3.605)***	5.991 † (2.884)***	7.877 † (2.957)***			
Constant			28.221	24.677	35.416	29.035	34.305	32.788	30.626	41.926
Observations			62	62	62	62	62	62	62	62
R-squared			0.799	0.813	0.829	0.861	0.808	0.740	0.798	0.814
AIC (OLS)			5.973	5.933	5.854	5.639	5.938	6.219	5.976	5.916
SC (OLS)			6.419	6.482	6.437	6.188	6.418	6.631	6.422	6.431

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

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Table 8
Out-of-sample statistics for SAFE EWS short-lag models.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Combination
RMSE	13.86	20.74	13.07	16.13	15.83	21.47	11.49	16.67	17.14
MAPE	18.68	26.36	16.87	21.96	19.17	27.37	18.82	21.09	23.06
Theil *U*	0.150	0.231	0.138	0.178	0.173	0.246	0.117	0.185	0.185

Note: The out-of-sample forecast metrics for the short-lag and long-lag models are not directly comparable.

Table 9
Out-of-sample statistics for SAFE EWS long-lag models.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Combination
RMSE	27.99	30.36	23.04	24.68	28.47	27.21	29.28	30.20	28.00
MAPE	29.89	33.57	25.20	24.88	29.94	29.35	31.91	33.08	30.34
Theil *U*	0.231	0.256	0.178	0.197	0.235	0.223	0.244	0.254	0.230

Note: The out-of-sample forecast metrics for the short-lag and long-lag models are not directly comparable.

Table 10
Distribution of supervisory data among imbalance classes.

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

† – Confidential supervisory data (category 1).
†† – Constructed supervisory data (category 2).

Table 11
Proportion of supervisory variables among imbalance classes.

Imbalance class	Supervisory series	Proportion FRS (%)
Total	33	50
Return imbalances	1	10
Liquidity imbalances	3	43
Risk imbalances	28	82
Structure imbalances	1	7

more than in the comparatively quiet years leading up to the crisis (see Fig. 6B).

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 increasing value of interbank concentration imbalance and the shrinking value of a credit risk imbalance were this model's leading contributors to the rising stress level in the forecast period. This forecast indicates that previous values of interbank concentration imbalance were increasing, a sign that the model's top institutions were becoming more highly concentrated in the interbank market. Moreover, a decreasing value of the credit risk imbalance indicates an increase in future financial stress because this value measures larger firms' through-the-cycle credit capital, whereby a decrease in this value indicates a strain on firms' ability to withstand losses.

Other models predicted that stress would be present at different horizons and to different extents based on model specifications. The quarters leading to the out-of-sample period which coincides with the beginning of the subprime crisis saw an increase and decrease in several variables that provided an early warning for financial stress. Specifically, stress was driven by a slightly different set of imbalances such as AL imbalance (greater than 3 years maturity), interest rate risk (IRR) imbalance, as well as concentrations in foreign exchange and cross-country exposure among others. Imbalances which contributed negatively included the interbank exposure, capital market concentration, and bank capital-at-risk. The following bar chart shows selected significant contributions in the forecast.

It is possible that all variables could either add to stress or decrease stress at any point in time. For example, movement in the return imbalance for currency markets – interbank exposures decreases stress in the second and third quarters of 2007 while several variables, particularly structural imbalances, add significantly to stress.

4.2.2. 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).

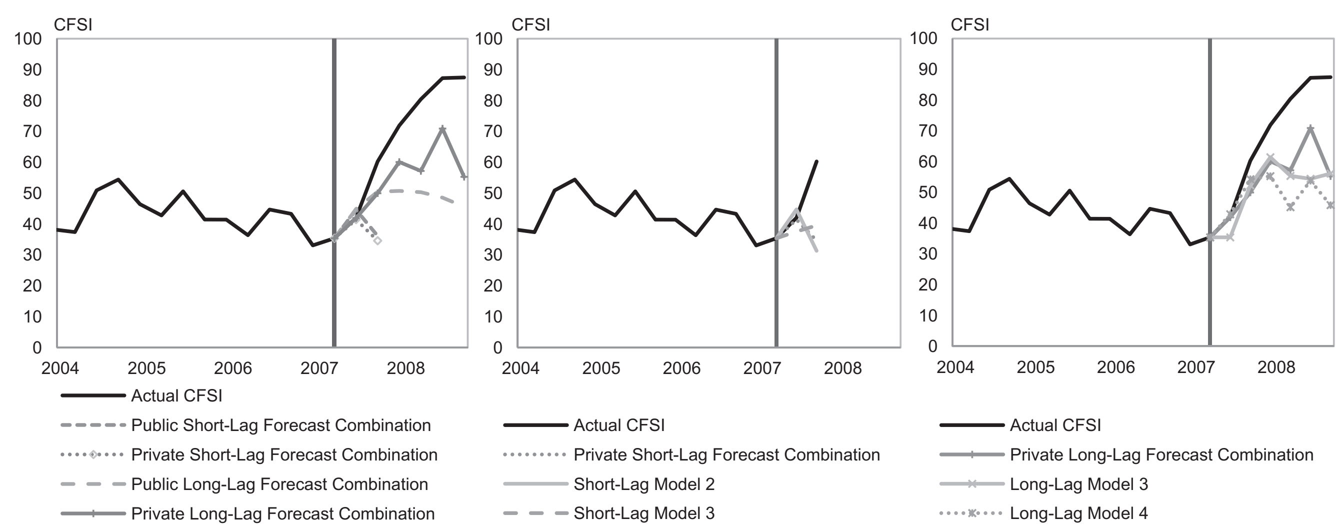
As in the shorter-horizon forecasts, we can analyze which variables were important in signaling financial stress. Several long-lag forecasts predicted a notable increase in stress through Q3:2008 (see Fig. 6C).

As with the short-lag forecasts, we employ the forecast combination and are able to identify the variables that significantly influence stress during the longer out-of-sample period.

Table 12
Comparative statistics of supervisory and public specifications.

	Benchmark	Base	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	Combo
Panel A: Short-lag comparison											
PUBLIC in-sample											
Obs.	58	61	61	61	61	61	61	61	62	61	61
R-squared	0.51	0.57	0.63	0.70	0.59	0.54	0.66	0.66	0.63	0.53	0.80
AIC	6.74	6.66	6.52	6.39	6.66	6.78	6.47	6.47	6.51	6.77	5.91
SIC	6.85	6.87	6.67	6.81	6.97	7.09	6.81	6.79	6.78	7.01	6.18
PUBLIC out-of-sample (dynamic forecast)											
RMSE	13.56	15.13	13.86	20.74	13.07	16.13	15.83	21.47	11.49	16.67	17.14
MAPE	18.99	17.83	18.68	26.36	16.87	21.96	19.17	27.37	18.82	21.09	23.06
Theil *U*	0.147	0.164	0.150	0.231	0.138	0.178	0.173	0.246	0.117	0.185	0.185
PRIVATE in-sample											
Obs.		61	61	61	61	61	61	61	62	61	61
R-squared		0.67	0.73	0.82	0.82	0.80	0.78	0.78	0.77	0.78	0.90
AIC		6.41	6.22	5.90	5.92	5.97	6.08	6.08	6.08	6.06	5.24
SIC		6.65	6.54	6.49	6.44	6.42	6.56	6.57	6.49	6.44	5.52
PRIVATE out-of-sample (dynamic forecast)											
RMSE		9.85	17.09	20.53	14.98	19.08	19.39	18.84	13.82	15.23	18.14
MAPE		13.08	25.81	27.20	22.49	28.08	25.15	24.63	17.42	20.80	21.98
Theil *U*		0.102	0.193	0.227	0.166	0.219	0.219	0.212	0.149	0.167	0.201
Panel B: long-lag comparison											
PUBLIC in-sample											
Obs.		62	62	62	62	62	62	62	62	62	62
R-squared		0.34	0.59	0.70	0.71	0.54	0.65	0.67	0.57	0.72	0.80
AIC		7.06	6.66	6.39	6.34	6.78	6.51	6.43	6.69	6.28	5.92
SIC		7.23	7.00	6.83	6.82	7.19	6.89	6.77	7.00	6.66	6.20
PUBLIC out-of-sample (dynamic forecast)											
RMSE		32.04	27.99	30.36	23.04	24.68	28.47	27.21	29.28	30.20	28.00
MAPE		36.35	29.89	33.57	25.20	24.88	29.94	29.35	31.91	33.08	30.34
Theil *U*		0.274	0.231	0.256	0.178	0.197	0.235	0.223	0.244	0.254	0.230
PRIVATE in-sample											
Obs.		62	62	62	62	62	62	62	62	62	62
R-squared		0.54	0.80	0.81	0.83	0.86	0.81	0.74	0.80	0.81	0.92
AIC		6.75	5.97	5.93	5.85	5.64	5.94	6.22	5.98	5.92	5.01
SIC		7.02	6.42	6.48	6.44	6.19	6.42	6.63	6.42	6.43	5.29
PRIVATE out-of-sample (dynamic forecast)											
RMSE		33.62	23.55	31.50	24.85	27.08	29.43	26.86	24.53	30.64	18.64
MAPE		38.24	26.11	34.84	27.37	27.46	32.44	29.44	27.27	32.27	19.68
Theil *U*		0.292	0.189	0.268	0.194	0.220	0.244	0.218	0.198	0.261	0.143

Note: The out-of-sample statistics for the short-lag forecast combination and long-lag forecast combination are not comparable due to differing forecast horizons.



A. Public vs. private out-of-sample forecasts combinations (Q2:2007).

B. Short-lag out-of-sample forecast (Q2:2007).

C. Long-lag out-of-sample sample forecast (Q2:2007).

Fig. 6. Public vs. private out-of-sample forecasts (Q2:2007). *Note:* Vertical bar marks the beginning of forecast.

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Table 13
Sample migration matrix (leverage).

	Leverage change (std)			
	Grade 1	Grade 2	Grade 3	Grade 4
Grade 1	–	$X_{1,2} = 3.5$	$X_{1,3} = 7.2$	$X_{1,4} = 10.4$
Grade 2	$X_{2,1} = (3.5)$	–	$X_{2,3} = 3.7$	$X_{2,4} = 6.9$
Grade 3	$X_{3,1} = (7.2)$	$X_{3,2} = (3.7)$	–	$X_{3,4} = 3.2$
Grade 4	$X_{4,1} = (10.4)$	$X_{4,2} = (6.9)$	$X_{4,3} = (3.2)$	–

Note: $X_{i,j}$ denotes the change in imbalance, measured in standard deviations, that is associated with transition of stress from grade *i* to grade *j*.

Fig. 6 shows that over the longer out-of-sample horizon, financial stress was predicted to increase rather rapidly and significantly throughout 2007 and 2008. Fig. 8 reveals that the most significant drivers of this stress were imbalances in the liquidity index, return imbalances in interbank and securitization markets, and structural concentration imbalance in foreign exchange. Additionally, several imbalances, such as leverage, anticipated stress of different degrees and directions at differing horizons. Whereas in the early forecast, the leverage imbalance contributed to decreasing stress, the contribution turned positive toward the middle and end of the horizon.

4.3. 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. Tactically, macroprudential applications are founded on information about the level, structure, and institutional drivers of systemic financial stress and aim to manage the financial system risk and imbalances in two dimensions: across time and institutions. Time related EWS policy applications are analyzed in pursuit of prevention and mitigation. EWS applications across institutions are considered via common exposures and interconnectedness.

Four potential SAFE applications are considered: three in the time dimension, and one in the institutional dimension. Potential time applications include: (1) action targets of forecast thresholds, (2) stress alerts, and (3) migration matrix for individual components. Potential institutional applications include: (4) stress contributions – targets and limits. Care must be taken in the calibration of macroprudential applications, given their reliance on the quality of the underlying systemic risk-modeling framework. New regulatory policies and institutional responses to them may involve a regime change in the historical pattern of interaction of institutional imbalances and the financial system stress. Therefore, a further pre-requisite for the calibration of policy tools is a better understanding of the distinct interaction regimes and the feedback mechanisms between the new regulatory policies and institutional responses.

A key question for supervisory applications is whether policymakers should respond to a potential systemic stress episode given the multiple feasible forecasts by the different stories within the SAFE EWS models. It is precisely for this purpose—to guide the interpretation of the multiple forecasts—that we create the set of forecast combinations. The forecast combination employ a regression approach[20] to resolve the question of weighting the relative importance of each model. Applying these weights, the combination forecast clarifies which variables are more/less significant in the out-of-sample forecast combination.

[20] The forecast combination gives weights to the individual forecasts that sum to unity, where the contributions are calculated as the product of the forecast weight, coefficient, and the respective *X* variable, see Eqs. (3) and (4).

4.3.1. Action targets of forecast thresholds

SAFE EWS assists policymakers' decision process by allowing them to target a particular action threshold above the previous mean of the financial stress series. Probit-based empirical analysis of the financial system stress (Oet et al., 2011, pp. 58–60; Bianco et al., 2012, pp. 2–3) establishes a set of thresholds to guide supervisors in targeting the optimal level of stress at which policymakers should become involved. When forecasts of stress fall short of the target action level, the historical evidence supports the case that markets can self-resolve. 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. This analysis supports a target threshold of 0.59 standard deviations, when financial stress has historically migrated into the moderate range (grade 3) and is associated with a significant probability (26.3%) of a systemic stress episode.

4.3.2. Stress alerts

Observations of financial stress time series in the SAFE EWS enable operationalizing of stress alerts (Oet et al., 2011): systemic stress is two consecutive periods of distress above previous period thresholds, or concurrent distress in at least two distinct markets. These operational alerts enable observations of significant stress both within a particular market and in the system. Signals are provided when stress begins to propagate through several markets and offer a significant time advantage in the interpretation of financial system stress.

A comparison of the housing bubble peak in 2006 with the financial system stress accumulation in the 3rd quarter of 2007 serves as a "crucial experiment" (Stinchcombe, 1968). The evidence from the national housing prices is lagged[21] and would not alert a critical supervisor focused on the housing prices until the spring and July of 2007 for quarterly and monthly data, respectively. At the same time, contemporaneous observations of the financial stress action target would trigger moderate stress alarms (grade 3) only in mid-August 2007, an important loss of several months of information.

However, the above operational stress alerts deliver a significant informational advantage. Monitoring stress alerts in individual markets triggers systemic stress alarms almost 1 year earlier, when in June 2006 both funding sector stress and FX sector signal stress alerts of an emerging systemic episode.[22]

4.3.3. Migration matrix for individual components

The SAFE EWS, based on the interaction of institutional imbalances and financial stress, provides the corresponding migration matrices as potential monitoring instruments. A typical monitoring migration matrix describes the change of a particular aggregate imbalance that is associated with transition of stress from one grade to another, *ceteris paribus*. A sample migration matrix for leverage is shown in Table 13. This particular sample also suggests that single factor migrations may have very limited practical

[21] Monthly housing prices are provided by S&P/Case-Shiller Home Price Index: Composite 20 (seasonally adjusted). *Source:* Haver Analytics. Quarterly housing prices are provided by S&P/Case-Shiller Home Price Index: US National (seasonally adjusted). *Source:* Haver Analytics. The data is reported with a three months lag for monthly data and two quarters lag for quarterly data.

[22] After Q2: 1998, stress is signaled when observed stress exceeds the previous quarter's benchmark by ¼ std (Oet et al., 2011). Raw data from funding and FX markets for the CFSI is available daily and accompanied by estimated sector weights. The market stress observations are adjusted with one quarter lag, when re-estimated sector weights become available. Therefore, observant supervisors should recognize a systemic stress episode sometime between June and September 2006. Historical record suggests that it was precisely in the fall of 2006 that many astute market participants were turned away from investments tied to mortgages (Bernstein and Eisinger, 2010; Lewis, 2010).

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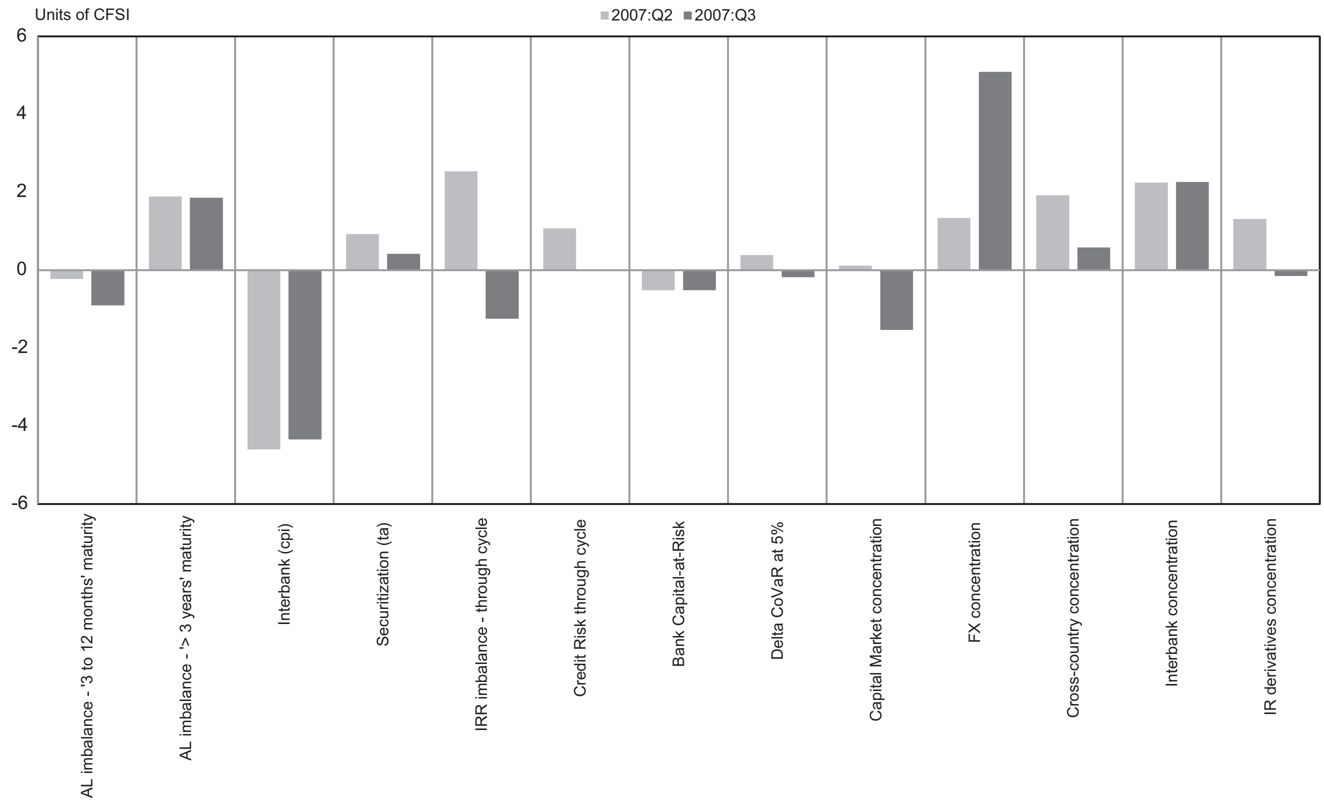

Fig. 7. Selected contributions to short-lag out-of-sample forecast.

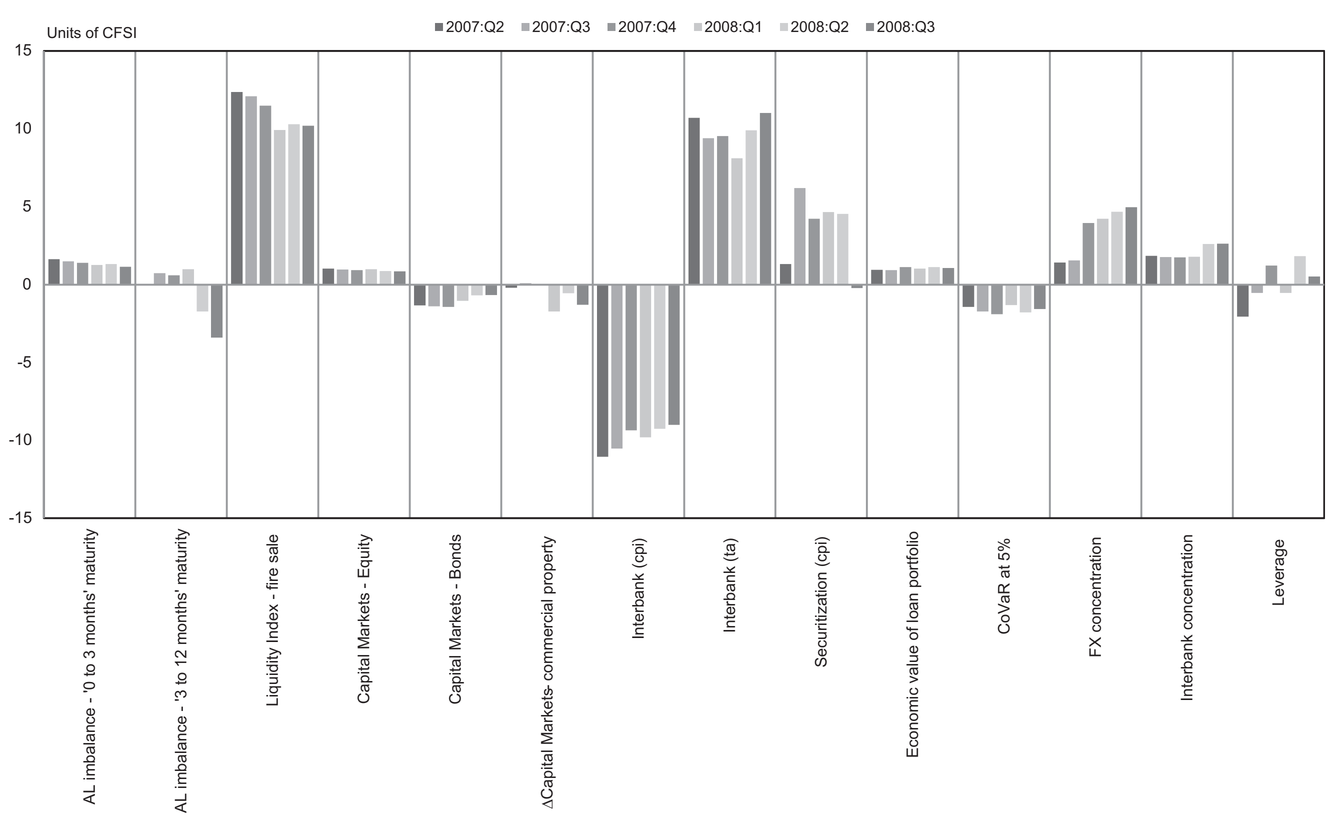

Fig. 8. Selected contributions to long-lag out-of-sample forecast.

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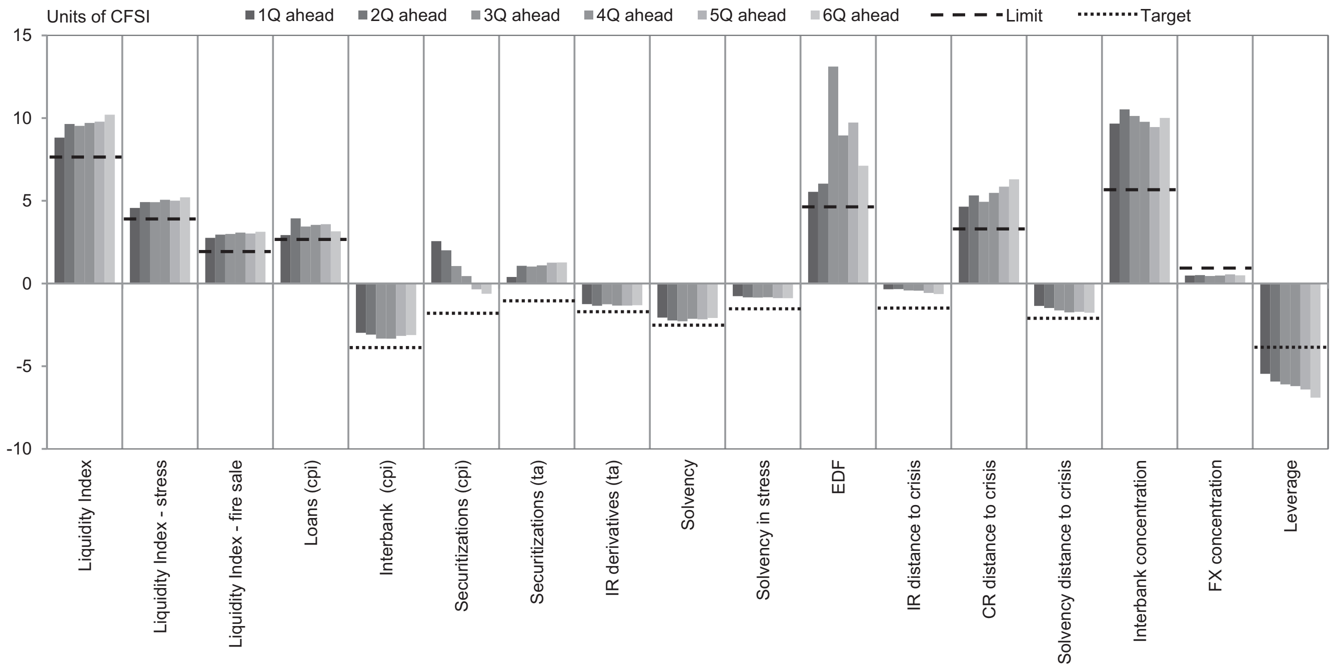

Fig. 9. Potential targets and limits through monitoring of imbalance percentage contribution to stress. *Note:* The figure describes sample long-lag contributions of a subset of the top twenty five bank holding companies as of 1Q 2012.

importance due to the large migrations required to compel a change in the stress grade. A more productive supervisory application should instead involve related sets of multi-factor migrations. For example, a relatively small-migration across the multi-factor set of structural imbalance variables would be intuitively impactful on financial stress, as would the migrations of highly correlated imbalances (see Table 3). The monitoring migration matrices may be integrated into (1) the assessment of overall level of stress, where transition of stress components may be observed; (2) the analysis of the contributions of individual stress components and institutional imbalances to overall stress; and (3) the design of policy actions (whether any action is warranted, in what area of exposure, and how to act).

4.3.4. Stress contributions – targets and limits

The out-of-sample contributions from imbalances to financial stress (see Figs. 7 and 8) allow supervisors to distinguish among those imbalances that tend to increase financial stress (above the horizontal axis) from those that decrease it (below the axis). Because of the dynamics of the interaction of these imbalances with financial stress, the sensitivity of the contribution of individual imbalances does not remain static, but varies in time as the series changes. Therefore, a supervisory use of stress contributions as a policy instrument needs be considered flexibly—beyond some static countercyclical schema. Specifically, such instruments should recognize the varying weight of the imbalance's contribution to overall predicted financial stress. Fig. 9 shows a Q1: 2012 example of possible supervisory target and limit policies as the actions of the financial agents result in varying sensitivities of the long-lag imbalances to financial stress. As this example illustrates, recent evidence emphasizes those imbalances[23] with particularly high stress interaction sensitivities. Some of them significantly contribute to financial stress and some serve to lessen it. SAFE EWS thus enables policymakers to consider time-varying instruments like limits or limit ranges linked to the aggregate imbalances.[24] For example, based on recent analysis, the potential EWS time-varying limits can include the liquidity index, aggregate expected default frequency, and interbank concentration.

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 important 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. Compared with the preceding EWSs, the SAFE EWS adds a number of innovative features. It benefits from a very rich dataset of institution-specific 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,

[23] These are, of course, predominantly the imbalances with consistent Granger properties to financial stress.

[24] The time-varying limit instruments are also relevant in the cross-sectional dimension, as policymakers further attribute imbalances to specific institutions and form detailed microprudential limits.

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Table B.1
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 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 imbalance – 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 imbalance – point-in-time/stress function	Interest Rate Risk Capital – stress function	℗ Calculated	RSK_4	6/30/1997
IRR imbalance – extreme stress/crisis function	Change in economic value of equity	℗ FRS – IRR FOCUS	RSK_6	6/30/1997†Δ
Credit Risk imbalance – through the cycle function	Book Value: 12 call report loan portfolios – reported ALLL (allowance for loan and lease losses)	FRS – FDR	RSK_7.1	12/31/1976
	Credit Capital – through the cycle function	℗ Calculated		9/31/1991*
Credit Risk imbalance – extreme stress/crisis function	Economic Value: 12 call report loan portfolios – 99.5% 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 imbalance – '0 to 3 months' maturity band	AL imbalance | 0 to 3 months maturity	℗ Calculated ℗ IRR FOCUS specification	LIQ_1	6/30/1997†Δ
AL imbalance – '3 to 12 months' maturity band	AL imbalance | 3 to 12 Months	℗ Calculated ℗ IRR FOCUS specification	LIQ_2	6/30/1997†Δ
AL imbalance – 'greater than 3 years' maturity band	AL imbalance | > than 3 years maturity	℗ Calculated	LIQ_4	6/30/1997†Δ
Liquidity Index – immediate fire sale	Liquidity Index – immediate fire sale	℗ Internal Model	LIQ_7	9/31/1991*
Structure				
Connectivity imbalance – CoVaR	Connectivity imbalance – CoVaR	℗ CoVaR Model (FRS)	STR_1.2 STR_1.3 STR_1.4	9/31/1991*
Concentration imbalance – Capital Markets (Equity)	Concentration imbalance – Capital Markets (Equity)	℗ Calculated FRS – Flow of Funds	STR_2	9/31/1991*
Concentration imbalance – Currency Markets (FX)	Concentration imbalance – Currency Markets (FX)	℗ Calculated FRS – Flow of Funds	STR_4 STR_4.1	9/31/1991*
Concentration imbalance – Currency Markets (Interbank)	Concentration imbalance – Currency Markets (Interbank)	℗ Calculated FRS – Flow of Funds	STR_5	9/31/1991*
Concentration imbalance – Risk Transfer Markets (Interest Rate Derivatives)	Concentration imbalance – Risk Transfer Markets (Interest Rate Derivatives)	℗ Calculated FRS – Flow of Funds	STR_8	9/31/1991*
Leverage imbalance – normal	Leverage imbalance – 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 B.2
Return variables: definitions, expectations, and Granger causality.

Variable	Series	Exposure	Granger lag	Theoretical expectation
RET_1.1cpi	*ΔPMKTCP5*$^+$	Capital Markets – Bonds (total-assets based)	††: 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	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)	–	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	*LNSCAT5*$^-$ *ΔLNSCAT5*$^-$	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_5.2ta	*IXDRTAGt*$^-$	Interbank Derivative Exposure	–	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 derivatives 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)	†: 3, 4, 5, 6, 8, 11††: 9, 10, 12	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[a]
RET_6ta	*ITBKTAGt*$^+$	Currency Markets – Interbank Exposures (TA-based)	†: 4, 5, 6, 8††: 9, 10, 11, 12	
RET_7cpi	*SECEG_t*$^{\#0}$	Risk Transfer Markets – Securitizations (price-based)	–	This series describes return expectations associated with securitization exposures of financial institutions. The association between increasing securitizations and systemic financial stress is ambiguous. On one hand, in well-functioning financial markets, securitizations transfer risk away from the financial institutions, and, thus an increase in overall level of this exposure should be associated with decrease in systemic financial stress. On the other hand, an increase in securitizations may be indicative of increasing contingent exposures in securitization pipelines, a likely demand-driven decrease in risk management of origination of the underlying assets, and possibly growing information asymmetry between the originators and the consumers of securitizations—all of which should serve to increase the probability of systemic financial stress
RET_7ta	*SECETAGt*$^{\#0}$	Risk Transfer Markets – Securitizations (total assets-based)	–	
RET_9ta	*IRDETAGt*$^-$	Risk Transfer Markets – Interest Rate Derivatives	–	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

Note: Theoretical expectations are noted by +/−/≠0. †† indicates Granger causality with 90% or better confidence. † indicates Granger causality with 80% or better confidence.
[a] See Blåvarg and Nimander (2002), Rajan (1996), Furfine (2003), and Degryse and Nguyen (2004).

Table B.3
Liquidity variables: definitions, expectations, and Granger causality.

Variable	Series	Exposure	Granger lag	Theoretical expectation
LIQ_1	*Gt_AL03*$^+$	AL imbalance – '0 to 3 months' maturity	††: 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	Asset Liability mismatch describes a simple gap difference between assets and liabilities of a specific maturity. A larger mismatch indicates a larger imbalance in re-pricing and maturity and reflects a larger interest rate risk exposure
LIQ_2	*tAL*3122$^+$	AL imbalance – '3 to 12 months' maturity	†: 7, 8††: 6	
LIQ_4	*Gt_ALG3*$^+$	AL imbalance – 'greater than 3 years' maturity	†: 11††: 2, 3, 4, 5, 6, 7, 8, 9, 10, 12	
LIQ_7	*Gt_LX_EV*$^-$	Liquidity Index – immediate fire sale	†: 8	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

Note: Theoretical expectations are noted by +/−/≠0. †† indicates Granger causality with 90% or better confidence. † indicates Granger causality with 80% or better confidence.

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. 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 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.

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Table B.4
Risk variables: definitions, expectations, and Granger causality.

Variable	Series	Exposure	Granger lag	Theoretical expectation
RSK_2	*ΔEQLGDW3*$^{-}$	IRR imbalance – through-the-cycle function	†: 12††: 7, 8, 9, 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_7.1	*ΔCRCAP_NV*$^{-}$	Credit Risk imbalance – through the cycle function	†: 5††: 2, 3	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_8a	*EDF*$^{+}$	Credit Risk imbalance – point-in-time/stress function	–	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_81	*LNS_MVEDF*$^{-}$	Market Value: 12 call report loan portfolios (w. EDF uncertainty)	††: 2, 3	This series measures a stress level of market value of the total loan portfolio which is a function of available liquidity, institutional probability of reserves and the intrinsic value of the credit portfolio. Thus, a rise in market value should be negatively related to the probability of systemic financial stress
RSK_82	*LNS_MVSEE*$^{-}$	Market Value: 12 call report loan portfolios (w. SEER uncertainty)	–	
RSK_9	*LNS_EV*$^{-}$	Economic Value: 12 call report loan portfolios – 99.5% BankCaR	–	For an individual institution, this indicator measures residual economic value of the loan portfolio evaluated at extreme stress (proxied by 99.5% BankCaR). Rise in the series indicates greater residual capacity to withstand extreme stress and lesser potential for systemic stress
RSK_9a	*BCAR*$^{+}$	Bank Capital-At-Risk	††: 7, 8, 9, 10, 11, 12	
RSK_E	*IR_SVEV*$^{-}$	Interest Rate Risk – stress distance-to-systemic stress	†: 12††: 10, 11	This series describes aggregate economic value of securities evaluated under jump from stress to 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 (rolling) mean of this series should be negatively related to the systemic financial stress
RSK_I	*ΔTCEVNV5*$^{-}$	Credit Risk – normal distance-to-systemic stress	–	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_N	*SLV_SVNV*$^{-}$	Solvency – normal distance-to-stress	–	Solvency at each point in time is measured as the difference between available financial resources and required internal capital. Hence, a rise in a long-term real-time (rolling) mean of solvency – normal distance-to-stress should be negatively related to the systemic financial stress

Note: Theoretical expectations are noted by +/−/≠0. †† indicates Granger causality with 95% or better confidence. † indicates Granger causality with 80% or better confidence.

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, while 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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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: bonds; international and interbank exposure in the currency markets; securitizations, credit derivatives, and interest-rate derivatives in the risk-transfer markets.

Table B.5
Structure variables: definitions, expectations, and Granger causality.

Variable	Series	Exposure	Granger lag	Theoretical expectation
STR_1.2	*Gt_P5PCV*$^{+}$	Connectivity imbalance – CoVaR at 5%	†: 9, 10 ††: 2, 3, 4, 5, 6, 7, 8, 11, 12	For an individual institution, the conditional value at risk indicates the relative contribution of the institution to the aggregate 5% quantile Value at Risk. A rise in the aggregated series corresponds to greater contribution to systemic risk
STR_1.3	*Gt_D5PCV*$^{+}$	Connectivity imbalance – Delta CoVaR at 1%	†: 1, 8, 9	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 imbalance – Delta CoVaR at 5%	††: 2, 3	
STR_2	*ΔHEQ5*$^{+}$	Concentration imbalance – Capital Markets (Equity)	†: 10	This series measures the concentration time series of market capitalization of top 25 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	*ΔHFX4*$^{+}$	Concentration imbalance – Currency Markets (FX)	††: 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	This series measures the concentration time series of FX exposures of top 25 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 imbalance – Currency Markets (FX)	†: 12	
STR_5	*Gt_HIB*$^{+}$	Concentration imbalance – Currency Markets (Interbank)	–	This series measures concentration in currency interbank markets. A 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	*ΔtHIRD5*$^{+}$	Concentration imbalance – 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)	†: 8, 10, 11, 12	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: Theoretical expectations are noted by +/−/≠0. †† indicates Granger causality with 95% or better confidence. † indicates Granger causality with 80% or better confidence.

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.

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 liquidity index measure based on the valuations of all assets and liabilities relative to immediate fire 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.[25] *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."[26] CoVaR, as a connectivity indicator, is estimated using quantile regressions. *Concentration data* describes structural fragility due to 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

[25] There is a conceptual parallel between Thomson's (2009) "4C's" (correlation, concentration, contagion, and conditions) and SAFE architecture when correlation, concentration, and contagion are considered as forms of structural variables and conditions as a form of expectations variables.

[26] Adrian and Brunnermeier (2008), abstract.

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 transmission channels, for example, direct transmission via interbank credit and liquidity markets and indirect transmission resulting from the general deterioration of financial-market conditions. Thus, it may be useful to think of financial contagion epidemiologically. From the same perspective, a good proxy for contagion may describe an institutional susceptibility to a variety of shocks. We consider leverage to be an informative measure of this susceptibility and, thus, a useful proxy for contagion.

Appendix B. Data sources and variable expectations

See Tables B.1–B.5.

Appendix C. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jbankfin.2013.02.016.

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