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Abstract

This paper introduces a new methodology to date systemic financial stress events in a transparent, objective and reproducible way. The financial cycle is captured by a monthly country-specific financial stress index. Based on a Markov-switching model, high financial stress regimes are identified, and a simple algorithm is used to select those episodes of financial stress that are associated with a substantial negative impact on the real economy. By applying this framework to 27 European Union countries, the paper is a first attempt to provide a chronology of systemic financial stress episodes in addition to the expert-detected events that are currently available.

JEL classification: C54, G01, G15
Bank classification: Central bank research; Econometric and statistical methods; Business fluctuations and cycles; Economic models; Financial markets; Financial stability; Monetary and financial indicators; Financial system regulation and policies

Résumé

L'article qui suit présente une nouvelle méthode permettant de dater les événements porteurs de tensions financières systémiques de façon transparente, objective et reproductible. Le cycle financier est représenté par un indice mensuel de tensions financières propre à chaque pays. À l'aide d'un modèle de Markov avec changement de régime, les événements caractérisés par de fortes tensions financières sont recensés, après quoi sont sélectionnés, au moyen d'un algorithme simple, les épisodes de tensions associés à un effet négatif important sur l'économie réelle. Par l'application de ce cadre analytique à 27 pays de l'Union européenne, l'article constitue une première tentative d'établir une chronologie des épisodes de tensions financières systémiques, en complément des événements actuellement identifiés par les spécialistes.

Classification JEL : C54, G01, G15
Classification de la Banque : Recherches menées par les banques centrales; Méthodes économétriques et statistiques; Cycles et fluctuations économiques; Modèles économiques; Marchés financiers; Stabilité financière; Indicateurs monétaires et financiers; Réglementation et politiques relatives au système financier

Non-Technical Summary

It is widely agreed that the global financial crisis that started in 2007 was an episode of severe financial market stress, which spilled over to the real economy causing the Great Recession. However, it is much more difficult to identify and classify other periods of, possibly systemic, financial market stress. The expert-based approach to identifying episodes of systemic financial stress prevails so far, but an objective and reproducible method for the detection of periods of low and high financial stress is lacking. A comprehensive analysis of the succession of tranquil and stress periods is a prerequisite to determining the leading indicators of systemic financial stress and evaluating the effectiveness of prudential policies implemented over the course of the financial cycle.

This paper provides a new framework for a transparent and objective identification of systemic financial stress episodes, i.e., periods of high financial stress associated with a substantial and prolonged decline in real economic activity. By applying the framework to the countries of the European Union (EU), this is the first paper to build a consistent monthly chronology of EU systemic financial stress episodes beyond the expert-detected crises currently available. In fact, a continuous measure of financial stress is converted into a binary systemic stress dummy, commonly used in early-warning models.

The model-based framework consists of three steps. First, we build on the existing financial stress literature and construct a simple country-specific financial stress index for 27 EU countries starting as early as 1964 for core EU countries. The essential feature of the financial stress index is that it captures co-movements in key financial market segments. Second, we apply the Markov-switching model, commonly used in the business cycle dating literature, to endogenously determine low and high financial stress periods. Third, in order to characterize the systemic nature of financial stress episodes, we create a simple algorithm to select the episodes of financial stress that are associated with a significantly negative impact on the real economy.

We identify 68 systemic financial stress episodes that are defined as coincident periods of financial market and real economic stress, possibly reinforcing each other. Financial market stress is considered to be "systemic" if there are six consecutive months of real economic stress within at least one year of financial market stress. Real economic stress corresponds to a simultaneous decline of both industrial production as well as GDP.

Our model-implied systemic financial stress dates encompass about half of all recessionary events and are shown to be consistent with many expert-detected crises. 82% of the systemic financial stress dates we identify are also included in crises datasets compiled by experts. We capture, respectively, 100%, 92%, 90% and 89% of the banking crises identified by Laeven and Valencia (2013), Babecky et al. (2012), Detken et al. (2014) and Reinhart and Rogoff (2011). In addition, our systemic financial stress dates tend to be robust to event-reclassification once new data become available.

1 Introduction

The classification of the global financial crisis as a period of "systemic" financial stress, during which severe financial market stress spilled over to the real economy causing the Great Recession, appears straightforward. More generally, it seems rather challenging to identify and classify other periods of, possibly systemic, financial stress (Liang, 2013). The expert-based approach of identifying systemic financial stress episodes prevails so far, but a reproducible method for the detection of periods of low and high financial stress is lacking. As well, a comprehensive analysis of the succession of tranquil and stress periods is a requirement to determine the best leading indicators of systemic financial stress and to evaluate the effectiveness of policies implemented over the course of the financial cycle.[1]

This paper is the first to apply the dating method commonly used for recessions to systemic financial crises, with the view of providing a transparent, objective and reproducible method for the identification of systemic financial stress events. We bridge the gap between the literature on measuring financial stress and that on dating the business cycle. The real economic stress dimension is absent from most of the literature on financial stress indices, although the regulator should pay much more attention to those events that impact the real economy. In this paper, systemic financial stress episodes are defined as those events that qualify both as periods of financial market stress and periods of real economic stress. Financial stress is defined as simultaneous financial market turmoil across a wide range of assets, reflected by (i) the uncertainty in market prices, (ii) sharp corrections in market prices, and (iii) the degree of commonality across asset classes. Real economic stress is characterized by a substantial and prolonged negative impact on the real economy, namely, GDP recessions with a drop in the industrial production index of at least six consecutive months. So the focus of this paper is on real economic stress periods that are not ordinary recessions but are also associated with high financial market stress.[2] No assumptions are made about the sequence of events, i.e., whether the financial market stress or real economic stress occurred first. Instead, the focus is on the detection of periods in which financial market and real economic stress mutually reinforce each other.

To the best of our knowledge, this paper is the first that aims at providing a chronology of systemic financial stress episodes for a large cross-section of countries based on a simple and reproducible method and thereby complements the existing expert-based crises databases. Several papers have already explored the connection between financial stress

[1] While there is no consensus on the definition of the financial cycle, Borio (2014) characterizes it as "self-reinforcing interactions between perceptions of value and risk, attitudes towards risk and financing constraints, which translate into booms followed by busts".

[2] We use the terms financial market stress and financial stress interchangeably to refer to a turmoil occurring simultaneously in several financial market segments.

and financial crises for specific countries by looking at the response of economic activity to changes in financial stress (e.g. Hakkio and Keeton, 2009; Hollo et al., 2012) or by creating indices of financial stress that are best able to replicate or predict a given sequence of expert-identified crises events (e.g. Illing and Liu, 2006; Oet et al., 2011; Jing et al., 2015). However, their focus is on creating an index of financial stress, not on dating episodes of possible systemic financial stress. This paper takes the opposite approach by comparing endogenously determined stress events with expert-based crises events given a simple measure of financial stress. Note that model-based systemic financial stress periods are not supposed to coincide perfectly with expert-based crises since they represent two different concepts.[3] Model-based stress episodes are identified on the basis of market prices of traded instruments and are thus broader than expert-detected episodes, usually focusing on financial institutions, that rely on qualitative information and on past policy actions.

Laeven and Valencia (2013) provide the most widely used database on systemic banking crises where a banking crisis is defined as being systemic under two conditions: (i) the presence of *significant* signs of banking distress and (ii) the presence of *significant* banking policy intervention measures.[4] However, the qualitative assessment of such events, as well as the time lag until the next update becomes available, call for a new model-based approach.[5] Both approaches have specific advantages and disadvantages. Model-based methods aim at providing timely, transparent and reproducible dating of systemic financial stress episodes in order to perform real-time[6] assessments for financial stability purposes, but the events might have a broader definition than banking stress owing to the available data. Expert-based approaches provide a historical chronology tailored to each country but might be biased by the perceptions of experts. Two other datasets for European Union (EU) countries, Babecky et al. (2012) and Detken et al. (2014), have been compiled by relying on the judgment of national central banks. Note that, so far as the EU is concerned, Reinhart and Rogoff (2011) cover the crises of 16 EU countries, which are taken into consideration for robustness.

The model-based approach outlined in this paper consists of three main steps that are subsequently described in more detail: (i) constructing a simple financial stress index

[3] Schwartz (1987) finds that the word "crisis" is often used to describe ordinary situations. Most events since 1933 in the United States are identified as pseudo-financial crises, characterized by a decline in asset prices, depreciation of the currency, or financial distress of large entities. A real financial crisis is then narrowly defined as situations when institutions do not exist or when preventive measures have not been credibly undertaken.

[4] Laeven and Valencia (2013) build on previous work by Caprio et al. (2005) but focus on banking crises with a systemic impact by adding the second criterion noted above.

[5] Chaudron and de Haan (2014) find that there are large and statistically significant discrepancies in the identified crises between three expert-based datasets.

[6] Since financial stress relies on market data, while real economic stress is based on data obtained from statistical agencies, there is typically a time lag of a few months before a financial stress event qualifies as systemic.

(FSI), (ii) identifying periods of high financial market stress, and (iii) narrowing down the financial market stress episodes to those with "systemic" characteristics.

First, contrary to the business cycle dating literature, where GDP is the de facto benchmark measure of the business cycle, there is no commonly accepted metric for financial market stress. Thus, the first step is to construct an appropriate coincident measure of financial market stress that is comparable across countries and covers a long time span. Since systemic stress should not be limited to the summation of individual risks (Allen and Carletti, 2013), our computation choice emphasizes the role of correlations across risk segments. Many alternative methods have been proposed to compute FSIs (for a survey, see Kliesen et al., 2012). However, only a few of these indices are available for EU countries, and, owing to their specific nature, computation choices and time spans, their comparability is limited.[7]

Second, taking the country-specific FSIs as an input, a Markov-switching (MS) model – often applied in the detection of business cycle turning points – is used to distinguish between periods of low and high financial market stress.[8] Burns and Mitchell (1946) investigated the distribution of turning points of a large number of disaggregated time series. However, recent efforts mostly focused on the analysis of a single aggregate indicator of business cycle fluctuations. On the one hand, the Bry and Boschan (1971) algorithm identifies local minima and maxima in possibly non-stationary time series. On the other hand, a more structural approach follows the seminal work by Hamilton (1989) to distinguish between different states of the economy and infer the probability of being in a specific state. Chauvet and Piger (2008) show that the latter method improves upon the NBER methodology in the speed at which business cycle troughs are identified. The underlying assumption is that the data, usually GDP, are generated by a mixture of two distributions, one for the phases of expansions and the other for the phases of recessions. Thus, the transition between these two phases can be modelled as a hidden Markov chain.

Nevertheless, several challenges arise when dating turning points in the "financial cycle" and establishing a chronology of systemic financial stress episodes. First, financial market stress and systemic financial stress are still pervasive concepts for which a single coherent measure both in the time dimension, as well as in the cross-sectional dimension, is missing. Second, financial market stress periods are usually characterized by a larger co-movement of variables related to financial sector activity, which is more consistent with the "average-then-date" approach than the "date-then-average" method of Burns and Mitchell (1946). Third, if one is interested in the turning points themselves or the ability to forecast the buildup of financial market stress, then the identification of the evolution of financial market stress between peaks and troughs makes sense. However, if one wants

[7]For the euro area as a whole, see Blix Grimaldi (2010) or Hollo et al. (2012). Only very few FSIs are computed for individual EU countries.

[8]For a recent survey on automatizing the dating of business cycle turning points, see Hamilton (2010).

to identify episodes of low versus high financial market stress, the moment at which the data suggest that an episode is more likely to be a high stress period is the relevant information. Therefore, using an MS model is better suited for the purpose of dating the episodes of financial market stress.[9] Fourth, financial market stress variables tend to be mean-reverting, which is consistent with the assumption of the MS data-generating process, i.e. a mixture of two time-invariant distributions. This feature supports the detection of a threshold above which financial market stress may adversely impact the real economy.

Third, once the periods of high financial market stress have been identified, the events associated with a substantial and prolonged decline in real economic activity need to be isolated. Since financial market stress could be limited to financial markets without spillovers to the real economy, the stress episodes that are considered "systemic" have to be narrowed down.[10] To this end, a simple algorithm is implemented, which detects financial market stress episodes associated with a substantial and prolonged decline in both industrial production and GDP.

The model-based approach identifies 68 episodes of systemic financial stress in 27 EU countries. About 50% of all recessionary events are classified as systemic, while the other half are not characterized by simultaneous financial market stress. 84% of the model-detected systemic financial stress periods are also included in the crises datasets compiled by experts. Out of the banking crises identified by Laeven and Valencia (2013), Babecky et al. (2012), Detken et al. (2014) and Reinhart and Rogoff (2011), on average, 100%, 92%, 90% and 89%, respectively, are captured by the model-based approach. The identified systemic financial stress episodes have recurrent patterns. In most cases, financial market stress occurs first, followed by real economic stress. As documented by Reinhart and Rogoff (2009), real economic stress lasts on average six months longer and the GDP decline is three percentage points larger when it is associated with financial market stress. The broad country coverage allows us to construct an EU crisis simultaneity index (CSI), which shows that systemic financial stress usually occurs in the form of "clusters" with many countries entering a systemic stress event simultaneously. In this respect, our results reveal that the global financial crisis and the subsequent Great Recession can only be compared to the "first oil shock" of 1973, where many countries simultaneously entered the systemic stress event. Finally, the model-based systemic financial stress periods tend to be robust to event-reclassification once new data become available.

Several caveats have to be kept in mind. The number of systemic events identified depends on the required severity of real economic stress. For instance, one may want to

[9] For instance, Coe (2002) applies this tool to reassess the timing of the US systemic financial crisis of the 1930s by looking at simultaneous switches in the deposit-currency ratio and the corporate versus government bond spread.

[10] Using spectral analysis applied to EU countries, Schüler et al. (2015) show that the real and financial cycles coincide about two-thirds of the time.

limit systemic events to be associated only with the subset of the most severe recessions. Thus, the depth and length of the real economic stress associated with each systemic financial stress episode are also reported, so that the dataset can be easily adjusted for different purposes.

Second, we focus on the joint evolution of stress on three core segments of financial markets (equity, government debt, currency). However, additional market segments could be considered. Banking-related variables are not always available and are left as an extension, but could still be partly reflected by the commonality in financial market stress. Housing stress is usually not included in financial stress indices since the availability of data is very limited. Although housing stress is a very important feature of the recent crises events, this is left for future work.

Third, the proposed methodology does not take into account policy actions that could prevent financial stress from spilling over to the real economy if measures are taken at a sufficiently early stage. This caveat more broadly applies to all measures relying on market data. The identification of banking crises in Laeven and Valencia (2013) relies on government interventions as an identification mechanism. Using only market prices, the proposed methodology identifies all of these events as systemic financial stress periods. This suggests that policy actions did not remove all stress ex ante, and using market data is still meaningful.

The remainder of the paper is structured as follows. Section 2 describes the construction of the monthly FSIs for 27 EU countries over a time span of up to 50 years. Section 3 outlines our method for identifying episodes of systemic financial stress. Section 4 compares our chronology of systemic events to existing expert-based episodes both in the cross-sectional and in the time dimension. Section 5 provides robustness checks. Section 6 concludes.

2 Designing a Simple Financial Stress Index

For 27 out of the 28 EU countries, we construct a monthly coincident measure of financial stress covering up to 50 years from February 1964 to December 2014.[11] By doing so, we pay particular attention to ensure (i) cross-country comparability, and (ii) a sufficiently long time span to cover as many financial stress events as possible. Financial stress is defined as simultaneous financial market turmoil across a wide range of assets. It is reflected by (i) the uncertainty in market prices, (ii) sharp corrections in market prices, and (iii) the degree of commonality across asset classes. As in the literature on measuring systemic risks based on market prices, this last component ensures that broad financial

[11] At the time of writing, there are no Estonian sovereign debt securities that comply with the definition of long-term interest rates for convergence purposes. Since no suitable proxy indicator has been identified, we focus on 27 instead of 28 EU countries.

market stress corresponds to the realization of a risk that is harder to diversify away than non-synchronized stress occurring in specific market segments. We focus on three core segments of financial markets and, as a result, we provide a broad coincident measure of financial stress, instead of a measure of stress occurring in one specific segment. Unfortunately, the number of countries we aim to cover and the long time span impose some restrictions on the underlying data.

The construction of our FSI follows the approach of the composite indicator of systemic stress (CISS) proposed by Hollo et al. (2012) that relies on the correlation of stress across different market segments. Figure A.1 illustrates the different elements involved in the computation of our FSI.

2.1 Measuring financial market stress

Underlying data. The ideal financial stress index should capture stress on asset classes associated with the major types of crises, such as equity crashes, debt crises, currency crises, housing crises or banking crises. To this end, our benchmark FSI includes data covering three financial market segments: (i) equity markets: stock price index (STX); (ii) bond markets: 10-year government yields ($R10$); and (iii) foreign exchange markets: real effective exchange rate ($rEER$) computed as the geometric average of bilateral exchange rates weighted by bilateral trade volumes. Alternative series, such as the interbank rate or the three-month treasury bill rate, are typically available only for the most recent years and thus left for robustness checks. In particular, we lack data that capture developments in the real estate market despite its major contribution to the 2008 crisis. This could be a source of concern, since tools aimed at mitigating a possible overheating of the real estate market are key macroprudential instruments one would like to calibrate throughout the cycle. However, we focus on the co-movements of prices across markets that possibly indirectly capture sharp variations in real estate prices.

Most data are taken from the Statistical Data Warehouse (SDW) of the European Central Bank at a daily frequency[12] and are retropolated or extended using Global Financial Data (GFD) for longer time spans where available. The real effective exchange rate is taken directly from the Bank for International Settlements (BIS) at a monthly frequency.[13]

Sample homogeneity. We want to make sure that the data are broadly comparable throughout the entire sample from 1964 onwards, as they encompass periods such as the

[12] In order to fill possible data gaps at the daily frequency, we interpolate using the last available observation.

[13] The BIS provides either a broad real effective exchange rate or a narrow one. The former includes bilateral exposures to more countries, but is available only from 1994 onwards, while the latter is restricted to fewer countries but starts in 1964. Depending on the availability of the other data, the longer series are preferred.

Great Moderation.

First, in many countries, inflation rates declined substantially over time. To account for this, we use real stock prices ($rSTX$) and real government bond yields ($rR10$).[14]

$$\begin{cases} rSTX_t &= \dfrac{STX_t}{CPI_t} \\ rR10_t &= R10_t - \dfrac{CPI_t - CPI_{t-261}}{CPI_{t-261}} \cdot 100 \end{cases} \tag{1}$$

Second, as outlined in the business cycle dating literature, there could be potential complications due to structural breaks in output volatility. This issue was also raised in the financial stress literature, especially for the national financial condition index (NFCI) starting in 1973 computed by the Federal Reserve Bank of Chicago. Brave and Butters (2012) show that accounting for the decline in the volatility of output and inflation makes the stress index more stable in the post-1984 period. Owing to the parsimonious nature of our dataset, corrections as in Hatzius et al. (2010) using principal-component techniques are not feasible. Instead, before computing volatilities, we divide the data by a 10-year trailing standard deviation.[15] A tilde denotes this rolling standardization.

Equity market stress. Stress in the equity market is captured by two variables. First, the monthly realized volatility ($VSTX$) is computed as the monthly average of absolute daily log-returns of the real stock price index. Second, we compute the cumulative maximum loss ($CMAX$) that corresponds to the maximum loss compared to the highest level of the stock market over two years. Except for the first two years, the CMAX is computed over a rolling window of 522 days.

$$\begin{cases} lnSTX_t &= \log\left(rSTX_{t-i}\right) - \log\left(rSTX_{t-1-i}\right) \\ \widetilde{lnSTX}_t &= \dfrac{lnSTX_t}{\sigma_{lnSTX\, t,t-2609}} \\ VSTX_t &= \dfrac{\sum_{i=0}^{19} \left|\widetilde{lnSTX}_t\right|}{20} \\ CMAX_t &= 1 - \dfrac{rSTX_t}{\max_{i=0}^{521}\left(rSTX_{t-i}\right)} \end{cases} \tag{2}$$

Bond market stress. Stress in the bond market is also captured by two variables. First, the monthly realized volatility ($VR10$) is computed as the monthly average of

[14] In order to obtain real daily returns, the monthly consumer price index (CPI) is linearly interpolated using the last known value. As the bond yields are annualized, we subtract the annual inflation rate. Since we later use an ordinal standardization and get an index at the monthly frequency, the choice of the base or scale is irrelevant.

[15] As expected, this does not impact the crisis-detection ability of countries for which we have data only from the 1990s onwards. Hence, an alternative method would be to restrict our dataset to the post-1990 era. Similar results are obtained in the crisis-dating part of the paper.

absolute daily changes in the real yield on 10-year government bonds. We prefer using changes and not growth rates since, for some periods, very low real yields would create excessively large variations. Second, we compute the cumulative difference ($CDIFF$) corresponding to the maximum increase in basis points of the real government bond spread with respect to Germany over a two-year rolling window. We prefer using the spread instead of the 10-year yield in order to disentangle changes in the risk profiles from changes in a proxy for the risk-free rate.

$$\begin{cases} chR10_t &= rR10_t - rR10_{t-1} \\ \widetilde{chR10}_t &= \dfrac{chR10_t}{\sigma_{chR10t,t-2609}} \\ VR10_t &= \dfrac{\sum_{i=0}^{19} \left|\widetilde{chR10}_{t-i}\right|}{20} \\ CDIFF_t &= rR10_t - rR10_{DE,t} - \min_{i=0}^{521}\left(rR10_{t-i} - rR10_{DE,t-i}\right) \end{cases} \tag{3}$$

For Germany, we instead compute the increase in the 10-year yield compared to the minimum ($CMIN$) over a two-year rolling window.[16]

$$CMIN_{t,DE} \quad = \frac{\left(100+rR10_{t,DE}\right)}{\min_{i=0}^{521}\left(100+rR10_{t-i,DE}\right)} - 1 \tag{4}$$

Foreign exchange market stress. Stress in the foreign exchange market also relies on two variables, available only at a monthly frequency. First, the realized volatility ($VEER$) is computed as the absolute value of the monthly growth rate of the real effective exchange rate. Second, longer-lasting changes in the real effective exchange rate should be associated with more severe stress, owing to the necessary adjustment of the real economy. Thus, we compute the cumulative change ($CUMUL$) over six months: if $CUMUL > 0$, then the real effective exchange rate is volatile around a changing rate.

$$\begin{cases} lnEER_t &= \log\left(rEER_t\right) - \log\left(rEER_{t-1}\right) \\ \widetilde{lnEER}_t &= \dfrac{lnEER_t}{\sigma_{lnEERt,t-119}} \\ VEER_t &= \left|\widetilde{lnEER}_t\right| \\ CUMUL_t &= \left|rEER_t - rEER_{t-6}\right| \end{cases} \tag{5}$$

[16] We consider a bond whose price is normalized to 100 at the beginning of the period and use the value of the bond at the end of one year. Thus, we compute the cumulative stress on a positive variable, while real yields could be negative with misleading economic interpretations in the $CMIN$ framework. The choice of a base of 100 does not impact the results, as we subsequently use the relative ranking of the observations.

2.2 Aggregation to capture cross-market linkages

Standardization. The second step consists of converting the individual stress indicators, two for each financial market segment, into a common unit. While there are various ways of standardization, with specific advantages and disadvantages (for a survey, see Kliesen et al., 2012),[17] we follow the strategy of Hollo et al. (2012) and use the empirical cumulative density function (CDF) computed over an initial window of 10 years that expands progressively to take new data points into account.[18]

$$\hat{z}_t = F_n(z_t < z) = \begin{cases} \dfrac{r}{n} & \text{for } z_{[r]} < z_t < z_{[r+1]}, r = 1, 2, ..., n-1 \\ 1 & \text{for } z_t > z_{[n]} \end{cases} \tag{6}$$

where $z_t \in \{VSTX, CMAX, VR10, CDIFF, CMIN, VEER, CUMUL\}$.

The empirical CDF $F_n(z_t < z)$ transforms each variable into percentiles by computing, at each point in time t, the rank r of the new observation z_t in the sample of all past data that has n observations. The output $\hat{z}_t$ is a unit-free index where, at each point in time, the most extreme (smallest) values, corresponding to the highest (lowest) levels of stress, are characterized by the 99th (1st) percentile.

Aggregation. Since the individual stress indicators capture the same facets of risk (i.e. volatility and large losses) for each financial market segment, we aggregate them by computing their average.[19] The sub-indices are given by

$$\begin{cases} I_{STX} & = \dfrac{\widehat{VSTX} + \widehat{CMAX}}{2} \\ I_{R10} & = \dfrac{\widehat{VR10} + \widehat{CDIFF}}{2} \\ I_{EER} & = \dfrac{\widehat{VEER} + \widehat{CUMUL}}{2} \end{cases} \tag{7}$$

Similar to Hollo et al. (2012), we aggregate the sub-indices for the three financial market segments based on a portfolio theory approach that weights each sub-index by its cross-correlation with the others.[20] By aggregating correlated sub-indices, the resulting

[17] One could compute each sub-index per unit of variance to make them comparable, but this is equivalent to assuming a normal distribution for the values of the sub-index. In addition, the variance-equal method is less robust to the presence of outliers.

[18] The implicit assumption is that, as more points become available, the CDF distribution is increasingly accurate, which amounts to assuming a certain stationarity of the distribution over time. Otherwise, if the features of the financial cycle are themselves time-varying, old observations may not always be a good benchmark to classify and rank current observations, especially since we have 50 years of data for some countries. We discuss this issue in the robustness section.

[19] For Germany, the bond sub-index is $I_{R10} = \frac{\widehat{VR10} + \widehat{CMIN}}{2}$.

[20] The commonality across market segments could be captured by a principal-component analysis (Hakkio and Keeton, 2009; Kliesen and Smith, 2010; Brave and Butters, 2011), but this method is

index reflects increased risk due to the stronger co-movement with overall financial stress. In contrast, less correlated sub-indices result in a lower composite index as it captures non-systematic components and diversifiable risk across market segments. Since our FSI should be meaningful for financial stability purposes and the detection of systemic financial stress episodes, it is crucial to capture the systematic co-movement across financial market segments.[21] The FSI is thus computed as follows:[22]

$$FSI_t = \mathbf{I}_t \cdot C_t \cdot \mathbf{I}_t^{'}, \tag{8}$$

where $\mathbf{I}_t$ is the 1×3 vector of standardized sub-indices and C_t is the 3×3 time-varying cross-correlation matrix of the sub-indices:

$$C_t = \begin{bmatrix} 1 & \rho_{STX,R10,t} & \rho_{STX,EER,t} \\ \rho_{STX,R10,t} & 1 & \rho_{R10,EER,t} \\ \rho_{STX,EER,t} & \rho_{R10,EER,t} & 1 \end{bmatrix}$$

The time-varying cross-correlations $\rho_{i,j,t}$ are estimated using an exponentially weighted moving average (EWMA) specification with smoothing parameter $\lambda = 0.85$.[23] Similar results are obtained with a multivariate GARCH but it unnecessarily adds estimation uncertainty to an otherwise simple FSI. $\sigma_{i,j,t}$ stands for the covariance, $\sigma_{i,t}^2$ for the volatilities

very data intensive and thus does not fit well with the purpose of the paper. Alternative aggregation techniques use credit or variance weights to emphasize the relative importance of the different asset classes, but financial stress is still additive and, thus, does not reflect systemic stress in the financial sector.

[21] Across countries, the average correlation of the FSI with and without cross-correlation weights is 0.87, and ranges from a minimum of 0.79 for Cyprus to a maximum of 0.93 for Slovenia. When looking at the contribution of the cross-correlation components to the overall FSI (see the online appendix for each country at http://sites.google.com/site/thibautduprey/research/crisesdating), it is obvious that it largely contributes to a better identification of known crises events as it tends to increase the FSI precisely during those periods.

[22] Note that our measure is bounded between 0 and 9, where the maximum is obtained when the cross-correlations are all equal to unity. In addition, one could weight the stress on each market segment by the associated credit share (Illing and Liu, 2006) or the estimated impact on the real economy (Hollo et al., 2012), but this requires more data or introduces more estimation uncertainty.

[23] The smoothing parameter λ gives exponentially less weight to older observations. It is found by minimizing, across countries, the squared errors compared to a multivariate diagonal BEKK GARCH(1,1) process for countries with sufficient data for a meaningful estimation (i.e. those with at least 300 data points, starting in 1990 at the latest). When looking at individual countries, the fit of the GARCH(1,1) is better in terms of log-likelihood or Schwarz criterion over models with more lags. We find a λ equal to 0.85 (see the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating).

and $\bar{s}_{i,t} = I_{i,t} - 0.5$ the demeaned sub-indices from the "theoretical" median.[24]

$$\begin{aligned} \sigma_{i,j,t} &= \lambda\sigma_{i,j,t-1} + (1-\lambda)\bar{s}_{i,t}\bar{s}_{j,t} \\ \sigma^2_{i,t} &= \lambda\sigma^2_{i,t-1} + (1-\lambda)\bar{s}^2_{i,t} \\ \rho_{i,j,t} &= \frac{\sigma_{i,j,t}}{\sigma_{i,t}\sigma_{j,t}} \end{aligned} \tag{9}$$

where $i, j = \{STX, R10, EER\}$, $i \neq j$. The initial values for the covariance and volatilities are set to the average over the first 10 years where the sub-indices are available.[25]

3 A Judgment-Free Dating of Systemic Financial Stress

In the next step, we combine information on financial market conditions, captured by the country-specific FSIs, and on real economic conditions, captured by annual growth in the industrial production index (IPI), to date episodes of systemic financial stress. Systemic financial stress episodes are defined as periods of financial stress associated with a substantial and prolonged negative impact on the real economy.

We use a sequential approach to identify systemic financial stress events. We first identify financial stress events that correspond to episodes with high financial stress. We then narrow these down to the subset of financial stress events that are also associated with real economic stress. We label those events as systemic financial stress (Figure A.2). An alternative strategy would be to identify real and financial stress in a bivariate framework. This more complex approach is left as a robustness check.

3.1 Identifying financial stress: A Markov-switching model

Most kernel densities of the country FSIs are characterized by a fat tail or a bi-modal distribution. This suggests that the data can be approximated by a mixture of two distributions with different mean and variance parameters. This is exactly what the MS model does by distinguishing whether a given data point was drawn from a distribution corresponding to a low or high FSI regime.

We take the simplest regime-switching model as a benchmark, namely, the fixed transition probability Markov-switching framework proposed by Hamilton (1989). We allow for a regime-specific mean and variance (μ^s and σ^s with $s = \{L, H\}$ corresponding, respectively, to a low and high financial stress regime). It is likely that a high financial

[24] The sub-indices have been mapped into the bounded $[0:1]$ space using their relative ranking, so that values in the middle of the distribution were assigned the number 0.5.

[25] So far, there is no assumption on the existence of different regimes in the variances of the sub-indices. The idea here is to allow for time-variation in the joint co-movement of the sub-indices so that correlations are allowed to vary anywhere from -1 to 1.

stress regime exhibits both a larger absolute level of stress as well as more uncertainty. Models with only regime-specific means may generate very volatile signals of financial stress during the same financial stress episode if the financial stress is reduced for a short period of time, e.g. following temporarily good news or government interventions. Allowing for regime-specific variances results in a more robust identification of financial stress episodes. In the absence of lagged dependent variables, we can loosely interpret the mean of the FSI in the high financial stress regime as a country-specific threshold above which the corresponding FSI value is most likely associated with a financial stress period.[26]

$$FSI_t = \left[\begin{array}{l} \mu^H + \sigma^H \epsilon_t \text{ in the high stress regime} \\ \mu^L + \sigma^L \epsilon_t \text{ in the low stress regime} \end{array} \right. \tag{10}$$

With $\epsilon_t \rightarrow N(0,1)$ and the transition probability across regimes $S_t \in \{L, H\}$ is driven by a hidden two-state Markov chain whose transition probability matrix is given by

$$P\left(S_t = s \,|S_{t-1}\right) = \left[\begin{array}{cc} p = \frac{\mathtt{exp}(\theta_p)}{1+\mathtt{exp}(\theta_p)} & 1-p \\ 1-q & q = \frac{\mathtt{exp}(\theta_q)}{1+\mathtt{exp}(\theta_q)} \end{array} \right] \tag{11}$$

We identify the financial stress regime as the one with the largest mean FSI ($\mu^H > \mu^L$). The output of the model is a time series of the smoothed probability of being in one regime $P\left(S_t = s\right)$ that we discretize in order to get a vector $\mathbb{C}$ of binary variables proxying the time series of financial stress episodes. At each point in time, it takes a value of one for cases where the probability of being in the high financial stress regime H is greater than 0.5 and a value of zero otherwise.[27]

$$\mathbb{C} = \left\{ \mathbb{1}_{P(S_t=H)>0.5} \right\}_{t=1,\cdots,T} \in \{0;1\} \tag{12}$$

The results of the benchmark MS model are shown in Table B.1. One concern could be that the MS model identifies two regimes in the FSI, irrespective of the actual existence of different regimes. However, the following aspects seem to suggest the presence of at least two regimes in the FSI. First, the long time span of up to 50 years captures several financial crises with high levels of financial market stress as well as benign periods. Second, for all countries, the regime-specific means are significantly different across the two regimes.[28] Third, standard tests for breaks in univariate time series confirm the

[26]The robustness checks with lagged dependant variables yield similar results. When introducing an autoregressive term, the coefficient might be so high for some countries (especially for those where the data cover only a short time span) that the estimation fails. In such cases, for AR(1) terms above 0.9, we use a second lag.

[27]The choice of this threshold has no impact on subsequent results.

[28]However, regular tests in the MS framework are known to be hard to compute as they do not follow standard asymptotic distributions. Thus, we restrict ourselves to testing regime differences in the mean computed in the case where variances are constant across regimes.

presence of breaks in the FSI of each country.

This Markov-switching approach has several advantages over alternative methods to determine thresholds above which financial stress is identified. Looking only at percentiles[29] or rolling standard deviations of the distribution of financial stress still requires the definition of an exogenous threshold (the percentile or the number of standard deviations) which directly impacts the start and end dates of the financial stress event. Conversely, the Markov-switching approach requires fewer assumptions and classifies an event as being a financial stress event if it is most likely to belong to a different regime with higher stress. In addition, using a fixed threshold can generate more noise as a small breach of the threshold would qualify as a stress event. Conversely, the Markov-switching model could also capture this as a tranquil event with a low mean stress and simply a large shock drawn from the right tail of the tranquil distribution.

3.2 Selecting systemic financial stress events: An algorithm

Periods of real economic stress are defined as events with (i) at least six consecutive months of negative annual industrial production growth,[30] and which (ii) overlap at least partly with a decline in real GDP during at least two – possibly non-consecutive – quarters.[31] Thus, taking GDP explicitly into account allows restriction to real economic stress events that qualify as recessions. We define periods of real economic stress as a prolonged and substantial decline in real economic activity occurring both in the production sector as well as in the overall economy. Industrial production growth is used as a benchmark for the start and end dates of real economic stress instead of GDP, since the former is available at a monthly frequency like the FSI.

Figure A.3 displays annual industrial production growth for different quantiles of the FSI distribution averaged across time and countries. It clearly shows that, on average, levels of financial stress above the 90th percentile of the distribution are associated with a substantial drop in industrial production. Figure A.4 illustrates the annual industrial production growth and the deviation from its long-term trend during the months following high financial stress. It shows that average annual industrial production growth becomes negative during the month in which the FSI exceeds the 90th percentile threshold. Industrial production recovers 12 months after the beginning of high financial stress, while it takes on average 2.5 years to get back to its long-term trend. This simple exercise

[29]The results of this very simple method are also reported in the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating.

[30]Alternatively, we could use an MS model to obtain periods of real economic stress. All episodes of real economic stress identified based on negative growth rates are also captured by an MS model. We rely on the simple rule-based criterion since consecutive months of decline in industrial production is a more severe criterion selecting fewer events.

[31]When only one of the two variables (industrial production or GDP) is available, we keep only one of the two criteria for defining real economic stress.

offers two valuable insights. First, episodes of high financial stress tend to be associated with real economic turmoil. Second, looking at a window of one year after the start of the financial stress seems to be reasonable to investigate whether financial stress is indeed associated with a pronounced decline in real economic activity.

As a consequence, among the episodes of financial stress identified by the Markov-switching model, an event is considered to be "systemic" if there are at least six consecutive months of real economic stress either during one year following the start of the financial stress period, or during the whole financial stress period if it lasts more than one year. This is consistent with the graphical analysis that suggests a mean recovery of the real economy with positive growth rates after 12 months.

The algorithm to identify systemic financial stress episodes loops over the time periods starting with the earliest data point for which the FSI is available:

1. Identify the start date of the next financial stress period, as obtained from the Markov-switching model.

2. Identify the end date of the financial stress period.[32]

3. If the real economic stress did not stop since the previous period of systemic financial stress, then it is assumed that the current period of financial stress is the mere continuation of the previous period of systemic financial stress. Back to point 1.

4. Check if the period qualifies as "systemic" financial stress: a period of at least six consecutive months of real economic stress is identified either during one year following the start of the financial stress period or during the whole financial stress period if it lasts more than one year.[33] Several cases are considered:

   (a) The financial stress period is "systemic" and is followed by real economic stress. Back to point 1.

   (b) The financial stress period is "systemic" but real economic stress started earlier:

      - If another financial stress period ended less than two quarters before the currently identified start date, both periods are considered as being part of the same financial stress episode and are thus merged. Identify the start date of this merged financial stress episode. Back to point 3.

[32] If no end date is identified, it means that, at the end of the sample, the country is still in a period of financial stress. Hence, the sample end date is taken as the end date of the financial stress episode.

[33] For financial stress episodes that occurred at the beginning of the sample period, the stress episode might have started earlier if we had been able to compute the FSI over a longer time span. Thus, periods at the beginning of the sample may also qualify as "systemic" if there is only a *partial* overlap with six consecutive months of real economic stress around the start date of financial stress.

- If no other financial stress episode is identified in the previous six months, this financial stress event is flagged as being "late". Back to point 1.

(c) The financial stress episode is not considered as being "systemic":

- If another financial stress period ended less than two quarters before the currently identified start date, both periods are considered as being part of the same financial stress episode and are thus merged. Identify the start date of this merged financial stress episode. Back to point 3.
- If no other financial stress episode is identified in the previous six months, back to point 1.

3.3 Systemic financial stress events: Results

Chronology of systemic financial stress. The upper part of Figure A.5 shows all systemic financial stress episodes identified by the MS model and the filtering algorithm described above. Systemic financial stress periods are in black, while tranquil periods are in white and periods of insufficient data are in light grey. Separately, we also identify periods where the financial stress started more than one quarter after the start of the real economic stress (shown in dark grey). For these few events, either the stress started in the real economy and subsequently spilled over to the financial market, or our FSI fails to capture some dimension of the financial stress leading to a late detection of the event. In addition, Figure A.6 shows the intensity of financial and real economic stress during each period of systemic financial stress. If systemic financial stress events are always characterized by an FSI above the 70th percentile, systemic financial stress events around 2008 are associated with a stronger loss in industrial production that can reach 30%.

As the methodology is identical for all countries, one can take a closer look at the chronology of the global financial crisis and how it spread across Europe. The lower part of Figure A.5 ranks the countries by the starting date of the systemic financial stress episode occurring from January 2007 onwards. The group of countries hit first in mid-2007 is composed of Slovenia, Ireland, the Czech Republic, Croatia, as well as Bulgaria, Romania and the United Kingdom at the end of 2007. A second group of countries hit in the first quarter of 2008 consists of Denmark, Italy, Luxembourg, the Netherlands, Spain, Portugal, Austria, France, Greece and Hungary. A later wave of countries hit in the second half of 2008 consists of Germany, Sweden, Latvia, Lithuania and Finland. Apart from Germany, countries of this group were confronted with financial stress only after the real economic stress had materialized.

In addition, the results allow us to infer for which countries the sovereign debt crisis starting in 2011 can be considered as a systemic financial stress episode. In the cases of Croatia, France, Luxembourg, the Netherlands and Cyprus, the sovereign debt crisis is identified as being clearly separated from the global financial crisis. In other countries, such as Belgium, Slovenia, Ireland, Italy, Portugal, Spain and Greece, the systemic financial stress period expanded beyond the global financial crisis. Finally, in the cases of Poland, Malta and Slovakia, the financial market stress occurring from 2008 to 2012 did not have sufficiently severe or prolonged real economic stress to be considered as "systemic".

Depth and length of systemic financial stress. Table B.2 compares important characteristics of ordinary recessions (left columns) and recessions occurring simultaneously with financial market stress (right columns). Accordingly, 42% (44%) of the recessionary events characterized by two (two consecutive) quarters of declining GDP are not associated with simultaneous financial market stress.[34] As expected, recessions occurring simultaneously with financial stress episodes feature an average FSI in the 70th percentile of the distribution during the quarter before the start of the recession, while the FSI is below the median for recessions without simultaneous financial market stress.

In line with the literature on financial crises (Reinhart and Rogoff, 2009; Reinhart and Rogoff, 2014), recessionary events are longer when they are associated with simultaneous financial market stress.[35] Ordinary recessions last on average eleven months, while recessions associated with financial stress have an average duration of 17 months. In addition, according to Jorda et al. (2013), the magnitude of output losses is much larger during recessions coinciding with financial market stress than during ordinary recessions. We find that the difference in GDP decline is three percentage points larger. Even prior to 2008, recessionary events associated with financial market stress were on average two months longer, with the GDP decline being one percentage point larger.

Cross-country simultaneity of systemic financial stress. Our broad country coverage and the unified framework allow us to construct a measure of the simultaneity of systemic financial stress in Europe. The crisis simultaneity index (CSI) shown in Figure A.7 corresponds to the share of countries experiencing a systemic financial stress episode at a given point in time. The difference between the black line and the black area corresponds to those periods of systemic financial stress where the real economic stress started at least three months before the financial market stress. We observe that three main episodes of systemic financial stress affected more than 50% of the EU countries at the same time: (i) the episode between the first and second oil shocks in 1973 and 1979; (ii) the years from 1993 to 1994 with banking, currency and real economic stress; and (iii) the global financial crisis.

[34] Note that several recessions can occur during one financial stress episode.

[35] However, the recent paper by Romer and Romer (2015) suggests that output decline following financial crises varies across OECD countries and depends on the length of the financial stress itself.

Country-by-country results. Table B.5 lists all identified systemic financial stress episodes. It also reports the intensity of real and financial stress, the degree of simultaneity with other countries as well as the associated classification identified by experts.[36]

4 Comparison with Other Chronologies

We now turn to the comparison of our chronology of systemic financial stress periods with identified crises periods based on expert judgment. The expert-based events consist of the banking crises of Detken et al. (2014); the banking, currency and debt crises identified by Babecky et al. (2012); the systemic banking crises of Laeven and Valencia (2013); and the crises dates of the 16 EU countries covered by Reinhart and Rogoff (2011), which are classified as banking and currency crises as well as stock market crashes. The first two datasets are at a quarterly frequency, while the last two are at an annual frequency. Figure A.8 provides a graphical comparison of the FSI and its distribution across EU countries with a few major crises events.[37]

4.1 Comparison methodology

Since frequencies are different, we compare model- and expert-based events, rather than monthly signals as is common in the early-warning literature. We require at least a one-month overlap to consider that systemic financial stress episodes coincide with expert-identified crises.[38] As a result, the "missed crises" or "false alarm" rates that we compute are not, strictly speaking, equivalent to their meaning in the early-warning literature,[39] but rather correspond to, respectively, the share of expert-based crises not captured by the model, and the share of systemic financial stress events not identified by experts.

We do not expect systemic financial stress events to coincide perfectly with expert-identified crises. On the one hand, we may fail to capture crises identified by experts for several reasons. First, the expert-based stress episodes are more narrowly defined than our systemic financial stress periods, thus limiting their comparability. Second, stress

[36]The online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating provides, for each country, a detailed overview of (i) the FSI with the threshold above which financial market stress is identified, (ii) the contribution of each financial market sub-index and their correlations to the overall FSI, and (iii) various model- and expert-based systemic financial stress periods. It is worth noting that cross-correlations tend to contribute positively to the FSI in periods of systemic financial stress and negatively in tranquil periods and are thus an important component of the FSI.

[37]Country-by-country graphical comparisons are provided in the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating.

[38]Jing et al. (2015) consider banking crises to be correctly identified when money market stress was signalled up to two years before the expert-identified crisis and until one year after the start of the crisis. Still, they only obtain a rate of correctly identified crises of 28% compared to the crises of Laeven and Valencia (2013).

[39]In practice, we cannot compute the share of events with no crisis, while in the early-warning literature, one can compute the number of months without a signal.

episodes identified using our approach rely on market data while expert-based episodes usually use policy actions as a key criterion. Thus, we compute an ex post measure of market stress, while public interventions occurring in the meantime might mitigate the observed stress.

On the other hand, our approach may capture systemic financial stress episodes that were not identified by the experts for several reasons. First, surveyed experts often identify crises events based on qualitative criteria, which might introduce a subjectivity bias leading to fewer identified crises. Second, there exists a time lag before the next update of the expert-based crises events becomes available, so that our approach is more likely to identify additional events at the end of the sample. Third, since our criterion to identify systemic financial stress is a prolonged decline in industrial production and GDP during a financial market stress period, we may also capture periods of real economic stress that spilled over to the financial sector and led eventually to an acceleration of the overall level of financial market stress. This interplay between real economic and financial market stress may result in the identification of more stress episodes. However, about half of the recessions did not occur during periods of high financial market stress, and, except for a few cases,[40] financial market stress occurred first, and real economic stress materialized in the subsequent twelve months.

4.2 Model- vs. expert-based episodes in the cross-section

Table B.3 compares systemic financial stress episodes with the expert-identified crises dates. The first two columns report the share of model-based stress episodes that were also identified as crises events by experts. On average, 62% of the systemic financial stress episodes identified by our approach are also in the list of banking crises identified by experts. Overall, 84% of the model-based systemic financial stress periods are captured by experts, irrespective of the type of crisis considered. This percentage is up to 95% if we exclude the eleven countries not covered by Reinhart and Rogoff (2011). The other two columns report the share of expert-based crises that are also captured by the model-based approach. 85% of all expert-based banking crises were also identified by our approach as systemic financial stress periods. When all crises are considered, only 51% of them were also identified as systemic financial stress episodes according to our definition.

These results suggest that most of the model-based systemic financial stress episodes are banking crises. Table B.4 confirms that the model-based stress periods coincide particularly well with banking crises. All of the systemic banking crises identified by Laeven and Valencia (2013) are captured by our model-based approach as well as, on

[40] Out of 17 "late" events where financial stress started at least one quarter after the real economic stress, four events were not identified by experts (namely France, Austria and Germany in the early 1980s, and France in 2002) and one event falls outside the time span covered by experts (Finland in 2012-3).

average, 92%, 90% and 89% of the banking crises identified by Babecky et al. (2012), Detken et al. (2014) and Reinhart and Rogoff (2011), respectively. The crises types that are identified by the model-based approach in only less than half of the cases are the currency and equity crises of Babecky et al. (2012) and Reinhart and Rogoff (2011), respectively.

4.3 Model- vs. expert-based episodes in the time dimension

Figure A.9 shows the share of expert-based crises not captured by the model-based approach ("missed crises") and the share of systemic financial stress events not identified as crises by experts ("false alarms") by pooling *all* available countries and crises dates at each point in time (banking, currency, debt, equity).[41] The left axis shows the monthly ratio (black area), while the right axis shows the number of events missed or identified in excess of expert dates (red line). The upper graph reveals that most "missed crises" occur in the late 1960s, the early 1980s and during the 1990s, while almost all expert-based events around 2008 are captured by the model-based approach. From the lower graph it becomes clear that we capture very few events in addition to the expert-based crises. The main discrepancy occurs during the global financial crisis, where the model-based approach captures three additional events that were not identified by experts (for Bulgaria, Croatia and the Czech Republic).

These results are rather reassuring, as they mean that (i) the model does not capture all possible crises of the different types identified by experts, and (ii) the model-identified episodes do not tend to signal periods not captured by experts, irrespective of the type of crisis considered. However, these overall results hide some heterogeneity across the different crises types.

When we look at the different types of crises separately, the share of "missed crises" is much lower. Only three systemic banking crises of Detken et al. (2014) in the early 1990s (Figure A.10) and a few currency crises around 1980 and in the early 1990s of Babecky et al. (2012) (Figure A.11) are not captured by the model-based approach.

Figure A.12 reports the share of "false alarms" when considering only systemic banking crises (upper graph) and systemic banking crises as well as stock market crashes (lower graph). Even if the stock market crashes of Reinhart and Rogoff (2011) cover only 16 countries, it becomes clear that most of the crises captured by the model-based approach, besides systemic banking crises, seem to be stock-market-related events. Three clusters of "false alarms" can be observed in Figure A.12. The first period is the one after the two oil shocks of 1973 and 1979. About five stress episodes are identified by the model-based

[41]The possible few months of difference between the start or end dates of the model- and expert-based episodes are not included for the computation of the ratios. Otherwise, a model-based stress episode starting in June 2007 but identified by experts only from 2007Q3 onwards would wrongly show up as a "false alarm" during the three initial months.

approach only, which amounts to a share of “false alarms” above 50%. Oil shocks had a negative impact on the economy and led to financial market turmoil and strong price co-movements among the assets in the financial system, above and beyond what can be attributed to the banking sector.[42] The second period corresponds to the currency stress of the early 1990s, which might be captured more often as the foreign exchange market is one of the three components of the FSI. The third period is the global financial crisis from 2008 until 2013. Up to six additional events that represent about 20% of all crises dates over this period are identified by the model-based approach. The countries concerned are Bulgaria, Croatia, the Czech Republic, Finland in 2012, as well as Finland and Romania in 2008 where the last two are identified as stock market crashes by Reinhart and Rogoff (2011).

5 Robustness Analysis

5.1 Alternative FSI with banking data

Including banking sector variables into the computation of the FSI allows us to change its scope from a broad index capturing aggregate financial market developments to a narrower, bank-focused, index. However, data availability and quality are limited, which reduces cross-country comparability and may weaken the robustness of the MS model estimations.

One way of incorporating banking sector information into the FSI is to compute a stock market sub-index based on banks’ stock prices. For large countries such as France, Germany, Italy, the Netherlands, Spain, Sweden and the United Kingdom, the stock market sub-index of the FSI uses the stock index of Globally Systemically Important Banks (G-SIBs) instead of the stock index of non-financial corporations used in the benchmark model.[43] The underlying hypothesis is that the equity valuation of large banks is a sufficient proxy for the valuation of the overall banking sector. However, the activities of these banks changed substantially over time with mergers and acquisitions. For the seven countries for which banking data are available, the periods identified as systemic banking stress are very similar to the benchmark case. However, the stock market stress that occurred during the early 2000s in France and Germany is no longer captured. Note that the French banking crisis identified by some experts during the mid-1990s does not qualify as systemic since it was not accompanied by simultaneous real economic stress.

An alternative is to introduce, for the 19 countries for which the relevant data are

[42] As displayed in country-by-country figures in the online appendix, the cross-correlations are large contributors to the FSI during this period.

[43] If necessary, stocks are weighted by the relative market capitalization of the different banks in each country.

available, a money market sub-index[44] by computing the spread between the three-month interbank offered rate[45] and the three-month treasury bill rate. This fourth FSI sub-index is constructed as described in Section 2.1 by combining a measure of volatility and a measure of large variations ($CDIFF$). However, the government interventions during the global financial crisis potentially affected interbank markets through a flattening of the spread and a reduction of the volatility. Overall, systemic stress episodes are similar to the benchmark case. As above, the stock market stress that occurred in the early 2000s in France and Germany does not qualify as systemic banking stress, nor does the currency stress in Denmark that occurred from 1979 to 1980. In addition, the banking stress in Greece during the early 1990s is better captured. Last, additional periods are identified as systemic stress for Portugal in 1992 and Malta in 2007.[46]

5.2 The stationarity of the stress distribution over time

When computing the realized volatilities, the variables are adjusted for a possible change in the volatilities that might otherwise overstate financial market stress during the 1970s and 1980s. This volatility adjustment of the FSI allows for a somewhat better identification of the financial stress in Portugal in 2008 and in Sweden in the first part of the 1990s. An alternative is to restrict the sample to start in 1990, so that financial stress is compared across more similar periods. The correlation of the benchmark FSI with the volatility-adjusted FSI and the FSI based on the restricted sample are very high. On average, the correlations are, respectively, 0.94 and 0.91. For those countries in which the FSI started after 1990, as expected, there is almost no difference between the benchmark FSI and the volatility-adjusted one.

The possible presence of different volatility regimes is an issue because the MS model estimation requires a stationary FSI distribution over time. If the structural features of the FSI changed over time, recent stress periods might not be adequately identified. For example, the level of financial stress could be structurally lower today owing to lower volatilities compared to the early 1970s. One way to test the stationarity assumption is to consider alternative standardization windows when converting the different stress indices into a common unit using the empirical cumulative distribution function. To this end, a 10-year rolling window can be used to gradually discard older periods when classifying new observations. Alternatively, the entire time series, including past and future information, can be used for the standardization. The resulting systemic financial

[44] Jing et al. (2015) extend the existing literature on indices of money market pressure and compare it with episodes of banking stress.

[45] Before the adoption of the euro, this corresponds to the interbank rate on the national market. Once a country joined the euro area, the rate is replaced by the three-month EURIBOR.

[46] Episodes of systemic banking stress using either methods are reported in the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating.

stress episodes are similar, which suggests that the stationarity assumption holds.[47]

5.3 The stability of event classification

The stability of event classification can be tested in-sample by identifying the systemic financial stress episodes over gradually expanding samples. To this end, an initial sample covering the first 25 years of data is used to estimate the MS model, and, in each of the subsequent rounds, the sample is expanded by one year.

Overall, the model-based approach appears to be relatively robust to the reclassification of events when new data become available. However, since the MS model, by definition, uses the unconditional sample mean and variance to infer the two regimes in the FSI, future stress episodes may still impact the precise dating of stress periods, especially when only a limited history of financial stress is available or when financial stress has a mild intensity (as in the Netherlands in 1974-75). In addition, since our approach requires six consecutive months of real economic stress within a 12-month window, a consistent classification of systemic financial stress periods might be complicated if the financial stress identified by the MS model is one month longer or shorter (as in the United Kingdom in 1990). Moreover, in a few cases, when new data are taken into account, the start and end dates of systemic financial stress episodes differ substantially from the previous update. This is due to the filtering algorithm which merges successive stress episodes occurring within a window of six months, as in the case of Spain in the late 1970s or Germany in 1994.[48]

Still, as there is at least one large systemic financial stress episode (i.e. the global financial crisis) included in the dataset, the identified systemic stress periods are unlikely to vary substantially over time. It is reassuring that previous systemic financial stress episodes were not reclassified once the global financial crisis was included in the dataset.

5.4 Modelling the joint dynamics of economic and financial variables

The last robustness test investigates a model that explicitly captures the joint dynamics of financial market and economic variables.[49] We use a threshold vector-autoregressive

[47] Those episodes are reported in the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating.

[48] Those events are flagged in Table B.5. More detailed results are displayed in the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating.

[49] Hartmann et al. (2013) use a large Markov-switching vector-autoregressive model to capture changes in the joint dynamics between financial stress and other macroeconomic aggregates. The authors confirm that when financial instability is high, the behaviour of macroeconomic aggregates is significantly different from tranquil periods.

(TVAR) model[50] with the FSI and annual industrial production growth ($gIPI$) in which each variable depends on its own n lags as well as those of the other variable. The TVAR model distinguishes between periods of significantly different joint dynamics above (A) or below (B) a specific percentile of the FSI, possibly lagged by d periods. This allows us to infer the country-specific FSI threshold τ that best separates the joint dynamics of financial and real economic stress into two regimes. Hence, the regime-switching now directly depends on observables, namely, the level of financial stress, instead of an unobserved Markov chain:

$$\begin{cases} FSI_t = c_1^A + \sum_{p=1}^{n} \left(\beta_{1,1,p}^A FSI_{t-p} + \beta_{1,2,p}^A gIPI_{t-p}\right) + \epsilon_1^A \\ gIPI_t = c_2^A + \sum_{p=1}^{n} \left(\beta_{2,1,p}^A gIPI_{t-p} + \beta_{2,2,p}^A FSI_{t-p}\right) + \epsilon_2^A \end{cases} \quad \text{if } FSI_{t-d} > \tau \tag{13}$$

$$\begin{cases} FSI_t = c_1^B + \sum_{p=1}^{n} \left(\beta_{1,1,p}^B FSI_{t-p} + \beta_{1,2,p}^B gIPI_{t-p}\right) + \epsilon_1^B \\ gIPI_t = c_2^B + \sum_{p=1}^{n} \left(\beta_{2,1,p}^B gIPI_{t-p} + \beta_{2,2,p}^B FSI_{t-p}\right) + \epsilon_2^B \end{cases} \quad \text{if } FSI_{t-d} < \tau$$

The periods obtained from the benchmark model are roughly consistent with those obtained from the TVAR model (when $FSI_{t-d} > \tau$). The average threshold estimated with the TVAR model corresponds to the 81st percentile of the FSI.[51]

The TVAR model is not the benchmark for several reasons. (i) It does not take the length of the real economic stress into account while the filtering algorithm can handle cases of very short-lived stress periods or identify periods of prolonged real economic stress to justify the classification as "systemic". (ii) Systemic financial stress periods are "mechanically" identified as episodes above the threshold, while the MS model also includes a regime-dependent variance that is observed in the empirical distributions of the FSI. (iii) The MS model provides the probability to be in the high or low stress regime, allowing for some degree of uncertainty in the estimation of the regime, while any small breach of the TVAR threshold leads to the classification of one period as a stress event. (iv) The TVAR model requires the correct estimation of many more parameters whose uncertainty is likely to be excessively large for countries with a limited time span. (v) Finally, the estimation of the TVAR model fails for countries with a limited time span, namely, Latvia, Lithuania, Romania and Slovenia.

[50] Hollo et al. (2012) use this approach as a robustness check to endogenously determine the stress threshold above which their financial stress measure, the CISS, significantly distorts the real economy.

[51] The results are reported in the online appendix at http://sites.google.com/site/thibautduprey/research/crisesdating.

6 Conclusion

The goal of this paper is to provide a framework for identifying systemic financial stress episodes in a transparent, reproducible and objective way. Systemic financial stress episodes are periods in which high financial market stress coincides with a substantial and prolonged decline in real economic activity. We bridge the gap between the literature on measuring systemic financial stress and that on business cycle dating using Markov-switching (MS) models. The approach follows a three-step strategy: (i) construct a financial stress index (FSI), (ii) identify periods of high financial market stress, and (iii) narrow down the financial stress episodes to those with a "systemic character". By applying this framework to the EU countries, this paper is a first attempt to provide a chronology of EU systemic financial stress episodes in addition to the expert-based stress events available so far.

The 68 systemic financial stress episodes identified by the model-based approach are shown to be consistent with many expert-based stress periods. In particular, 82% of the model-based systemic financial stress periods are also identified as crises by experts. Focusing on banking crises, the approach captures on average 100%, 92%, 90% and 89% of the crises identified by Laeven and Valencia (2013), Babecky et al. (2012), Detken et al. (2014) and Reinhart and Rogoff (2011), respectively. In addition, the identified systemic financial stress episodes tend to be robust to event reclassification once new data become available. Overall, systemic financial stress events have recurrent patterns: (i) financial stress usually occurs first and is followed by real economic stress; (ii) when associated with financial market stress, recessionary periods last on average six months longer, and the output decreases on average by three additional percentage points; (iii) a crisis simultaneity index shows that systemic financial stress usually occurs in "clusters" affecting several EU countries at the same time. In this respect, the global financial crisis is only comparable to the first oil shock.

This work has important implications for further macroprudential analyses. First, the proposed objective approach limits the bias potentially arising when relying on expert judgment to identify financial crises. Second, the model-based approach allows for the identification of systemic financial stress events in real time, while expert-based episodes are only updated occasionally. Third, in order to measure the buildup of risks, early-warning models use past crises episodes to assess the predictive power of candidate leading indicators. Fourth, to analyze the effectiveness of macroprudential measures, policy actions should be evaluated throughout the cycle. A robust identification of periods of systemic financial stress provides valuable information for all these purposes.

Still, more efforts are needed for a disaggregated analysis of cyclical dynamics in specific market segments, such as the real estate market. As well, the broad definition of systemic stress events used in this paper may have to be adjusted for the analysis of disaggregated macroprudential policies. Nevertheless, the country-specific approach adopted here can be considered as a first step that should allow for a better analysis of domestic versus EU-wide policies.

A Graphical Appendix

Figure A.1: **Construction of the Financial Stress Index**

[a] We use the sovereign spread with respect to Germany to compute the CDIFF. For Germany, however, we use the real yield on 10-year government bonds to compute the CMIN.

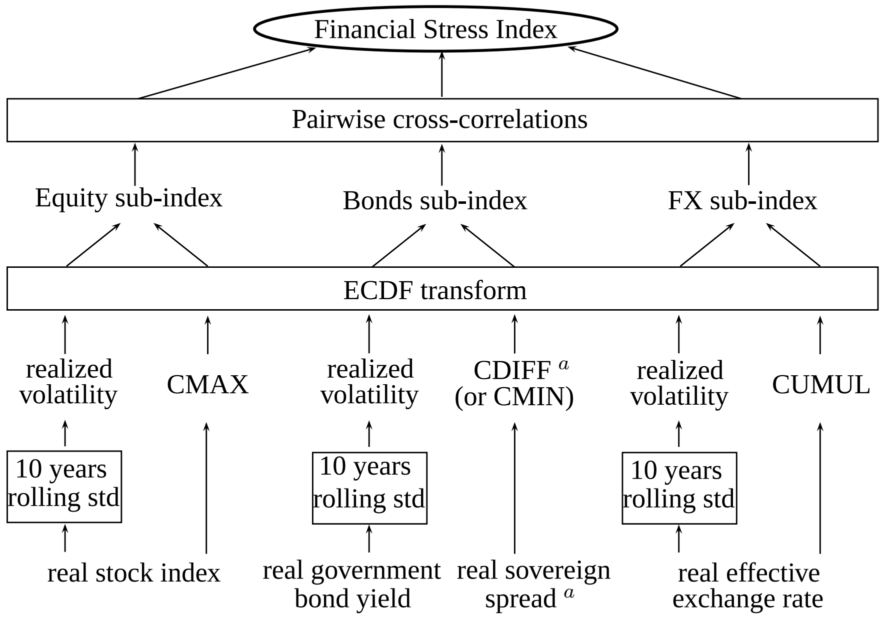


Figure A.2: **Identifying systemic financial stress episodes**

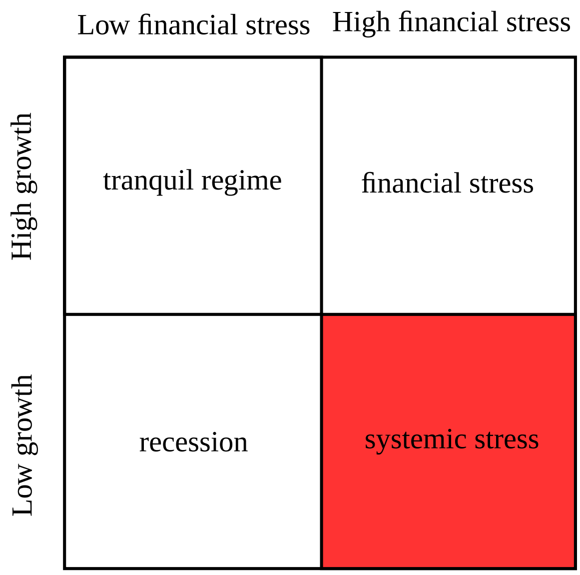


Figure A.3: **Industrial production growth per quantiles of FSI**

Note: This figure shows the average annual industrial production growth on the y-axis and the quantiles of the country-specific financial stress indices on the x-axis. The blue line corresponds to the country average, while the grey area corresponds to the 20th and 80th percentiles. The data are pooled both in the time and cross-sectional dimension over the 27 EU countries.

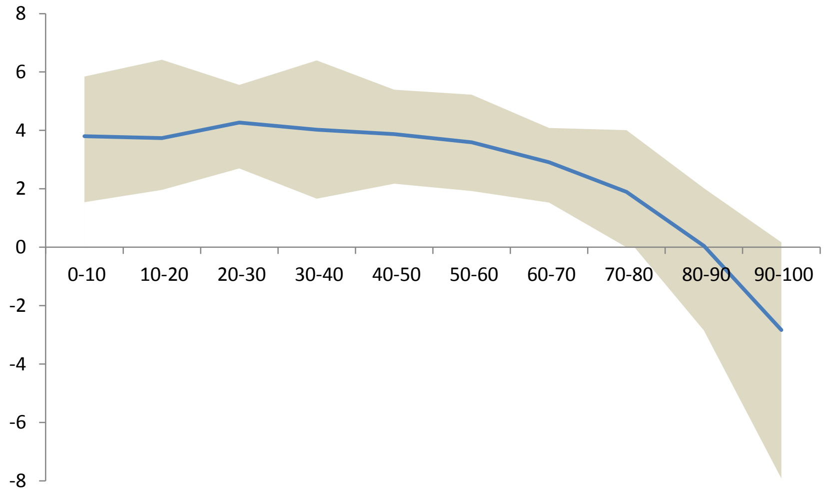


Figure A.4: **Decline in industrial production for different horizons conditional on high financial stress**

Note: The blue line shows average annual industrial production growth around the months following high financial stress. The dashed red line shows the difference between the average annual industrial production growth and its long-term trend around the months following high financial stress (FSI above its 90th percentile) on the x-axis. The long-term trend is obtained using a one-sided HP filter with a smoothing parameter $\lambda = 129600$. The x-axis refers to the months around the breach of the 90th percentile threshold identified in Figure A.3. Only cases where the FSI breaches the 90th percentile threshold for the first time over the previous 12 months are considered. Both lines are averages in the time and cross-sectional dimension over the 27 EU countries.

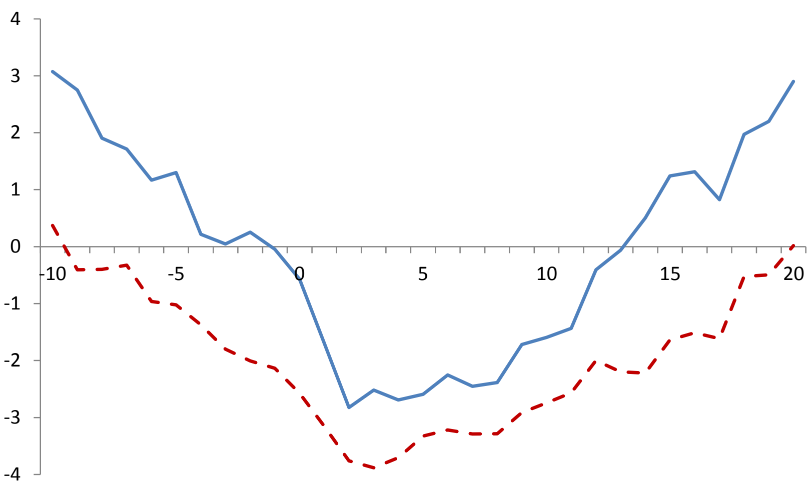


Figure A.5: **Chronology of systemic financial stress across countries**

Note: This figure shows the chronology of systemic financial stress across 27 EU countries. In the upper graph, systemic financial stress periods are in black while tranquil periods are in white. Stress episodes in dark grey correspond to periods where the financial stress started at least three months after the start of the real economic stress was identified using a decline in industrial production. Periods for which sufficient data were not available are in light grey. The lower graph focuses on the period starting in 2007 and countries are ranked based on the start date of the global financial crisis. The list of ISO country codes is provided in Table B.6.

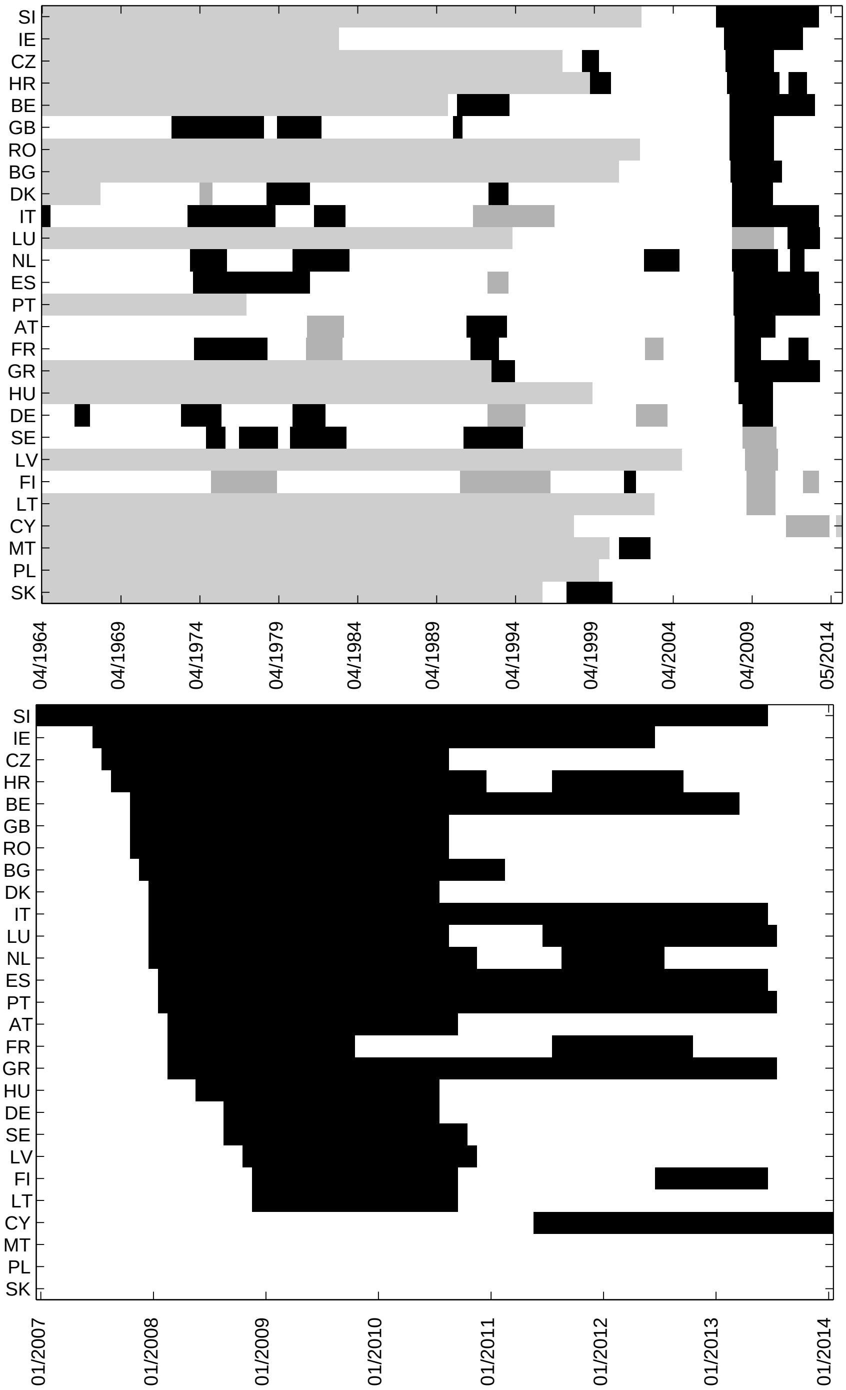
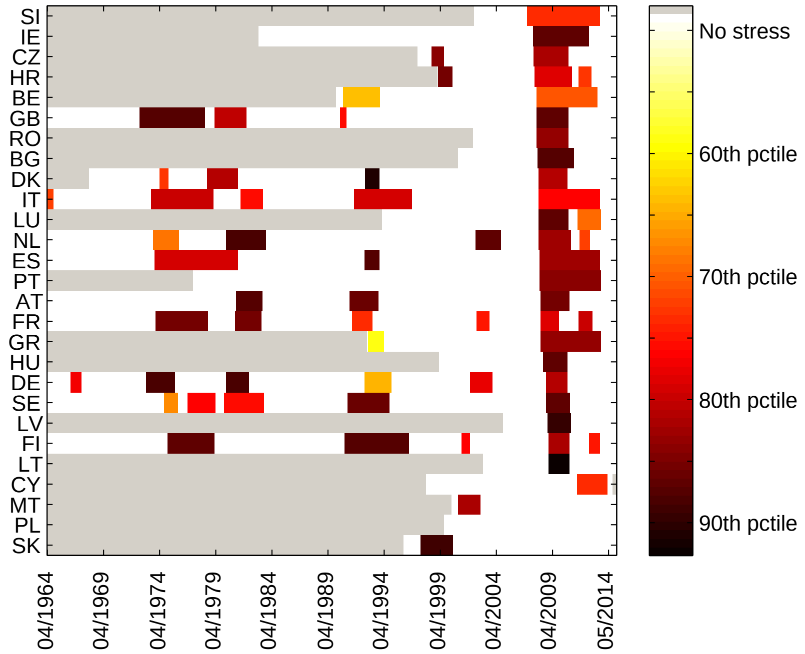


Figure A.6: **Intensity of financial market and real economic stress during periods of systemic financial stress**

Note: This figure shows the intensity of financial market and real economic stress during the periods of systemic financial stress in the 27 EU countries. In the upper graph, the average intensity of financial market stress during each systemic financial stress period is represented by the colours from yellow (low stress, FSI around 50th country-specific percentile) to black (high stress, FSI around 90th country-specific percentile). In the lower graph, the average intensity of real economic stress during each systemic financial stress period, as proxied by the industrial production index (IPI), is represented by the colours from yellow (low stress, small IPI loss from peak to trough) to black (high stress, IPI loss from peak to trough around 30%). Periods for which sufficient data were not available are in light grey. Countries are ranked based on the start date of the global financial crisis. The list of ISO country codes is provided in Table B.6.



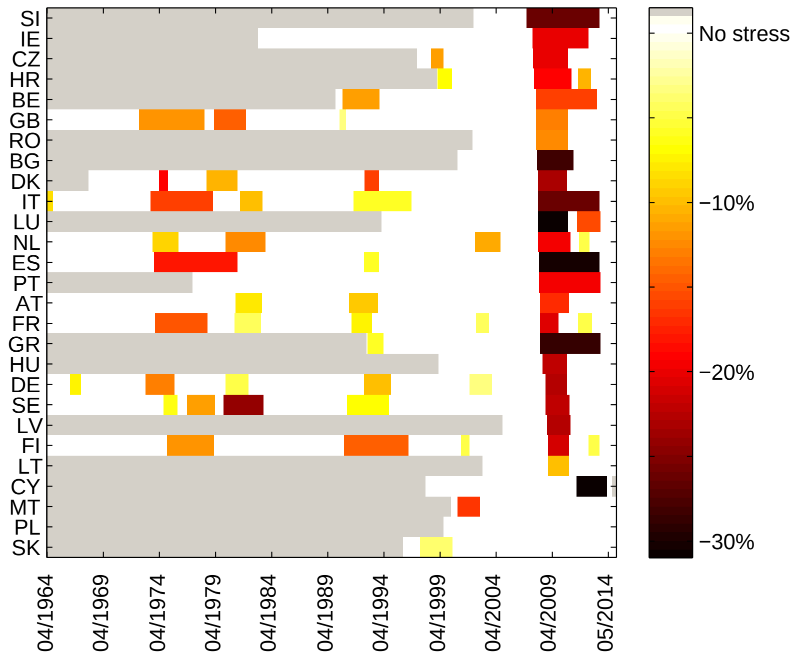


Figure A.7: **Crisis Simultaneity Index (CSI)**

Note: The crisis simultaneity index (CSI) corresponds to the share of countries experiencing systemic financial stress in a given month. The difference between the black line and the black area corresponds to those episodes of systemic financial stress where the real economic stress started before the financial market stress. The list of events is as follows: 1 - first oil shock; 2 - second oil shock; 3 - Mexican debt crisis; 4 - Black Monday; 5 - crisis of the European exchange rate mechanism; 6 - Peso crisis; 7 - Asian crisis; 8 - Russian crisis; 9 - dot com bubble; 10 - subprime crisis; 11 - Lehman Brothers; 12 - 1st bailout Greece; 13 - 2nd bailout Greece.

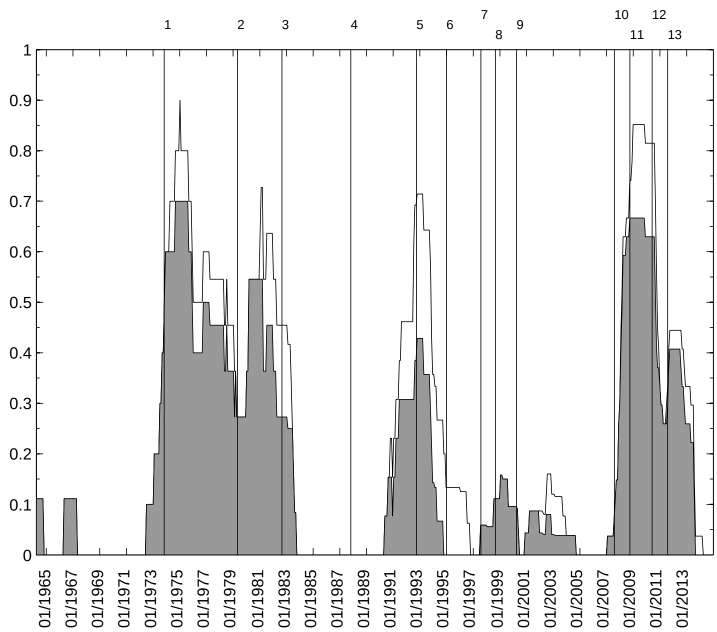


Figure A.8: **Financial Stress Index (FSI)**

Note: The figure displays the median as well as the 10th/90th percentile range of the financial stress index across EU-27 countries. See Figure A.7 above for the list of events.

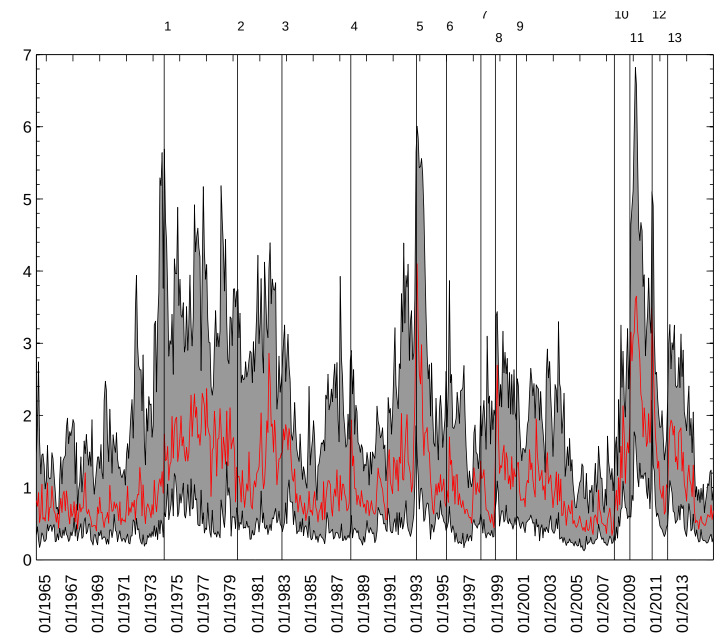


Figure A.9: **Comparison with all expert-based crises dates in the time dimension**

Note: This figure compares model-based systemic financial stress episodes with expert-based crises in the time dimension. The expert-detected crises correspond to those identified by Detken et al. (2014), Babecky et al. (2012) (banking, currency and debt crises), Laeven and Valencia (2013) and Reinhart and Rogoff (2011) (banking, currency, equity). The upper graph focuses on the “missed crises”. The left (right) axis shows the share (number) of expert-based crises not captured by the model-based approach as the black area (red line). The lower graph focuses on the “false alarms”. The left (right) axis shows the share (number) of systemic financial stress events not identified as crises by experts as the black area (red line).

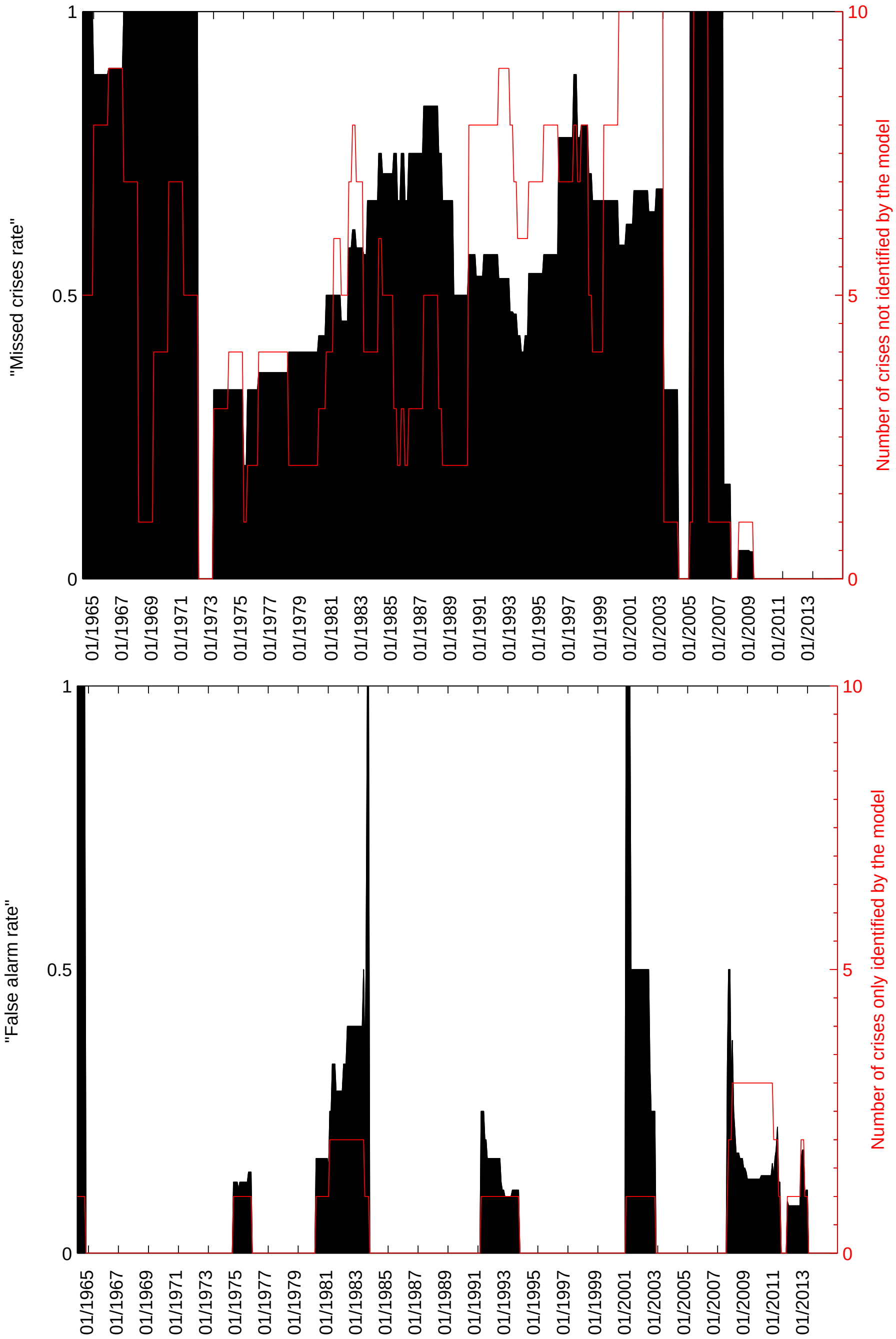


Figure A.10: **Comparison with Detken et al. (2014) dates in the time dimension**

Note: This figure compares model-based systemic financial stress episodes with crises from one particular expert database. The focus is on banking crises only. The left (right) axis shows the share (number) of crises identified by Detken et al. (2014) not captured by the model-based approach as the black area (red line).

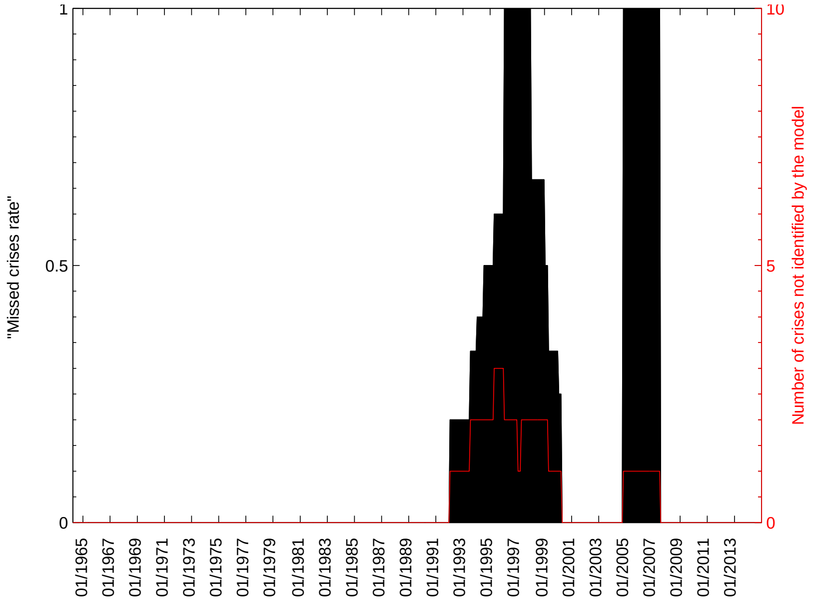


Figure A.11: **Comparison with Babecky et al. (2012) dates in the time dimension**

Note: This figure compares model-based systemic financial stress episodes with crises from one particular expert database. The events considered encompass currency, debt and banking crises. The left (right) axis shows the share (number) of crises identified by Babecky et al. (2012) not captured by the model-based approach as the black area (red line).

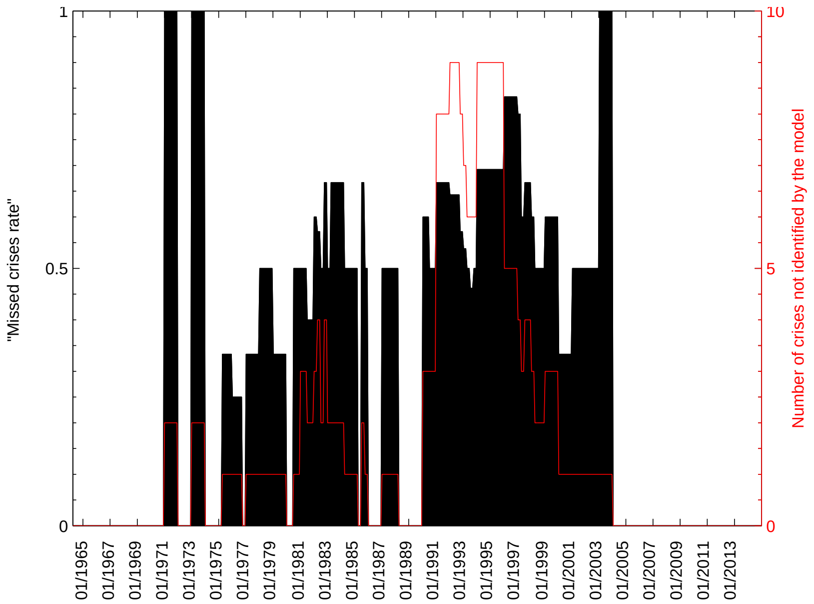
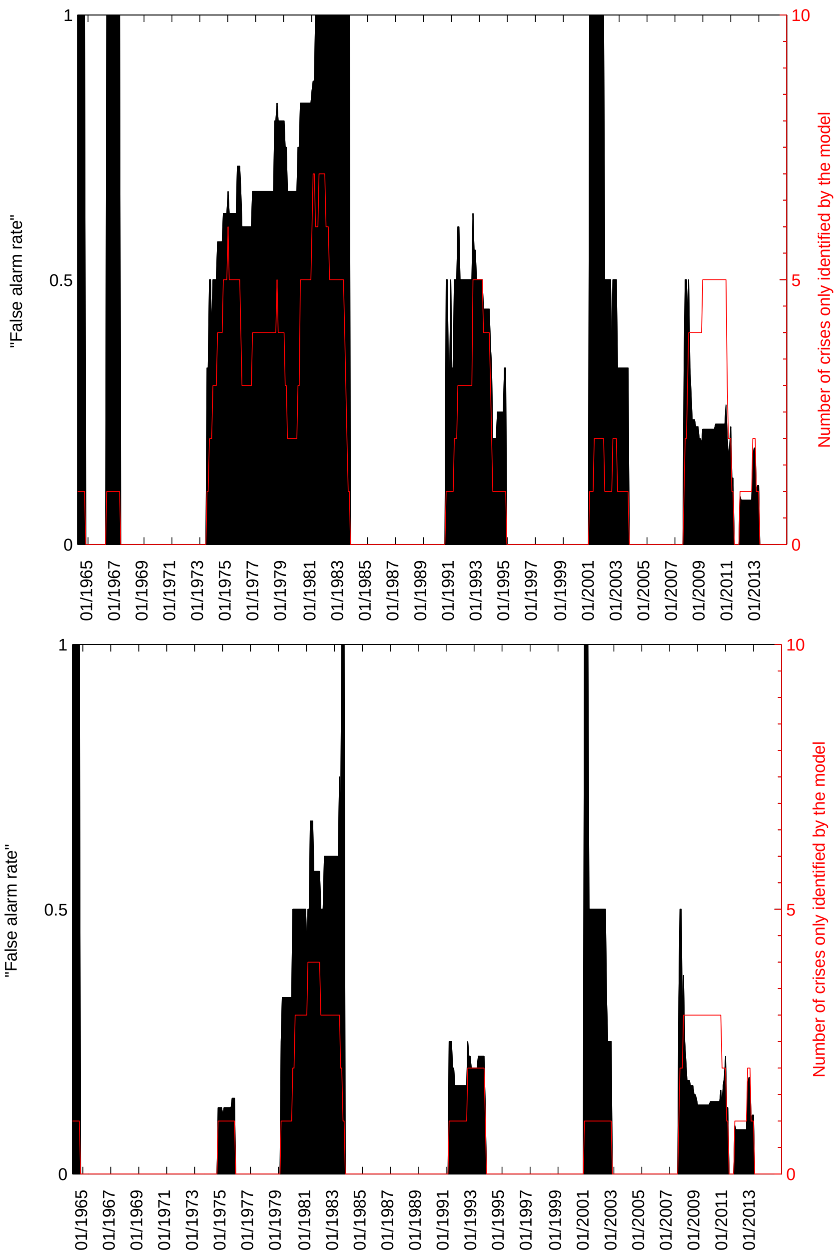


Figure A.12: **Comparison with all expert-identified systemic banking crises and stock market crashes in the time dimension**

Note: This figure compares model-based systemic financial stress episodes with expert-based crises in the time dimension. The expert-detected crises correspond to all banking crises identified by Detken et al. (2014), Babecky et al. (2012), Laeven and Valencia (2013) and Reinhart and Rogoff (2011) (the last dataset covers only 16 EU countries). Both the upper and the lower graphs focus on the “false alarms”. The left (right) axis shows the share (number) of systemic financial stress events not identified as crises by experts as the black area (red line). In the lower graph, the expert-based crises also include the stock market crashes identified by Reinhart and Rogoff (2011) for 16 EU countries. A large fraction of model-based stress episodes that are not identified as crises by experts are in fact stock market crashes.



B Table Appendix

Table B.1: **Results of the Markov-switching model and break tests**

	Crisis regime		Tranquil regime		Wald test $\mu_1 = \mu_2$		Breaks sequentially determined		Breaks globally determined	
	mean μ_1	std err $\ln(\sigma_1)$	mean μ_2	std err $\ln(\sigma_2)$	t-stat	F-stat	F-stat 0 vs. 1 break	Number of breaks	Significant F-stat largest	Schwarz criterion
AT	1.933	-0.262	0.684	-1.249	28	787	93	7	9	9
	(0.075)	(0.049)	(0.023)	(0.062)	(1.96)	(3.86)	(9.63)			
BE	1.867	-0.306	0.689	-1.205	-18	342	136	8	9	10
	(0.068)	(0.055)	(0.038)	(0.084)	(1.97)	(3.87)	(9.63)			
BG	2.571	-0.011	0.760	-0.936	16	263	67	9	10	8
	(0.171)	(0.299)	(0.039)	(0.081)	(1.97)	(3.90)	(9.63)			
CY	1.576	-0.579	0.614	-1.501	16	265	23	4	7	6
	(0.089)	(0.086)	(0.031)	(0.112)	(1.97)	(3.89)	(9.63)			
CZ	2.588	0.275	0.689	-1.212	-15	232	36	8	10	8
	(0.152)	(0.080)	(0.027)	(0.064)	(1.97)	(3.89)	(9.63)			
DE	2.103	-0.034	0.678	-1.171	23	546	91	4	10	10
	(0.073)	(0.046)	(0.021)	(0.051)	(1.96)	(3.86)	(9.63)			
DK	1.797	-0.249	0.623	-1.322	24	559	104	5	10	10
	(0.067)	(0.047)	(0.023)	(0.070)	(1.96)	(3.86)	(9.63)			
ES	2.096	-0.052	0.707	-1.178	-23	537	44	10	10	7
	(0.084)	(0.049)	(0.025)	(0.072)	(1.96)	(3.86)	(9.63)			
FI	2.954	0.249	0.959	-0.716	-29	831	149	6	8	8
	(0.108)	(0.052)	(0.027)	(0.038)	(1.96)	(3.86)	(9.63)			
FR	2.345	-0.152	0.847	-0.994	-28	774	126	8	10	10
	(0.078)	(0.053)	(0.022)	(0.042)	(1.96)	(3.86)	(9.63)			
UK	2.687	0.179	0.834	-0.897	25	636	59	10	10	9
	(0.110)	(0.052)	(0.026)	(0.046)	(1.96)	(3.86)	(9.63)			
GR	2.357	-0.090	0.653	-1.172	24	568	106	6	9	7
	(0.085)	(0.064)	(0.027)	(0.064)	(1.97)	(3.88)	(9.63)			
HR	1.581	-0.457	0.588	-1.352	15	222	24	4	4	4
	(0.094)	(0.087)	(0.031)	(0.100)	(1.97)	(3.89)	(9.63)			
HU	4.644	0.583	0.937	-0.608	-23	527	27	6	10	5
	(0.448)	(0.151)	(0.049)	(0.068)	(1.97)	(3.89)	(9.63)			
IE	3.045	0.378	0.810	-0.841	26	681	53	8	10	10
	(0.138)	(0.058)	(0.037)	(0.063)	(1.97)	(3.87)	(9.63)			
IT	2.095	0.055	0.597	-1.230	22	472	79	8	10	10
	(0.070)	(0.045)	(0.017)	(0.044)	(1.96)	(3.86)	(9.63)			
LT	3.366	-0.240	0.677	-1.049	26	687	30	4	6	4
	(0.180)	(0.171)	(0.033)	(0.068)	(1.98)	(3.91)	(9.63)			
LU	2.313	-0.078	0.936	-0.786	-13	161	29	8	10	10
	(0.123)	(0.077)	(0.050)	(0.076)	(1.97)	(3.88)	(9.63)			
LV	2.538	0.211	0.582	-1.548	18	336	44	4	6	5
	(0.231)	(0.127)	(0.024)	(0.081)	(1.98)	(3.92)	(9.63)			

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Note: This table reports in the first four columns the estimated parameters from the Markov-switching (MS) model, namely, the regime-specific mean and the regime-specific standard error (standard errors of the parameters are reported in parentheses). The fifth and sixth columns report the Wald test of the difference between the mean values of both MS regimes (critical values at the 5% level are reported in parentheses). Note that this test is computed for an MS model without regime-specific variance; otherwise, the asymptotic properties do not follow standard distributions. The last four columns report the results of testing for the presence of breaks in the FSI, which is a prerequisite for fitting an MS model. Critical values are reported in parentheses. The tests require at least 5% of observations per break and allow for heterogeneous error distributions across breaks. Reported results correspond to breaks that are significant at the 5% level using robust HAC standard errors. The list of ISO country codes is provided in Table B.6.

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	Crisis regime		Tranquil regime		Wald test $\mu_1 = \mu_2$		Breaks sequentially determined		Breaks globally determined	
	mean μ_1	std err $\ln(\sigma_1)$	mean μ_2	std err $\ln(\sigma_2)$	t-stat	F-stat	F-stat 0 vs. 1 break	Number of breaks	Significant F-stat largest	Schwarz criterion
MT	2.067	-0.305	0.883	-0.966	14	201	14	6	10	10
	(0.096)	(0.085)	(0.040)	(0.075)	(1.97)	(3.89)	(9.63)			
NL	1.731	-0.122	0.607	-1.353	-24	558	140	6	9	8
	(0.069)	(0.047)	(0.018)	(0.054)	(1.96)	(3.86)	(9.63)			
PL	1.890	-0.181	0.506	-1.463	20	394	87	8	7	8
	(0.110)	(0.085)	(0.027)	(0.095)	(1.97)	(3.89)	(9.63)			
PT	1.941	-0.346	0.550	-1.294	-26	669	88	10	10	10
	(0.068)	(0.063)	(0.017)	(0.043)	(1.97)	(3.86)	(9.63)			
RO	2.131	-0.271	0.733	-1.214	-15	221	58	4	6	8
	(0.101)	(0.092)	(0.033)	(0.081)	(1.98)	(3.90)	(9.63)			
SE	2.133	0.012	0.729	-1.119	-23	509	70	4	10	8
	(0.082)	(0.114)	(0.023)	(0.053)	(1.96)	(3.86)	(9.63)			
SI	2.064	-0.073	0.629	-1.464	-15	240	122	6	9	6
	(0.108)	(0.082)	(0.028)	(0.084)	(1.98)	(3.91)	(9.63)			
SK	2.208	-0.138	0.644	-1.129	19	365	44	8	9	7
	(0.162)	(0.109)	(0.027)	(0.063)	(1.97)	(3.88)	(9.63)			

Table B.2: **Real economic vs. systemic financial stress episodes**

	Ordinary recessions				Recessions with financial market stress			
Definition of recession in terms of GDP decline:	Number events	Length	GDP loss	FSI pcent	Number events	Length	GDP loss	FSI pcent
Two quarters	60	11	-0.62	44	84	17	-3.80	65
Two consecutive quarters	38	7	-1.46	41	48	13	-3.98	71
Before 2008 and two quarters	47	11	-0.44	46	48	13	-1.61	72
Before 2008 and two consecutive quarters	30	7	-1.42	42	27	9	-2.05	76

Note: This table provides summary statistics for two different types of stress events: (i) real economic stress periods (ordinary recessions), and (ii) systemic financial stress episodes (recessions coinciding with financial market stress). The following summary statistics are reported: the number of events across the 27 EU countries, the average length of the episodes in months, the average magnitude of GDP decline in percent, and the average percentile (*pcent*) of the FSI during one quarter prior to the start of the respective episode. Recessions correspond to periods of at least two quarters of GDP decline, either allowing for one quarter of recovery in-between, or limited to consecutive quarters of GDP decline. Systemic financial stress episodes correspond to recessionary periods coinciding with financial market stress, i.e. they are characterized by (i) high financial market stress identified by an MS model applied to the FSI, and (ii) at least six consecutive months of negative annual industrial production growth.

Table B.3: **Comparison of model-based systemic financial stress episodes with expert-based crises**

	Share of expert identified stress events among model-based events		Share of model identified crises dates among expert-based events	
	All banking crises	All experts crises	All banking crises	All experts crises
AT	0.33	0.33	1.00	1.00
BE	0.50	1.00	1.00	0.60
BG	0.00	0.00	0.00	
CY	1.00	1.00	1.00	1.00
CZ	0.50	0.50	1.00	1.00
DE	0.50	1.00	0.75	0.55
DK	0.50	1.00	1.00	0.57
ES	0.67	1.00	1.00	0.43
FI	0.20	0.80	1.00	0.67
FR	0.33	1.00	0.50	0.55
UK	0.75	1.00	0.75	0.57
GR	1.00	1.00	1.00	0.40
HR	0.33	0.33	1.00	1.00
HU	1.00	1.00	1.00	0.50
IE	1.00	1.00	0.50	0.17
IT	0.40	0.80	1.00	0.44
LT	1.00	1.00	1.00	1.00
LU	1.00	1.00	1.00	1.00
LV	1.00	1.00	1.00	1.00
MT	0.00	0.00		
NL	0.60	0.80	1.00	0.50
PL				
PT	1.00	1.00	0.50	0.14
RO	0.00	1.00		1.00
SE	0.40	0.80	1.00	0.50
SI	1.00	1.00	1.00	1.00
SK	1.00	1.00	1.00	1.00
Total	0.53	0.84	0.85	0.51
Mean	0.62	0.82	0.88	0.69

Note: This table compares the systemic financial stress episodes identified by the model-based approach with the crises episodes identified by experts, namely, Detken et al. (2014), Babecky et al. (2012), Laeven and Valencia (2013). The first and third crisis databases focus on banking crises only, while the second crisis database includes banking, currency and debt crises. We also report statistics for the 16 EU countries of the Reinhart and Rogoff (2011) crisis database, which includes banking and currency crises as well as stock market crashes. The *All banking crises* columns pool the banking crises of all four crises databases. The *All experts crises* columns pool all crises types of all four crises databases. We compute two ratios to capture the extent of the similarity between the model-based systemic financial stress episodes and the expert-based crises. First, the share of expert-identified stress events among model-based events is defined as the share of systemic financial stress periods also identified by experts. Second, the share of model-identified crises dates among expert-identified events is defined as the share of expert-based crises also identified by the model-based approach. We compute the ratios only on the relevant time spans for which both expert- and model-based episodes are available. The ratio cannot be computed when the denominator is zero or non-available. *Total* refers to the ratio over all episodes. *Mean* refers to the average across countries. The list of ISO country codes is provided in Table B.6.

Table B.4: **Expert-based crises captured by the model-based approach**

	Detken et al.	Babecky et al. Banking	Babecky et al. Currency	Babecky et al. Debt	Leaven Valencia	Reinhart and Rogoff Banking	Reinhart and Rogoff Currency	Reinhart and Rogoff Equity
AT		1.00			1.00			
BE		1.00	1.00		1.00	1.00	0.00	0.67
BG	0.00							
CY	1.00							
CZ	1.00	1.00	0.00		1.00			
DE	1.00	0.67			1.00	0.50	0.00	0.75
DK	1.00	1.00	0.50		1.00	1.00	1.00	0.50
ES	1.00	1.00	0.67		1.00	1.00	0.33	0.20
FI	1.00	1.00	0.50		1.00	1.00	0.50	0.80
FR	0.50	0.50			1.00	0.50	0.33	0.60
UK	1.00	0.50	0.00		1.00	0.40	0.60	0.50
GR	1.00	1.00	0.00	1.00	1.00	1.00	0.00	0.80
HR	1.00				1.00			
HU	1.00	1.00		1.00	1.00	1.00	0.00	0.50
IE	1.00	0.67		1.00	1.00	1.00	0.00	0.50
IT	1.00	1.00	0.67		1.00	1.00	0.67	0.57
LT	1.00	1.00						
LU		1.00			1.00			
LV	1.00	1.00			1.00			
MT								
NL	1.00	1.00			1.00	1.00	0.00	0.60
PL							0.00	0.00
PT	0.50	1.00	0.00		1.00	1.00	0.00	0.00
RO							1.00	1.00
SE	1.00	1.00	1.00	1.00	1.00	1.00	0.80	0.50
SI	1.00	1.00			1.00			
SK		1.00			1.00			
Total	0.89	0.85	0.56	1.00	1.00	0.78	0.36	0.54
Mean	0.90	0.92	0.43	1.00	1.00	0.89	0.33	0.53

Note: This table reports the ratio of expert-identified crises also captured by the model-based approach. The following expert databases are included: Detken et al. (2014), Babecky et al. (2012), Laeven and Valencia (2013), and Reinhart and Rogoff (2011). The first and third crisis databases focus on banking crises only, while the second crisis database includes banking, currency and debt crises. We also report statistics for the 16 EU countries of the Reinhart and Rogoff (2011) crisis database, which includes banking and currency crises as well as stock market crashes. We compute the ratios only on the relevant time spans for which both expert- and model-based episodes are available. An empty cell indicates that the country was not covered by the experts (Croatia in the Babecky et al. (2012) database and eleven countries in the Reinhart and Rogoff (2011) database), or that experts did not identify crises periods. *Total* refers to the ratio over all episodes. *Mean* refers to the average across countries. The list of ISO country codes is provided in Table B.6.

Table B.5: **Model-based systemic financial stress episodes**

Country	**Code**	**Start date**	**End date**	**Max CSI**	**Mean CSI**	**Max % FSI**	**Mean % FSI**	**IP loss**	**Number month loss**	**Banking**	**Equity**	**Debt**	**Currency**
Austria	AT	1981 February	1983 May	0.73	0.52	0.99	0.87	0.08	7				
Austria	AT	1991 March	1993 September	0.71	0.55	1.00	0.86	0.09	12				
Austria	AT	2008 March	2010 September	0.85	0.78	1.00	0.85	0.17	16	✓			
Belgium	BE	1990 August	1993 November	0.71	0.48	1.00	0.64	0.11	14		✓		✓
Belgium	BE	2007 November	2013 March	0.85	0.57	1.00	0.71	0.16	15		✓		
Bulgaria	BG	2007 December	2011 February	0.85	0.70	1.00	0.88	0.28	17	✓			
Croatia[a]	HR	1999 January	2000 April	0.16	0.12	1.00	0.85	0.07	4	✓			
Croatia	HR	2007 September	2010 December	0.85	0.68	0.98	0.79	0.19	22				
Croatia	HR	2011 August	2012 September	0.44	0.44	0.95	0.73	0.10	9				
Cyprus[b c]	CY	2011 June	2014 February	0.44	0.31	0.97	0.73	0.31	33	✓			

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Note: This table reports the episodes of systemic financial stress as identified by the model-based approach. These stress episodes are identified using an MS model that is applied to each country-specific FSI and a filtering algorithm that selects those financial stress episodes associated with a substantial and prolonged decline in real economic activity. *Max CSI* and *Mean CSI* correspond to the maximum and average crisis simultaneity index (CSI) during the period of systemic financial stress, respectively. The CSI reflects the share of the 27 EU countries experiencing systemic financial stress at the same time and thus provides an indication of the simultaneity or commonality of the shock. *Max % FSI* and *Mean % FSI* refer to the maximum and mean percentiles of the FSI during each systemic financial stress episode. The percentiles are computed for each country separately. *IP loss* is the loss from peak to trough of industrial production during the real economic stress period that corresponds to the period of systemic financial stress. *Number month loss* provides the number of months of consecutive decline in industrial production since the start of the systemic financial stress. The last four columns display the types of crises identified by experts (Detken et al., 2014; Babecky et al., 2012; Laeven and Valencia, 2013; Reinhart and Rogoff, 2011) that, if any, overlap at least partly with our model-based events.

[a] This episode was identified at the beginning of the sample, and thus only the end date of the event should be considered. The systemic financial stress might have started earlier.

[b] The real economic stress (a prolonged decline in industrial production) started at least one quarter prior to the identified period of financial market stress.

[c] The data quality of the 10-year government bond yield of Cyprus is limited, which may reduce the informational content of our FSI, and the dating of systemic stress should be taken as indicative only.

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Country	Code	Start date	End date	Max CSI	Mean CSI	Max % FSI	Mean % FSI	IP loss	Number month loss	Banking	Equity	Debt	Currency
Czech Republic	CZ	1998 July	1999 July	0.16	0.13	0.97	0.84	0.11	13	✓			
Czech Republic	CZ	2007 August	2010 August	0.85	0.69	1.00	0.82	0.20	17				
Denmark[b]	DK	1974 April	1975 January	0.90	0.76	0.92	0.73	0.19	15				
Denmark	DK	1978 July	1981 March	0.73	0.45	0.98	0.81	0.11	8		✓		✓
Denmark	DK	1992 August	1993 October	0.71	0.67	1.00	0.91	0.16	9	✓	✓		✓
Denmark	DK	2008 January	2010 July	0.85	0.77	0.99	0.81	0.23	23	✓	✓		✓
Finland	FI	1975 January	1979 February	0.90	0.58	0.98	0.87	0.12	16		✓		✓
Finland[b]	FI	1990 October	1996 June	0.71	0.36	1.00	0.88	0.14	17	✓	✓		✓
Finland	FI	2001 March	2001 November	0.09	0.09	0.88	0.76	0.05	7		✓		
Finland	FI	2008 December	2010 September	0.85	0.82	0.96	0.82	0.21	15		✓		
Finland[b]	FI	2012 July	2013 June	0.44	0.35	0.87	0.75	0.05	29				
France	FR	1973 December	1978 July	0.90	0.62	1.00	0.86	0.15	14		✓		✓
France[b]	FR	1981 January	1983 April	0.73	0.53	1.00	0.86	0.04	8		✓		
France	FR	1991 June	1993 March	0.71	0.55	0.98	0.74	0.08	21		✓		
France[b]	FR	2002 July	2003 August	0.16	0.13	0.89	0.75	0.04	15		✓		
France	FR	2008 March	2009 October	0.85	0.78	0.99	0.78	0.21	20	✓	✓		
France	FR	2011 August	2012 October	0.44	0.43	0.94	0.80	0.05	16	✓			
Germany	DE	1966 May	1967 April	0.11	0.11	0.88	0.77	0.07	14		✓		
Germany	DE	1973 February	1975 August	0.90	0.60	1.00	0.88	0.13	16	✓	✓		
Germany	DE	1980 March	1982 March	0.73	0.59	1.00	0.88	0.05	12		✓		
Germany	DE	1992 July	1994 November	0.71	0.50	0.99	0.64	0.10	19		✓		
Germany[b]	DE	2001 December	2003 November	0.16	0.11	0.95	0.78	0.04	10	✓	✓		
Germany	DE	2008 September	2010 July	0.85	0.82	1.00	0.81	0.23	16	✓	✓		

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[b] The real economic stress (a prolonged decline in industrial production) started at least one quarter prior to the identified period of financial market stress.

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Country	Code	Start date	End date	Max CSI	Mean CSI	Max % FSI	Mean % FSI	IP loss	Number month loss	Banking	Equity	Debt	Currency
Greece[a]	GR	1992 October	1994 March	0.71	0.58	0.70	0.59	0.06	9	✓	✓		
Greece	GR	2008 March	2013 July	0.85	0.56	1.00	0.83	0.28	49	✓	✓	✓	
Hungary	HU	2008 June	2010 July	0.85	0.81	1.00	0.87	0.22	17	✓	✓	✓	
Ireland	IE	2007 July	2012 June	0.85	0.57	1.00	0.87	0.20	8	✓	✓	✓	
Italy	IT	1964 February	1964 October	0.11	0.11	0.88	0.72	0.08	6				
Italy	IT	1973 July	1979 January	0.90	0.59	1.00	0.79	0.16	15		✓		✓
Italy	IT	1981 July	1983 June	0.64	0.49	0.97	0.75	0.10	15		✓		✓
Italy[b]	IT	1991 August	1996 September	0.71	0.36	1.00	0.79	0.06	3	✓	✓		✓
Italy	IT	2008 January	2013 June	0.85	0.57	0.99	0.77	0.26	18	✓	✓		
Latvia[b]	LV	2008 November	2010 November	0.85	0.78	1.00	0.89	0.23	14	✓			
Lithuania	LT	2008 December	2010 September	0.85	0.82	1.00	0.93	0.10	15	✓			
Luxembourg[b]	LU	2008 January	2010 August	0.85	0.77	1.00	0.87	0.31	3	✓			
Luxembourg	LU	2011 July	2013 July	0.44	0.38	0.95	0.70	0.16	24	✓			
Malta	MT	2000 November	2002 October	0.16	0.09	0.98	0.82	0.16	13				

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[a] This episode was identified at the beginning of the sample, and thus only the end date of the event should be considered. The systemic financial stress might have started earlier.
[b] The real economic stress (a prolonged decline in industrial production) started at least one quarter prior to the identified period of financial market stress.

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Country	Code	Start date	End date	Max CSI	Mean CSI	Max % FSI	Mean % FSI	IP loss	Number month loss	Banking	Equity	Debt	Currency
Netherlands[d]	NL	1973 September	1975 December	0.90	0.70	0.96	0.69	0.09	12		✓		
Netherlands	NL	1980 March	1983 September	0.73	0.50	1.00	0.88	0.13	8				
Netherlands	NL	2002 June	2004 August	0.16	0.09	1.00	0.87	0.11	6	✓	✓		
Netherlands	NL	2008 January	2010 November	0.85	0.74	1.00	0.82	0.20	14	✓	✓		
Netherlands	NL	2011 September	2012 July	0.44	0.44	0.86	0.72	0.05	6	✓			
Portugal	PT	2008 February	2013 July	0.85	0.56	0.99	0.84	0.19	22	✓			
Romania	RO	2007 November	2010 August	0.85	0.74	1.00	0.83	0.13	12		✓		✓
Slovakia	SK	1997 July	2000 May	0.16	0.09	1.00	0.89	0.04	6	✓			
Slovenia	SI	2007 January	2013 June	0.85	0.49	1.00	0.74	0.26	13	✓			
Spain[b]	ES	1973 November	1981 March	0.90	0.56	1.00	0.79	0.18	7	✓	✓		✓
Spain	ES	1992 July	1993 October	0.71	0.67	0.99	0.87	0.06	16				✓
Spain	ES	2008 February	2013 June	0.85	0.57	1.00	0.83	0.30	22	✓			
Sweden	SE	1974 September	1975 November	0.90	0.79	0.88	0.67	0.07	14				
Sweden	SE	1976 October	1979 March	0.60	0.52	0.97	0.76	0.11	20		✓		✓
Sweden	SE	1980 January	1983 July	0.73	0.51	0.98	0.76	0.24	22				✓
Sweden	SE	1991 January	1994 September	0.71	0.47	1.00	0.86	0.07	13	✓	✓	✓	✓
Sweden[b]	SE	2008 September	2010 October	0.85	0.79	1.00	0.87	0.22	16	✓	✓		✓
United Kingdom	UK	1972 July	1978 April	0.90	0.53	1.00	0.88	0.12	13	✓	✓		✓
United Kingdom	UK	1979 March	1981 December	0.73	0.49	0.96	0.80	0.15	19				
United Kingdom[b]	UK	1990 May	1990 November	0.23	0.14	0.88	0.76	0.03	20	✓			
United Kingdom	UK	2007 November	2010 August	0.85	0.74	0.99	0.87	0.13	20	✓	✓		

[b] The real economic stress (a prolonged decline in industrial production) started at least one quarter prior to the identified period of financial market stress.
[d] This episode does not always meet the criteria to be classified as a systemic financial stress period when the model-based approach is applied on a rolling window by including new data progressively starting with an initial window of 25 years.

Table B.6: **List of countries covered in the article**

	ISO code
Austria	AT
Belgium	BE
Bulgaria	BG
Croatia	HR
Cyprus	CY
Czech Republic	CZ
Denmark	DK
Finland	FI
France	FR
Germany	DE
Greece	GR
Hungary	HU
Ireland	IE
Italy	IT
Latvia	LV
Lithuania	LT
Luxembourg	LU
Malta	MT
Netherlands	NL
Portugal	PT
Romania	RO
Slovakia	SK
Slovenia	SI
Spain	ES
Sweden	SE
United Kingdom	UK

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