Occasional Paper Series

No 13 / July 2017

Updated December 2021

# A new database for financial crises in European countries

## ECB/ESRB EU crises database

*Developed by FSC MPAG and ESRB AWG*

by
Marco Lo Duca
Anne Koban
Marisa Basten
Elias Bengtsson
Benjamin Klaus
Piotr Kusmierczyk
Jan Hannes Lang
Carsten Detken (editor)
Tuomas Peltonen (editor)

ESRB
European Systemic Risk Board
European System of Financial Supervision

# Contents

# Abstract

This paper presents a new database for financial crises in European countries, which serves as an important step towards establishing a common ground for macroprudential oversight and policymaking in the EU. The database focuses on providing precise chronological definitions of crisis periods to support the calibration of models in macroprudential analysis. An important contribution of this work is the identification of financial crises by combining a quantitative approach based on a financial stress index with expert judgement from national and European authorities. Key innovations of this database are (i) the inclusion of qualitative information about events and policy responses, (ii) the introduction of a broad set of non-exclusive categories to classify events, and (iii) a distinction between event and post-event adjustment periods. The paper explains the two-step approach for identifying crises and other key choices in the construction of the dataset. Moreover, stylised facts about the systemic crises in the dataset are presented together with estimations of output losses and fiscal costs associated with these crises. A preliminary assessment of the performance of standard early warning indicators based on the new crises dataset confirms findings in the literature that multivariate models can improve compared to univariate signalling models.

**Keywords:** financial crises, macroprudential, crises database, early warning models, central bank statistics.

**JEL codes:** G01, E44, E58, E60, H12.

# Executive Summary

This occasional paper presents a new financial crises database[1] for European countries. The database focuses on providing precise chronological definitions of crisis events to support the calibration of models in macroprudential analysis and policy. The dataset will be an important tool for the ECB, the ESRB, and national authorities (NAs) and will inform financial stability analyses and discussions in policy committees. Its creation presents an important step towards establishing a common ground for macroprudential oversight and policymaking in the EU.

The database was developed under the umbrella of the Financial Stability Committee (FSC) of the Eurosystem and of the Advisory Technical Committee (ATC) of the European Systemic Risk Board (ESRB), which will be the main users of the dataset.[2] The dataset was created following common principles and rules. A key strength of the new crises database is that it benefited from the financial stability expertise of the national and European authorities represented in the aforementioned committees.

This dataset brings a number of innovations and amendments relative to the existing crises datasets in a number of ways. First, this dataset provides a unique and detailed overview of crises episodes specific to European countries, which are validated by financial stability experts from a wide range of policy institutions. Second, from a technical point of view, it identifies crises by combining a quantitative approach based on a financial stress index with expert judgement from national and European authorities. This approach ensures a more precise definition of crisis periods and also enables the separation between crisis and post-crisis adjustment periods, which facilitates the estimation and calibration of models. Third, the database also introduces a broad set of non-exclusive categories to classify events on the basis of the risks that materialised and the underlying causes of events (e.g. external vs domestic imbalances). This information is key in selecting the relevant set of events for the calibration or estimation of models designed to study specific aspects of crises. Finally, the dataset also provides qualitative information about the events and policy responses, which allows users of the dataset to better understand the nature of the events in the database.

The crises dataset covers all EU Member States and Norway for the period 1970-2016 and consists of a core set of 50 systemic crises, which fulfil a number of conditions including (i) the financial system acting as a shock originator or amplifier and/or (ii) systemic financial intermediaries experiencing distress or going bankrupt and/or (iii) substantial crisis management policy interventions.

The dataset covers crises from 1970 until 2016, and offers a relatively rich set of information with a particular focus on the delimitation of events and event descriptions, compared to existing crises datasets, e.g. Detken et al. (2014), Babecký et al. (2012) and Laeven and Valencia (2013).

The majority of the identified systemic crises are complex events which entail the materialisation of different risks. These include instability in the banking sector, sudden adjustments of external positions (i.e. currency or balance of payment adjustments), sovereign risk and significant asset price corrections (including in real estate markets). The majority of the identified systemic crises are related to combinations of pre-existing domestic and external imbalances, while a smaller number

1 See the **database**.

2 The central bank of Norway also contributed to the project.

of crises are of a purely domestic nature. The analysis of costs of the identified systemic crises shows high output losses regardless of the type of risks that materialised.

A preliminary assessment of the performance of standard early warning indicators based on the new crises dataset confirms the finding in the early warning model literature that multivariate models can improve compared to univariate signalling models. Interestingly, gap variables (e.g. credit gaps) are found to have slightly less information content for signalling systemic events than more simple transformations such as changes in ratios relative to GDP or growth rates.

For transparency purposes, the dataset also reports, separately, a set of 43 residual episodes of financial (market) stress, which were examined but not included in the final set of systemic crises.

Going forward, the dataset will allow researchers to analyse crises along several dimensions and draw relevant implications for macroprudential analysis and policy. The crises database will be updated on a regular basis.

# Section 1
# Introduction

This occasional paper presents a new financial crises database for European countries. It is an important step towards establishing common ground for macroprudential oversight and policymaking in the EU. The database focuses on the delimitation of crisis events to support the calibration of models in macroprudential analysis and policy. In delimiting crisis events, a quantitative crises identification approach has been cross-checked with expert judgement from national and European authorities, which is an innovative contribution to the literature on crises identification. In addition to this, the key innovations are (i) a distinction between event and post-event adjustment periods (ii) the introduction of a broad set of non-exclusive categories to classify events, and (iii) the inclusion of qualitative information about events and policy responses. Moreover, a regular review process will ensure that this dataset is updated on a regular basis.

The database was created under the umbrella of the Financial Stability Committee (FSC) of the Eurosystem and of the Advisory Technical Committee (ATC) of the European Systemic Risk Board (ESRB). The dataset covers all EU countries plus Norway and was created following common principles and rules, benefiting from the financial stability expertise of the national authorities (NAs) represented in the committees and working groups. In particular, two technical committees, the Macroprudential Analysis Group (MPAG) of the Eurosystem and the Analysis Working Group (AWG) of the ESRB, created the dataset, ensuring quality and consistency, and will update the crises database regularly. The database supports these groups in fulfilling their mandates in several areas.

First, the dataset is a key instrument for the identification of leading crisis indicators, the estimation of early warning models and related signalling thresholds (Alessi and Detken, 2011; Berg and Pattillo, 2000; Berg et al. 2004; Bussière and Fratzscher, 2006 and 2008; Detken et al., 2014; Edison, 2003; Frankel and Rose, 1996; Kaminsky and Reinhart, 1999; Lo Duca and Peltonen, 2013). The credibility of analytical approaches to predict crises strongly relies on the ex-ante identification and definition of past crises events. A precise event chronology leads to more accurate analysis and better models that support decision-making.[3] Conversely, an imprecise classification of past events can result in model misspecifications that could contribute to suboptimal policy decisions.

Second, in view of the dialogue among the institutions with macroprudential responsibilities in Europe, including NAs, the ECB and the ESRB, it is important to establish joint analytical frameworks and common databases. A common and agreed crisis chronology naturally complements the efforts by the ECB to establish a macroprudential database[4] of indicators for identifying and assessing risks, predicting crises and evaluating policies. The common crises database, together with the common macroprudential database, will allow researchers and policymakers across the European Union to work on a common framework of reference when identifying best crisis predictors and early warning thresholds. The existence of an agreed and credible crises chronology will enhance the credibility and transparency of the analytical work that relies on it, facilitating the dialogue between policymakers.

---

3 Tölö et al. (forthcoming) show that the early warning properties of models and indicators are sensitive to the crisis definition periods.

4 The Macroprudential Database (MPDB) is available in the **ECB Statistical Data Warehouse**.

Finally, this dataset brings a number of innovation and amendments relative to the existing crises datasets. First, the new dataset focuses on the delimitation of events, including identifying start and end dates for events. The proposed approach for identifying crises bridges the gap between "qualitative" (Laeven and Valencia, 2008 and 2013; Babecký et al., 2012; Reinhart and Rogoff, 2008 and 2009; Detken et al., 2014) and "quantitative" (Frankel and Rose, 1996; Lo Duca and Peltonen, 2013) methods to delimit crises. It does so by combining a mechanic approach to identifying relevant events with qualitative information provided by NAs on the basis of common definitions and criteria to decide on whether the events detected can be considered as systemic crises. As part of this process, additional information on events, including details about crisis policies, was collected from NAs. This makes this dataset more complete than the databases by Detken et al. (2014) and Babecký et al. (2012) in terms of the richness of the qualitative information on the events. Second, the dataset presents a distinction between crisis and post-crisis adjustment periods. Specifically, this crises database separates the acute phase of the event, between the starting date and the date when the last crisis management policy was adopted, and the post-crisis adjustment period (Bussière and Fratzscher, 2008), between the end of crisis management and the moment when the system is considered to be back to a "normal mode". This separation improves the analysis of crises and facilitates the estimation of early warning models by addressing the "post crisis bias". Third, in constructing this crisis dataset, events identified by Laeven and Valencia (2013) and Babecký et al. (2012) were also critically reviewed. In particular, events that were not identified by the approach adopted in this exercise, but were included in Laeven and Valencia (2013) and Babecký et al. (2012), were also submitted to NAs for revision in order to assess whether they should be included in the ECB/ESRB EU crises dataset.

The overall consistency of the dataset was checked along several dimensions. First, the authors and the editors ensured that the information provided was in line with the agreed common guidelines, including definitions and criteria. Second, the editorial team checked that the overall picture provided by the dataset was consistent across countries and over time.

The crises dataset covers all EU Member States and Norway for the period 1970-2016 and consists of the following.

1. **A core set of 50 systemic crises.** The list of systemic crises (the core part of the dataset) contains (i) systemic crises which were identified by a financial stress index and afterwards reviewed by NAs and (ii) other crises episodes flagged by NAs and/or in the related literature. A crisis is considered systemic when it satisfies a number of the criteria described in detail in the next section. In particular, a systemic crisis entails (i) the financial system acting as a shock originator or amplifier and/or (ii) systemic financial intermediaries experiencing distress or going bankrupt and/or (iii) substantial crisis management policy interventions.
2. **A set of 43 residual episodes of financial (market) stress,**[5] which were, however, not associated with a systemic crisis. These episodes, which are reported for transparency purposes, were either flagged by NAs or identified by the financial stress index approach, but do not fulfil the criteria for a systemic crisis. Some of these episodes were included in other crises datasets (Laeven and Valencia, 2008 and 2013; Reinhart and Rogoff, 2008 and 2009; Babecký, 2012). The episodes of financial stress are kept in a separate file in the dataset as they could still be useful for studying the resilience of the financial sector under stress. Given the very diverse nature of these episodes of financial stress, NAs have provided information on whether or not they consider individual episodes relevant for macroprudential analysis.

---

[5] The systemic crises and the residual events are reported in separate spreadsheets of the excel file containing the crisis dataset.

For all the above episodes, the database contains information on starting and ending dates, on crisis management and resolution policies, and other qualitative and quantitative information in order to enable its users to better understand underlying choices and to enhance transparency in the construction of event chronologies. For each event, the dataset reports the type of risk that materialised (currency/balance of payment capital flows, sovereign risk, bank risk, significant repricing in asset markets).

Section 2 of this paper explains key choices in the construction of the dataset, Section 3 provides stylised facts about the systemic crises in the dataset and Section 4 discusses the performance of standard signalling indicators and early warning models when estimated using the new dataset. Finally, Section 5 concludes and Annex A reports definitions of the fields in the crises dataset.

# Section 2
# Key choices in the construction of the dataset

This section gives an overview of how the crises database was constructed and explains the overall approach for identifying crises, as well as additional information which was collected for the creation of the dataset.

## 2.1 Two-step approach for identifying crises

There is a two-step approach for identifying crises: the first step consists of a quantitative analysis to identify historical episodes of elevated financial stress which were also associated with economic slowdowns (for details about the financial stress index, see Section 2.1.1). This step generates a preliminary list of potential events for consideration.[6] Episodes detected by Laeven and Valencia (2013) and Babecký et al. (2012) are added to this list if they were not detected by the financial stress index In the second step, National Authorities review the potential list of events in order to identify potential type I errors, and add events, which were not detected by the quantitative approach.[7] On the basis of the common criteria and expert judgement available in the respective institutions, the National Authorities introduce the distinction between systemic crises and residual episodes of financial stress and also specify for each residual episode, whether it is considered to be relevant from a macroprudential perspective.

This approach bridges the gap between qualitative and quantitative methods for crisis identification proposed by practitioners and academics. In the quantitative approach crises are identified by mechanic rules based on financial stress indexes. This approach, which was initially used to identify currency crises with an exchange rate pressure index (Frankel and Rose, 1996), is based on the idea that extreme financial stress can be observed when market participants' expectations start incorporating the future negative economic and financial outcomes of a crisis (Lo Duca and Peltonen, 2013). The qualitative method instead relies on the qualitative assessment of a number of indicators to detect financial crises. For example, in Laeven and Valencia (2008), a crisis occurs when defaults are widespread, non-performing loans increase and the capital of the banking system is exhausted.[8] By combining the qualitative and quantitative methods, the new crises dataset presented in this paper aims to exploit the complementarities between the two approaches: the quantitative part of the approach provides a list of potential events and a more objective criterion for identifying the start of an event. The qualitative part of the approach helps to separate systemic crises and potential "noise" or less relevant episodes. In addition, it helps to delimit the length of the crisis and the subsequent adjustment phase. Our approach is similar to Babecký et al. (2012) who validate a list of potential crisis events with a survey among country experts. In the new crisis dataset, however, potential crisis events are detected using a different method, which

---

6 For Estonia, the calculation of the financial stress index was not possible due to the limited availability of data. Estonian authorities were therefore asked to identify potential episodes of financial stress with real economic consequences using expert judgement and available indicators. A number of other countries also flagged other episodes of financial stress that were not identified by the financial stress index, probably due to thin markets in the earlier part of the sample.

7 These type II errors mainly occurred in Eastern European countries prior to the fall of the Iron curtain, as data availability and reliability significantly affected the robustness of the results of the quantitative approach. In the case of one country (Estonia), severe data gaps made the identification of events via the quantitative approach impossible.

8 A working definition of crisis events similar to that of Laeven and Valencia (2008) is adopted in several other studies, including Kaminsky and Reinhart (1999), Demirgüç-Kunt and Detragiache (2000), Berg and Pattillo (2000), Borio and Lowe (2002, 2004), Edison (2003), Berg et al. (2004), Bussière and Fratzscher (2006), Reinhart and Rogoff (2008, 2009), Schularick and Taylor (2011) and Jordá et al. (2011).

considers the real costs of crises. In addition, information on the events, including on crisis policies, was collected from NAs. This makes this dataset more complete than those produced by Babecký et al. (2012) and Detken et al. (2014) in terms of the richness of the qualitative information on the events.

The overall consistency of the final product was checked on several levels. First, the editorial team ensured that the information provided was in line with the agreed common guidelines, including the definitions and criteria. Second, the editorial team checked that the overall picture provided by the dataset was consistent across countries and over time.

### 2.1.1 Step 1: idenfication of a set of candidate crisis events with the financial stress index

In the first step, which is based on the paper by Duprey et al. (2015), systemic financial stress events are defined as periods in which extreme financial market stress is also associated with negative real economic outcomes. For this purpose, a country-specific financial stress index is constructed which captures co-movements in key financial market segments. A Markov switching model is applied to endogenously determine low and high financial stress events. Financial stress events that were associated with negative real economic outcomes are afterwards detected using a simple algorithm.[9] In particular, the events identified in this first step are characterised by six consecutive months of real economic slowdown occurring within one year of financial market stress. The events that were detected by Laeven and Valencia (2013) and Babecký et al. (2012) are added to this list if they are not detected by the financial stress index approach.[10] This step provides a preliminary list of potential events for consideration.

### 2.1.2 Step 2: separation between systemic crises and other residual episodes of elevated financial stress

In the second step, systemic crises are identified in the initial list of events of financial stress.

#### Systemic crises

NAs identify systemic crises by following a qualitative approach and common guidelines. In particular, events of financial stress are classified as systemic crises if they fulfil one or more of the following three criteria.

- The financial system played a role in originating or amplifying shocks, thereby contributing substantially to negative economic outcomes. A contraction in the supply of financial intermediation or funding to the economy took place during the financial stress event. These criteria are for example fulfilled when, despite remaining solvent, banks significantly contract the supply of credit to the real economy due to market distress and funding difficulties. Another situation fulfilling the criteria is a currency or balance of payment crisis in which foreign capital is withdrawn and the supply of credit to the domestic economy shrinks.

9 Industrial production growth is used as measure of real economic activity.

10 This ensures that no event is overlooked. This is especially the case for events that took place in periods or countries where the data coverage is limited and, therefore, the financial stress index is less representative. This could be the case for earlier periods of the sample or for transition economies.

- The financial system was distressed: market infrastructures were dysfunctional and/or there were bankruptcies among large/significant financial institutions.
- Policies were adopted to preserve financial stability (or bank stability). These policies include: different forms of external support (e.g. IMF interventions), extraordinary provision of central bank liquidity; direct interventions of the state in support of the banking system (liability guarantees, recapitalisation or nationalisation of banks, assisted/forced mergers among institutions; and creation of bad banks and/or asset management companies). Consideration is also given to monetary policy actions when they directly or indirectly incorporate a financial stability angle.[11]

In addition to financial stress events that fulfil the criteria above, the list of systemic crises also includes other crisis events flagged by NAs and/or by the related literature which were not detected by the financial stress index but fulfil the above criteria. In the case of Estonia, for example, where limited data availability did not allow for the calculation of the financial stress index, the systemic crises included in the dataset were provided by the NAs.

### Residual events of elevated financial stress

In a separate sheet, the dataset also reports residual "episodes of elevated financial (market) stress". These events, which are reported for transparency purposes, were either flagged by NAs or identified using the financial stress index approach, but do not fulfil the criteria for systemic crises.[12] Some of these episodes were however included in earlier crises datasets (Reinhart and Rogoff, 2008 and 2009; Babecký et al., 2012; Laeven and Valencia, 2013). The residual episodes are reported in the dataset as they could be useful for studying the resilience of the financial sector under stress.

### Macroprudential relevance

For the subset of residual episodes of elevated financial stress, an additional dummy variable was introduced to allow NAs to indicate whether or not the identified residual episode is considered to be relevant for macroprudential analysis and policy.[13] Episodes were classified as relevant for macroprudential analysis in cases where (i) the financial turmoil persisted for at least some months and/or (ii) the financial turmoil was perceived to have caused or amplified some negative macroeconomic outcomes and/or (iii) some non-systemic financial intermediaries experienced distress and/or (iv) according to NAs, macroprudential policy tools could have been used for attenuating the impact of the event. This is when the episode was associated with vulnerabilities that could have been addressed by macroprudential policy instruments, if available.

The approach was chosen to strike a balance between full transparency of all events with elevated financial stress and usability of the dataset for macroprudential analysis and policy purposes. In

---

11 While financial stability is not the direct objective of monetary policy in almost all jurisdictions, financial stability is a factor influencing monetary policy. This is because it has implications for the transmission mechanism of monetary policy and because it might have implications for price stability.

12 In the construction of the crisis dataset, showing all the identified financial stress episodes (beyond systemic crises) and indicating whether NAs consider them useful for macroprudential analysis was preferred to dropping some events and keeping other ones. This approach makes the construction of the dataset more transparent for the user.

13 While for residual episodes a critical assessment of the relevance for macroprudential policy is carried out, it is normally assumed that all systemic crises are relevant for macroprudential policy analysis. The only exceptions are some crisis episodes related to the transition to market economy in some central and eastern European countries.

particular, some episodes which were triggered by political development or other factors strictly outside the financial system might be less relevant for the identification of leading indicators for systemic risks. Therefore, the dummy variable (and an accompanying explanation where the event is considered not to be relevant for macroprudential analysis) can help users of the dataset to identify the most suitable sample for their analysis.

## 2.2 Additional information provided in the crises dataset

For each event, the dataset provides a rich set of information, including relevant dates and other features of the event. For ease of reference, in Annex A of this occasional paper, the fields of the dataset are reported with an explanation. For systemic crises an attempt was made to fill all relevant fields of the dataset. For residual episodes, which are of secondary importance in this exercise, information was filled in on a best-effort basis.

Each event is classified in one or more of the following non-mutually exclusive categories: currency/balance of payment/capital flow, sovereign, banking, significant asset price correction, transition.[14] Categories are simplifications which provide general indications of the type of risks that materialised during the event (and also in different phases of an event as it evolved).

Moreover, for each event, a distinction is made as to whether the episode originated in the domestic economy or was imported from abroad as a result of cross-border contagion (field "domestic vs imported"). This is important in order to study events from different angles, including the importance of domestic imbalances in causing distress episodes, the role of spillovers and the interaction between domestic imbalances and external shocks.

One of the innovations of the dataset is that it presents a distinction between different phases in the materialisation of crisis events. Specifically, it separates the acute phase of the event, which occurs between the starting date and the date when the last crisis management policy was adopted, and the post crisis adjustment period, which occurs between the end of crisis management and the moment when the system is considered to be back to a "normal mode". This could be of particular relevance for estimating early warning models and for modelling the transition between crisis phases. The approach facilitates addressing the "post-crisis bias" (Bussière and Fratzscher, 2008), which arises when crisis/post-crisis periods (i.e. the period when economic and financial variables go through an adjustment process before returning to a more sustainable level or growth path) are not accounted for in modelling choices. To distinguish between the acute and the post-crisis phases, strict criteria for the identification of key dates were followed in the construction of the dataset. These criteria are explained in the next subsections.

### 2.2.1 Starting date of the events

The "start date" field marks the start of the event. The start date relates to either (i) the emergence of systemic financial stress in asset markets, (ii) the first policy response in relation to the crisis or (iii) the first failure of a major market player, depending on which date is earlier and/or considered appropriate by NAs. This choice reflects the fact that the start date of the event normally coincides with the emergence of systemic financial stress in asset markets. This is normally the moment when economic agents start incorporating the expectations of future bad economic outcomes in

---

[14] The dataset contains a number of episodes that are marked as "transition" events. This concerns a number of episodes in central and eastern European countries in the 1990s. Transition events relate to the transformation from "centrally-planned economies" to markedbased economies which also involved complex privatisation processes.

relation to the occurrence of a crisis. Systemic financial stress is often triggered by bank distress and bank failures. Alternatively, systemic financial stress can co-occur with early policy interventions aimed at preventing or containing the outbreak of a crisis. In some cases, however, for various reasons, financial market stress might materialise only after the first bank bankruptcies or after policy interventions. This can occur, for example, when markets are not sufficiently developed or liquid. For these reasons, NAs were asked to critically review the initial starting date of the materialisation of systemic financial stress provided by the financial stress index and to indicate whether alternative event starting dates, which are linked to financial sector bankruptcies and policy interventions, would be more appropriate. Alternative starting dates were accepted when sufficient reasoning was provided. If different from the emergence of financial stress, the reasoning behind the starting date is reported in the field “brief description of the identified event”.

### 2.2.2 End of crisis management date

The end of the crisis management and resolution phase is marked by the last of the policy interventions aimed at containing the crisis. This can be considered as the end of the acute phase of the crisis and the start of the period of post-crisis adjustment (Bussière and Fratzscher, 2008). Reviewed policy interventions include: the adoption of liquidity support to banks, the introduction of guarantees for bank liabilities, the recapitalisation of banks or forced/assisted mergers, the creation of bad banks or asset management companies, the resolution of banks, general debt relief and the adoption of emergency fiscal packages and/or unconventional monetary policy measures that address market disturbances in connection with the materialisation of different types of risk (e.g. ECB Security Markets Programme (SMP) and Outright Monetary Transactions (OMT)). The end of the crisis management and resolution phase should anticipate or coincide with the date when the system is considered “back to normal”, see Subsection 2.2.3). Taking the example of the European sovereign and banking crises, for countries that participated in the EU/IMF economic adjustment programmes, the end of crisis management coincides with the exit from the adjustment programme, unless NAs suggest a valid alternative date (e.g. sale to private investors of a good bank resulting from the resolution of an earlier entity). Some of the reasons behind the choice for the end of crisis management date can be found in the fields “brief description of the identified event” and “crisis management policies”.

### 2.2.3 System "back to normal" date[15]

The system is considered to be back to a normal mode when the recovery is on a firm path and the fiscal and monetary policy become broadly neutral. This is when the overall policy mix in one country is no longer driven by factors related to the crisis and its manifestation, including legacy issues.[16] The return to “normal” does not normally occur before the end of the crisis management phase (see Subsection 2.2.2). The “back to normal” date essentially marks the end of the period of post-crisis adjustment (Bussière and Fratzscher, 2008). For the systemic crises which occurred after 2007 and notably European sovereign and banking crises in euro area countries, the “back to normal” date has been defined differently because monetary policy continues to be accommodative, while the recovery has been uneven across countries. In this case, the “back to normal” date does not exclude further post-crisis adjustment and is defined using one of the two

[15] The definition of the "back to normal" date was revised in December 2021.

[16] For some crises, the post-crisis adjustment phase might be long; for example, in cases where a debt overhang needs to be resolved.

following criteria: when 20% of the NPL-ratio increase following the start of the crisis has been reabsorbed or, alternatively, when the output gap has been closed[17] (some country exceptions are possible and are explained in the database[18]).

17 The NPL ratio considered is the ratio of non-performing loans to total gross loans taken from the International Monetary Fund's Financial Soundness Indicators database; and the output gap (AMECO database) is considered closed when it has been strictly positive for two consecutive quarters, applying a rounding to the nearest hundredth.

18 BE, DE, LU and SI chose "back to normal dates" which differ from the date suggested by the methodology (NPL or output gap). For BE, the "back-to-normal" date was set at the "end of crisis management" date instead of the dates suggested by the NPL or output gap criterion, as the latter are not particularly relevant in the case of BE. As NPL levels in BE are low and their increase following the crisis has been relatively limited, the date suggested by the NPL criterion is considered too late, whereas the date suggested by the output gap criterion falls before the "end of crisis management" date and is considered too early. For DE, the "back to normal" date was chosen to correspond with the end of crisis management measures, as the output gap would have indicated a return to normal while crisis measures were still ongoing. The NPL criterion was not applied owing to limited data availability. For LU, neither the NPL nor the output gap criterion proposed as one-size-fits-all criteria for the "back to normal" date are reliable indicators. In LU NPL levels are historically low, and the output gap results in a "back to normal" date that is considered too late. Based on internal analyses and the absence of a material impact of the sovereign debt crisis on LU, a "back to normal" date of June 2011 was mutually agreed on by the national authorities, the ECB and the ESRB. And for SI, using the NPL criterion for the "back to normal" date gives December 2013, which is only one month after SI banks reached their NPE peak in November 2013. In December 2013 a large portion of NPEs was transferred to a bad bank. This date is also a full year before the "end of crisis management" date, which implies that the latter is more appropriate.

# Section 3
# Stylised facts about the dataset

The following section presents an overview of all events in the dataset and stylised facts about the systemic crises in the dataset. It shows how the number of ongoing systemic crises has changed over time, how the dataset differs in comparison with other crises datasets in the literature, and it how certain features of the crises, such as length, origin, and cost, have evolved over time and in relation to the crisis type. Moreover, it illustrates how different types of risks materialised sequentially in the context of the global financial crises. Finally, a broad overview of policy measures is also provided.

## 3.1 Number of events and type of risk that materialised

The dataset includes 50 systemic crises and 43 residual events of elevated financial stress that have occurred in EU countries and Norway since 1970. Table 1 gives an overview of the frequency of systemic crises and residual events in the dataset and shows the break down in terms of classifications of risk materialisation. In this context, it is important to keep in mind that classifications are non-exclusive, meaning a crisis can be given more than one risk materialisation classification.

Table 1
**Overview of the identified events and and type of risks**

(absolute frequency; percentages)

| | Systemic Crises | | Residual Events | |
|---|---|---|---|---|
| | **Relevant for macroprudential analysis** | **Non-relevant for macroprudential analysis** | **Relevant for macroprudential analysis** | **Non-relevant for macroprudential analysis** |
| **Complex crisis: multiple risks** | 33 (66%) | - | 6 (14%) | 6 (14%) |
| including materialisation of banking risk | *31* | - | *4* | *1* |
| including materialisation of significant asset price correction | *30* | - | *5* | *4* |
| including materialisation of currency risk | *20* | - | *3* | *5* |
| including materialisation of sovereign debt risk | *10* | - | - | *2* |
| **Banking crisis (materialisation of banking risk)** | 2 (4%) | - | 2 (5%) | 1 (2%) |
| **Currency crisis / BoP / capital flow (materialisation of currency risk)** | - | - | 2 (5%) | 5 (12%) |
| **Sovereign crisis (materialisation of sovereign risk)** | 1 (2%) | - | - | - |
| **Significant asset price correction** | 1 (2%) | - | 7 (16%) | 10 (23%) |
| **Transition** | 9 (18%) | 4 (8%) | - | 4 (9%) |
| **Total** | 50 | | 43 | |

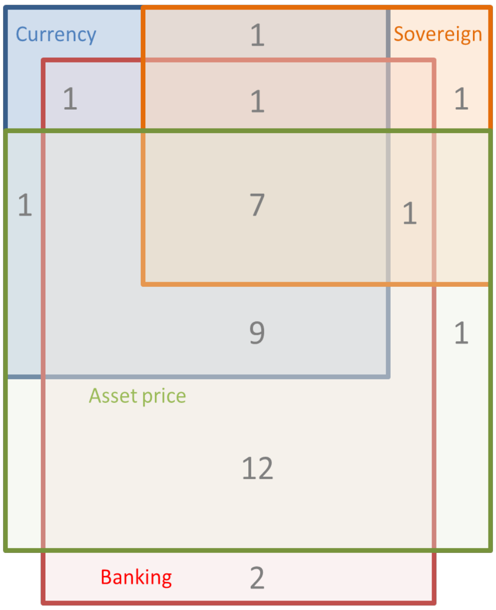
Notes: The dataset distinguishes between a core set of systemic crises and an additional set of residual events, further divided into (non-) relevant for the purpose of macroprudential analysis and policy. Complex events are defined as the simultaneous materialisation of multiple risks. With respect to complex events, this table reports the total frequency of all subcategories, which should not be interpreted as a sum. The materialisation of one type of risk does not exclude the materialisation of others. The share of each crisis type is indicated in brackets, e.g. 66% of the 50 identified systemic crises are complex events and relevant for macroprudential analysis. The totals refer to the major categories in bold, and disregard the subcategories for complex events.

The majority of the systemic crises, 33 events, are complex events which reflect the materialisation of a combination of several different risks, for example problems in the banking sector, sudden adjustments of external positions (i.e. currency or balance of payment adjustments), the materialisation of sovereign risk or significant asset price corrections (including in real estate markets). Generally, the most frequent type of risk across events is banking risk, which materialised 31 times in complex events and twice in isolation (see Table 1). The second most frequent type of risk is significant asset price corrections, including real estate downturns (30 occurrences in complex crises and one in isolation). The materialisation of sovereign risk and currency risk is less frequent (ten and 20 crises respectively in complex crises and one materialisation of sovereign risk in isolation). Finally, 13 of the identified systemic crises relate to the transition to a market economy in central and eastern European countries and four of these crises were associated with vulnerabilities that are not considered as pertaining to the sphere of macroprudential analysis. Therefore, the events were not deemed relevant for this exercise.

The dataset includes 43 residual episodes of financial stress, 17 of which are, however, flagged as potentially relevant for macroprudential policy analysis. Among residual events, asset price corrections, which are not related to any other materialisation of risk, play a particularly large role (see Table 1).

Chart 1
**Type of risks that materialised during "complex" events**

(absolute frequency)




Notes: This chart illustrates overlapping risk categories in a Venn diagram. The figures refer only to systemic crises which are deemed relevant for macroprudential analysis and not related to the transition of the economy.

A Venn diagram (Chart 1) illustrates more precisely how the crisis classification categories coincide and overlap for systemic crises. In seven of the 50 crises, all of the risk categories materialised and in nine crises all risks except sovereign risk materialised. The most common combination of risks is the occurrence of banking risk and significant asset price corrections (12 crises).

## 3.2 Comparison with the other datasets in the literature

In order to provide a broad idea of the coverage of this dataset in relation to other known datasets, a comparative assessment of the systemic crises included in this database and in the Laeven and Valencia (LV) database is provided below in Table 2.

Table 2
**Comparison with the Laeven & Valencia (2008 and 2013) datasets**

(absolute frequency; percentages)

| | Systemic Crises Relevant for macroprudential analysis | LV |
|---|---|---|
| **Banking crisis (materialisation of banking risk)** | 33<br>(94%) | 29 |
| **Currency crisis / BoP / capital flow (materialisation of currency risk)** | 20<br>(100%) | 11 |
| **Sovereign crisis (materialisation of sovereign risk)** | 11<br>(91%) | 3 |
| **Significant asset price correction** | 31<br>(97%) | - |
| **Transition** | 9<br>(33%) | - |
| **Total** | **46**<br>(78%) | **43** |

Notes: The share of complex events within a given subcategory is indicated in brackets, i.e. 94% of the 33 identified banking crises are complex events.

The new crises dataset includes 46 systemic events which are relevant from a macroprudential perspective while the LV crises database covers 43 events for the same set of European countries over the same period (see Table 2). Some of the events included in the new crises dataset cover one or more events included in the LV crises dataset.[19] As a result, there are a total of 30 event overlaps between the two datasets (see Table 3a).

Table 2 also reports the type of crisis (banking, sovereign, currency) according to the new dataset presented here and to the LV crises database. However, it should be noted that a direct comparison of the frequency of different types of events between the two dataset is not possible due to the use of a different approach to event classification. As described in the previous section, a more flexible approach was chosen for the construction of this dataset to enable events to be classified according to all risk types that materialised. As a consequence, many of the events that are in this dataset are complex events entailing the materialisation of different types of risks. This reflects the idea that it is unlikely that different types of risks occur in isolation and that it is difficult to identify the primary driver of events. In the LV database, a more stringent classification was used, focusing on the most significant risk.

There are 16 systemic crises in the new crises database which are not covered by the LV crises database, while only one crisis is included in the LV crises database and not reported in the new dataset. The latter is identified by Laeven and Valencia (2008), and describes a systemic sovereign debt crises in the early 1990s (please refer to Annex C for an illustration). Neither the financial stress index nor the Bulgarian Central Bank could confirm this finding. Therefore, it does not fulfil the criteria to be included in the dataset (Table 3a).

[19] The Swedish authorities, for example, report a complex crisis from January 1991 until June 1997, while Laeven and Valencia find a banking crisis from 1991 to 1995 and a currency crisis only in 1993. The Romanian authorities report a severe and long sovereign debt crisis from November 1981 until December 1989, whilst Laeven and Valencia identify a sovereign debt crisis starting in 1982 (no indication of end date) and a banking crisis from 1990 to 1992.

Table 3a

**Overlapping and non-overlapping events in this dataset and the Laeven and Valencia (2008 and 2013) datasets**

(absolute frequency)

| | In LV | Not in LV |
|---|---|---|
| **In ECB/ESRB database** | 30 | 16 |
| **Not in ECB/ESRB EU database** | 1 | - |

Notes: This table refers to systemic crises which are deemed relevant for macroprudential analysis. The comparison is based on the set of banking crises included in Laeven and Valencia (2013) and currency and debt crises included in Laeven and Valencia (2008). As described in the previous section, the construction of the new dataset offers, on the one hand, a more precise definition of crises periods and, on the other hand, a more flexible way of classifying crises according to the type of risks that materialised. For example, Laeven and Valencia frequently find several distinct crises episodes where the new database reports one long event (please refer to Annex C for an illustration). Consequently, the totals of this table are not equal to the reported frequencies in Table 1. The single event not covered by the new dataset relates to a crisis in Bulgaria in 1990, which Laeven and Valencia identify. This event has not been identified by neither the ECB / ESRB nor by the Bulgarian Central Bank.

Table 3b

**Features of the additional events in this dataset**

(absolute frequency; percentages)

| | Systemic Crises Relevant for macroprudential analysis |
|---|---|
| **Complex crisis: multiple risks** | 13 (81%) |
| including materialisation of banking risk | *11* |
| including materialisation of significant asset prices correction | *10* |
| including materialisation of currency risk | *9* |
| including materialisation of sovereign debt risk | *3* |
| **Banking crisis (materialisation of banking risk)** | 2 (13%) |
| **Currency crisis / BoP / capital flow (materialisation of currency risk)** | - |
| **Sovereign crisis (materialisation of sovereign risk)** | - |
| **Significant asset price correction** | 1 (6%) |
| **Transition** | - |
| **Total** | **16** |

Notes: This table refers to systemic crises which are deemed relevant for macroprudential analysis. As described in the previous section, the construction of the dataset offers, on the one hand, a more precise definition of crises periods, and on the other hand, a more flexible way of classifying crises according to the type of risks that materialised. For example, Laeven and Valencia frequently find several distinct crises episodes where the new database reports one long event (please refer to Annex C for an illustration).

Annex C contains a detailed overview of individual events by country and allows for a country-specific comparison of dates and types of risk that materialised according to the new dataset and the Laeven and Valencia dataset.

In addition, the new database was compared with the crisis database presented in Detken et al. (2014), based on previous work by Babecký et al. (2012). Also in this case, the comparison confirms that a high percentage of the historically recognised events are covered in the dataset. The new ECB/ESRB EU crises database contains 31[20] out of 33 events included in Detken et al. A more in-depth comparison with respect to event categorisation is not feasible as the Detken et al. (2014) dataset does not provide such a breakdown.

---

20 Out of 31 overlapping events, 30 crises are considered systemic and one residual, according to the ECB/ESRB EU database classification.

## 3.3 Detailed features of systemic crises: evolution over time, length, origin, output losses and fiscal costs

This subsection provides a detailed description of the features of the systemic crises included in the dataset.

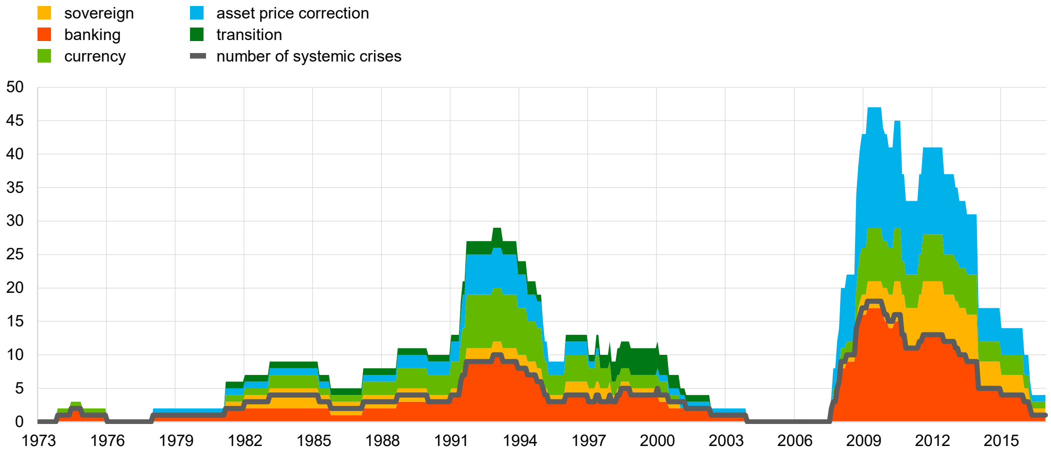
### Evolution of crises over time

Chart 2a and 2b illustrate the evolution of systemic crises over time distinguishing between different risk categories (Chart 2a) and between different phases of the crises (Chart 2b).[21] Two major waves of systemic crises can be identified in the charts 2a and 2b. While a number of crises occurred in the 1980s, the two big waves of crises occurred in the 1990s and from 2007 onwards. The first big wave of crises in the 1990s reflects the ERM crisis, the transition in central and eastern Europe and the transmission of global tensions to European countries in relation to crises in emerging markets, including the Russian crisis in 1998. The second big wave, with an even larger number of crises, reflects the transmission of the US subprime crisis and the materialisation of bank and sovereign risk in several European countries. Chart 2a also shows certain changes regarding the frequency of the different risk types which materialised. Currency and transitional crises played a larger role in Europe in the 1980s and 1990s, while asset price corrections and sovereign crises have tended to play a more prominent role in Europe after 2006.

Notably, the post-crisis adjustment phase (light blue areas in Chart 2b) appears to be longer for the recent set of crises than for crises in the 1980s and in the 1990s. Box 1 in Subsection 3.4 provides a more detailed review of the most recent wave of crises which started in 2007.

Chart 2a
**Frequency of crises and type of materialised risk**

(y-axis: absolute frequency)



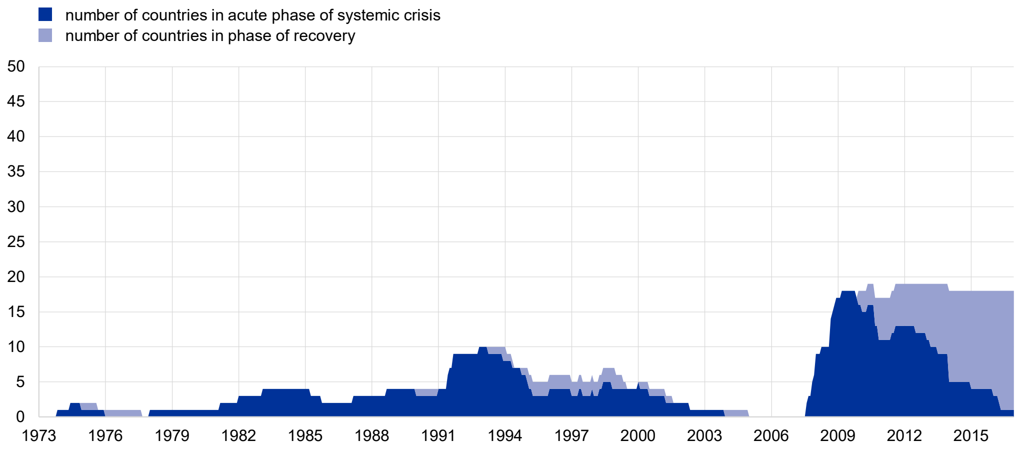

Notes: This chart refers to systemic crises which are deemed relevant for macroprudential analysis.

21 The acute phase of the crisis is between the “start date” and the “end of crisis management date”. The post-crisis adjustment period is between the “end of crisis management date” and the “system back to normal date” (see Section 2).

Chart 2b

**Frequency of crises, acute phases and recovery periods**

(y-axis: absolute frequency)




Notes: This chart refers to systemic crises which are deemed relevant for macroprudential analysis.

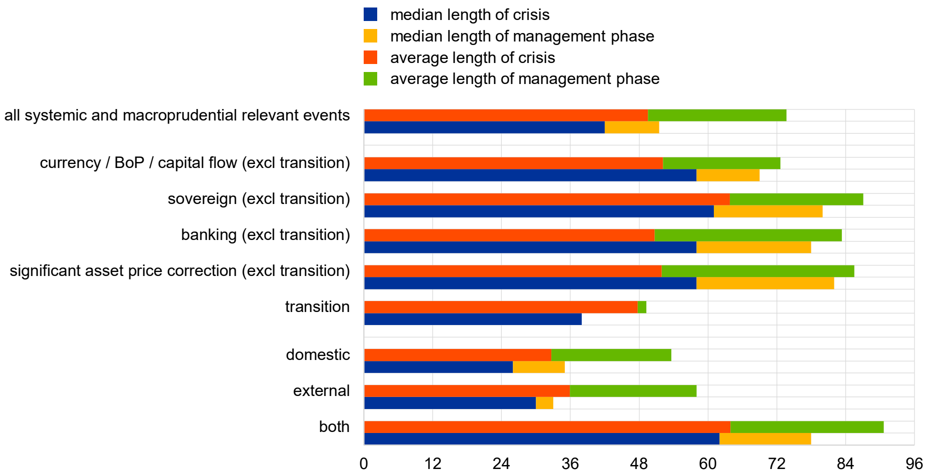
## Length of systemic crises

Chart 3 offers more insight into the lengths associated with the systemic crises identified. It reports the average and median lengths of systemic crises.

Chart 3

**Length of crisis phases by type of crisis**[22]

(x-axis: average (red/green) and median (blue/yellow) length in months)




Notes: This chart refers to systemic crises which are deemed relevant for macroprudential analysis. Complex events are not separated from single events in this chart, e.g. the average is calculated over all events where the currency dummy is activated, including those where another risk materialises for the same event. This results in double counting with respect to complex events. It is further important to note that the classification of crisis types and the origin are not mutually exclusive, i.e. the distinctions between crisis types and origins should be interpreted as complements. The length of an acute crisis phase is calculated by taking the time between the start of the crisis and the end of crisis management. The length of the recovery period is defined as being from the end of crisis management policies until the system is "back to normal"(please refer to Section 4 for definitions).

The differences between average and median lengths mostly stem from a few particularly long events. The dataset shows that international crises, i.e. those which are driven by both domestic and external factors, seem to be the most persistent.

However, a major influence on the type of risk which materialised cannot be found.[23] Sovereign and banking crises, as well as significant asset price correction, do not seem to differ in their length; only currency crises seem to be shorter on average. This is not necessarily closely linked to the type of risk which materialised, but could be explained by the period when most currency crises occurred. During the 1990s, many countries suffered from tensions in the ERM, which were able to be relatively quickly addressed by FX regime changes.

On average domestic crises do not last as long as crises stemming from international factors. This finding is potentially partially driven by the recent financial crisis, but might also shed light on spillover and contagion effects which often amplify domestic misalignments.

## Origination of systemic crises

As shown in Table 4, the majority of systemic crises in the dataset are associated with developments inside and outside the country (19 crises). For another eight cases, the NAs describe

---

22 The fact that both the mean and median of the "all systemic crisis" category are lower than for most of the crisis-specific categories, can be explained by two factors. The first is the impact of transition crises, with a relatively lower mean and median, which affect the aggregated result. The second stems from the chosen approach of double counting events, as each crisis-specific category includes a subset of long and complex events that increase the category's average and median crisis lengths. At the same time, the statistics calculated over the entire sample include all shorter single/double-category events which decrease the outcome.

23 Analysing the impact of different combinations of materialised risks on the length of crises could be considered for potential follow-up work.

the crisis as imported. Table 4 also reports a breakdown by type of materialised risk. However, since complex crises prevail in the dataset, further analysis is needed before conclusions can be drawn about the interaction of risk type and origination.

Table 4

**Frequency of crisis by origin of shocks/imbalances**[24]

(absolute frequency; percentages)

| | domestic | both | external |
|---|---|---|---|
| **Complex crisis: multiple risks** | 6 (13%) | 19 (41%) | 8 (17%) |
| including materialisation of banking risk | *6* | *18* | *7* |
| including materialisation of significant asset prices correction | *5* | *19* | *6* |
| including materialisation of currency risk | *4* | *12* | *4* |
| including materialisation of sovereign debt risk | - | *8* | *2* |
| **Banking crisis (materialisation of banking risk)** | 1 (2%) | 1 (2%) | - |
| **Currency crisis / BoP / capital flow (materialisation of currency risk)** | - | - | - |
| **Sovereign crisis (materialisation of sovereign risk)** | - | 1 (2%) | - |
| **Significant asset price correction** | 1 (2%) | - | - |
| **Transition** | 2 (4%) | 2 (4%) | 5 (11%) |
| **Total** | **10** | **23** | **13** |

Notes: This table refers to systemic crises which are deemed relevant for macroprudential analysis. It is further important to note that complex events are defined as the simultaneous materialisation of multiple risks. The table therefore also reports the total frequency of all subcategories, which should not be interpreted as a sum. The activation of this dummy does not exclude the activation of other categories. The reader should also be aware of the fact that the three classifications of origin are mutually exclusive, i.e. a complex event can only be purely domestic, purely external or both, external and domestic, but not a combination of these.

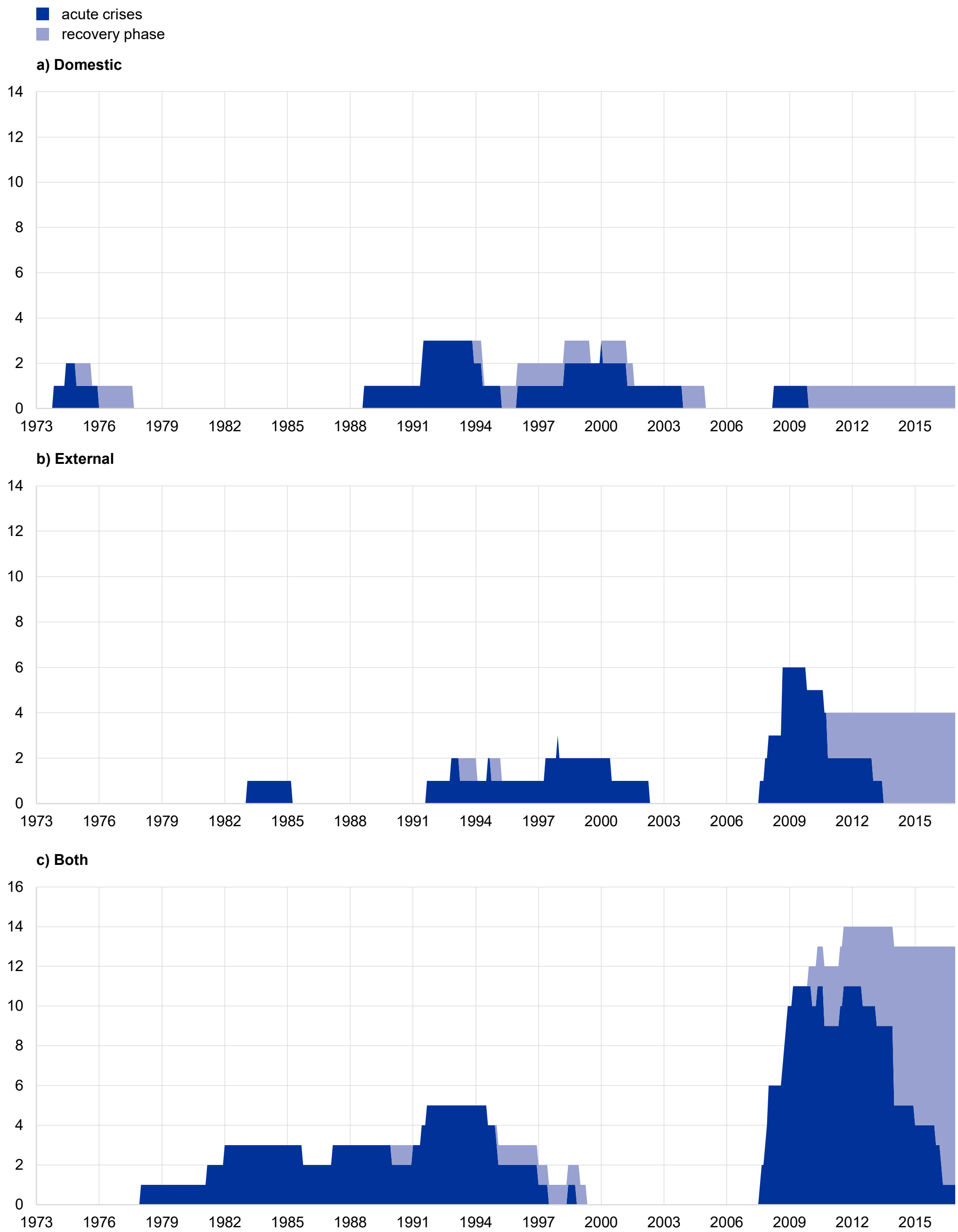
Chart 4 illustrates that purely domestic events were relatively more common among western European countries during the 1990s, while internationally or externally driven crises occurred more recently and were also common in eastern European countries following the fall of the Soviet Union. These figures can be interpreted as a result of increased globalisation and interconnectedness of financial markets and the banking sector.

24 In a small number of cases sovereign tensions materialised in one country in isolation from “visible” domestic imbalances (two episodes). These are complex episodes involving the materialisation of several types of risks. One of them was related to the ERM crisis, another episode was driven mainly by external trade imbalances, high foreign interest rates and high government deficits.

Chart 4

**Frequency of crisis over time by origin of shocks/imbalances**

(y-axis: absolute frequency)




Notes: This chart refers to systemic crises which are deemed relevant for macroprudential analysis. It is further important to note that the classifications of origin are mutually exclusive, i.e. an event cannot appear in more than one of the panels.

## Output losses and fiscal costs

Table 5 reports different proxies to estimate the cost of systemic crises in the dataset. The second column of Table 5 reports output losses as a percentage of GDP,[25] which, following an approach related to the one used by Laeven and Valencia (2013), are calculated based on a comparison of cumulative costs in terms of GDP relative to the historical trend.[26] The third column of the table shows increases in government debt-to-GDP ratios during the acute phase of the crises, which can be considered as a very rough proxy for the fiscal costs of a crisis. A detailed description of the underlying computational methods and choices is reported in Annex B.[27]

Table 5
**Costs of systemic crises**

(output loss: calculation time horizon: start of crisis to end of acute phase; unit: percentage of GDP. Increase in debt-to GDP ratio: time horizon: one year before start of crisis to end of acute phase; unit: percentage points.)

| | Output loss as percentage of GDP | | | Increase in debt-to-GDP ratio | | |
|---|---|---|---|---|---|---|
| **Crisis type** | **Mean** | **Median** | **Skewness** | **Mean** | **Median** | **Skewness** |
| **Total** | 8% | 6% | 1.07 | 0.21 | 0.16 | 1.15 |
| **Currency** | 9% | 7% | 0.96 | 0.25 | 0.18 | 0.77 |
| **Sovereign** | 12% | 12% | 0.5 | 0.39 | 0.46 | 0.05 |
| **Banking** | 9% | 7% | 1.02 | 0.22 | 0.17 | 1.08 |
| **Asset price correction** | 9% | 7% | 0.93 | 0.24 | 0.17 | 1.01 |
| **External origination** | 6% | 5% | 0.76 | 0.09 | 0.11 | -0.74 |
| **Domestic and external origination** | 11% | 10% | 0.58 | 0.30 | 0.27 | 0.78 |

Source: ECB ESRB calculations.
Notes: This table refers only to systemic complex crises which are deemed relevant for macroprudential analysis. Non-complex events are explicitly excluded, as there are too few observations in the dataset. Debt-to-GDP ratio refers to the general government consolidated gross debt as a percentage of GDP. For detailed explanation of the computational methods see Annex B.

In addition to the average, Table 5 also reports median and distribution skewness and provides a breakdown of different risk categories. As a general observation, the means tend to be significantly higher than the medians for nearly all of the breakdowns presented. This comparison highlights that average results are strongly affected by exceptionally costly events.

Comparing the level of **government debt-to-GDP ratio** one year before the start of the crisis with the level at the end of the acute phase, a substantial increase can be observed for almost all crises, with an average increase of 21 percentage points. While the mean for complex crises involving banking, asset price correction and currency stay relatively close to the total mean for complex crises; crises which involve sovereign risk are associated with an increase in the debt-to-GDP ratio of approximately 39 percentage points.

25 One important caveat is that this analysis does not consider the fact that, as a consequence of interventions in the banking sector, governments acquire assets (e.g. stakes in banks) and are exposed to contingent liabilities (e.g. in the form of guarantees).

26 Trends are computed based on an event's preceding ten years [T-11; T-1], with T being the year in which the crises started.

27 Possible caveats in the analysis are likely to stem from assumptions made for computational purposes. These might not necessarily yield the efficient potential output, and it cannot be excluded that events other than the identified crises impact the observed losses. High variance in the series also implies that the results need to be interpreted with caution. However, the use of multiple computational methods serves as a robustness check. For a detailed description of the computational methods and a comparison with the approach used in Laeven & Valencia 2013, see Annex B.

The average **output loss** equals approximately 8.5%, independent of the selection of the cut-off date for the loss calculation (end of acute vs. recovery phase), and the median output loss amounts to 6% to 7% across all methods. This comparison highlights that average results are strongly affected by exceptionally costly events.

Looking at the breakdown by type of risk, sovereign risk stands out. The median output losses of complex crises which include the materialisation of sovereign debt risks are almost two times higher than for all other complex events. This finding is linked with the observation of the extraordinarily high impact of sovereign risk on the government debt-to-GPD ratio described above, as a drop in GDP ceteris paribus leads to an increase in the debt-to-GPD ratio even without an increase in debt. Median and mean output losses across all other categories, on the other hand, seem relatively similar. A breakdown by origin of the crises indicates that crises which are connected to both external and domestic factors also tend to be associated with higher output losses.

The hypotheses above are tested with a mean difference test, with the results reported in Table 6. The analysis shows that the materialisation of sovereign debt risks is correlated with a statistically significant increase in average output losses across the complex events, while the test does not suggest any significant difference in terms of output losses for any other risk category.

However, crises driven by both domestic and international factors also coincide with higher output losses. Average output losses associated with purely domestic crises amount approximately to a range between 4% and 5% and are substantially lower compared with crises where external factors play an important role (approximately 11%, independent of the calculation approach). The mean difference between domestic and both domestic and external events is statistically significant on 95% confidence level.

Table 6

**Testing the significance of differences in output losses across types of events**

(difference in percentages)

| | Test: mean loss for selected crisis type against mean loss of remaining complex events | | | | Test: mean loss for selected crisis origination against mean loss of complex events with domestic origination source | |
|---|---|---|---|---|---|---|
| **Risk materialisation / crisis category / origination** | **Currency** | **Sovereign** | **Banking** | **Asset price correction** | **External** | **Both** |
| **Mean difference** | 2% | 5% | 5% | 4% | 2% | 8% |
| **P-value** | 0.339 | **0.032** | 0.263 | 0.355 | 0.198 | **0.012** |

Source: ECB ESRB calculations.
Notes: This table refers to systemic complex crises which are deemed relevant for macroprudential analysis. Non-complex events are explicitly excluded, as there are too few observations in the dataset. Transition events are also excluded due to limited comparability. For the sake of completeness, it should be noted that the mean and median output losses for transition episodes range from 4% to 5% (depending on the calculation approach).

The discovered relations between the costs and different types of financial crises differ to some extent from the findings in Laeven and Valencia's dataset (2013). Laeven and Valencia find that output losses stemming from banking or sovereign crises are significantly higher than those related to currency crises. These differences are likely related to the different sample size and composition[28], especially given the global scope of the Laeven and Valencia dataset compared to EU-restricted ECB/ESRB database. In addition, the structure of the two datasets is conceptually

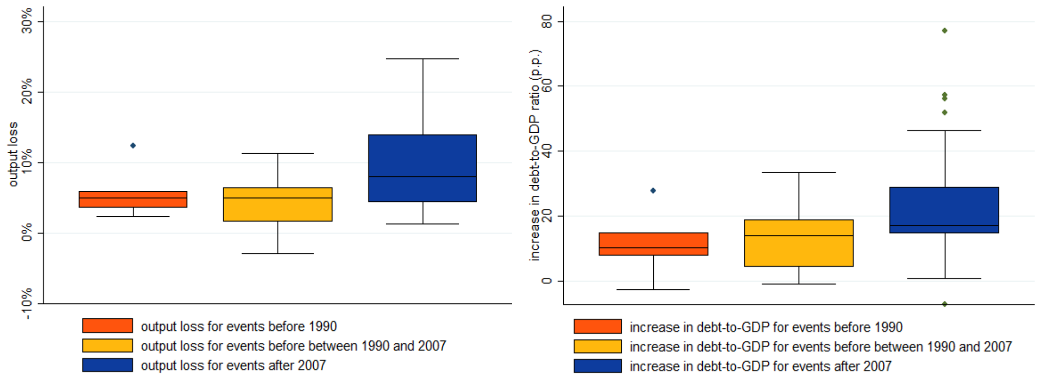
[28] The methodological approach, although relatively similar, differs to certain extent relative to Laeven and Valencia 2013. For details, please see Annex B.

different. This is due to a different approach regarding the classification of materialised risks. Moreover, it must be kept in mind that, for the analysis presented in Table 6, only complex crises are considered against the backdrop of the limited set of events when only one type of risk materialised.

Finally, Chart 5 presents losses and fiscal costs associated with distinct cohorts of crises over time, using a grouping of crises in three different phases as derived from Chart 2a and 2b. The three different periods which were used for the grouping of crises are: 1970-80s; 1990s until early 2000s, including the ERM crisis, emerging market crises and collapse of the high-tech bubble; and the recent financial crisis starting in 2007. It can be seen that the highest output losses and the highest increases in government debt-to-GDP ratio are associated with the recent financial crises.

Chart 5
**Costs of systemic crises over different time periods**[29]

(y-axis, output loss (as a percentage of GDP) and relative increase in debt-to-GDP ratio, percentages)




Sources: AMECO, World Bank and ECB ESRB calculations.
Notes: The charts present the average output loss and increase in government debt-to-GDP ratio in three selected time intervals for all systemic events.

## 3.4 Crises management policies

The database also includes qualitative information about crisis policy measures. Together with the brief crisis description, this information can provide researchers with important background information to better understand the nature and evolution of the crisis. Given the qualitative nature of this information, it has to be kept in mind that any comparison across countries can only be done with caution, as the level of detail and the exact wording for the description of measures can differ between countries. Moreover, it is likely that information for more recent crises is more complete in the dataset compared with crises in the 1970s and 1980s, for which information from archives often had to be retrieved.

29 Crises with theoretical output gains: BG 1996, CY 2000 and DE 2001.

Table 7
## Overview of crisis policies as reported in the database

(absolute frequency; percentages)

| | New banking regulation and strengthening of FSA | Monetary policy measures, including introduction of new currency and lowering minimum reserve requirements | SPV/bad banks/AMC | Capital or liquidity support and/or funding/deposit guarantee scheme | Restructuring of banks, M&As, liquidations |
|---|---|---|---|---|---|
| **Complex crisis: multiple risks** | 8 (24%) | 16 (48%) | 7 (21%) | 27 (82%) | 6 (18%) |
| including materialisation of banking risk | 8 | 14 | 7 | 27 | 6 |
| including materialisation of significant asset prices correction | 8 | 15 | 7 | 25 | 5 |
| including materialisation of currency risk | 5 | 10 | 5 | 14 | 4 |
| including materialisation of sovereign debt risk | 5 | 6 | 4 | 7 | 2 |
| **Banking crisis (materialisation of banking risk)** | 1 (50%) | - | - | 2 (100%) | 1 (50%) |
| **Currency crisis / BoP / capital flow (materialisation of currency risk)** | - | - | - | - | - |
| **Sovereign crisis (materialisation of sovereign risk)** | - | - | - | 1 (100%) | - |
| **Significant asset price correction** | - | - | - | - | - |
| **Transition** | 2 (22%) | 3 (33%) | 2 (22%) | 6 (67%) | 2 (22%) |
| **Total** | **11** | **19** | **9** | **36** | **9** |

Source: ECB ESRB calculations.
Notes: With respect to complex crises, this table reports the total frequency of policies across all subcategories, which should not be interpreted as a sum, since crises are usually addressed by a variety of measures. This table reports the most frequently named policies. The values denote the percentage shares of systemic crises within the respective subcategory in which the policy was applied, e.g. 24% of complex crises are associated with new banking regulation and the strengthening of the financial supervisory authorities (FSA).

Table 7 presents the results of a semantic analysis about the frequency of five categories of policy actions, which were identified in the dataset. Government responses to crises were mostly tailored to the banking sector, i.e. introduction of new regulation, strengthening the powers of financial supervisory authorities (FSA), the creation of so-called bad banks or special purpose vehicles (SPV) as well as restructuring, mergers and liquidations. In particular related to the ERM crises in the 1990s, NAs describe monetary policy measures, such as a change in interest rates and minimum reserve requirements and/or the introduction of a new currency in the course of the transition period in central and eastern Europe. In addition, quantitative monetary easing is commonly reported as measure against the recent crisis. Measures are relatively equally distributed across multiple crises types. Capital or liquidity support is the most commonly used crises management tool. Moreover, during the global financial crisis, many governments were forced to bail out banks or to provide support in form of capital or liquidity.

## Box 1
### The global financial crisis and the sovereign and banking crises in Europe

The evolution of the global financial crisis and of the sovereign and banking crises across European countries has been widely discussed in policy fora and in the academic literature.[30] After the subprime crisis erupted in the US between mid-2007 and 2008, 21 European countries experienced systemic crises, which started at different points in time between 2007 and 2011. The remaining seven European countries experienced episodes of elevated financial stress characterised by significant asset price corrections.

The chart (see next page) illustrates that, in most cases, sovereign risk materialised only subsequently, after the materialisation of banking crises, and that most residual events of elevated financial stress were concentrated in the first part of the global financial crises.

Among the 21 systemic episodes that were identified between 2007 and 2011, all of them were associated with the materialisation of risks in the banking system and significant asset price corrections (including real estate prices in most of the cases). Ten of these episodes also entailed significant adjustments of external positions and eight of them entailed the materialisation of sovereign risk.

Systemic crises initially materialised between 2007 and 2008, in the countries where banking systems were more vulnerable to external shocks due to prevailing business models and/or exposures to US housing markets via structured finance products. Notably, the United Kingdom and Germany are among the first European countries where a systemic crisis materialised. In the UK, the start of the crisis is in August 2007, right before the "run" on the mortgage lender Northern Rock. In Germany, in August 2007, KFW Bank had taken over the distressed IKB Deutsche Industriebank, which had provided outsized liquidity lines to special purpose vehicles.

From the policy point of view, the first wave of systemic crises in Europe largely coincides with the implementation of the European Economic Recovery Plan[31], an EU-wide fiscal stimulus coordinated by the European Commission. By the end of 2010, measures including an increase in public investment and tax rebates for households and employers were fully phased in, such that many countries entered the subsequent recovery period.

Regarding the group of countries that experienced severe distress in connection to the European banking and sovereign crisis, Ireland, Spain and Portugal reported bank failures or substantial interventions to preserve financial stability already in 2008 and early 2009. Therefore, the starting date for systemic crises in these three countries occurs earlier than for Greece, Italy, Cyprus and Slovenia. This latter group of countries experienced systemic crises starting between late 2009 and 2011 as a result of the deterioration of the macroeconomic environment, the materialisation of credit risk, the deterioration of public finances and the emergence of sovereign risk, which ultimately affected the stability of the financial system.

Looking at the recovery phases of the latest crises episodes, it can be seen that the crises are particularly persistent.

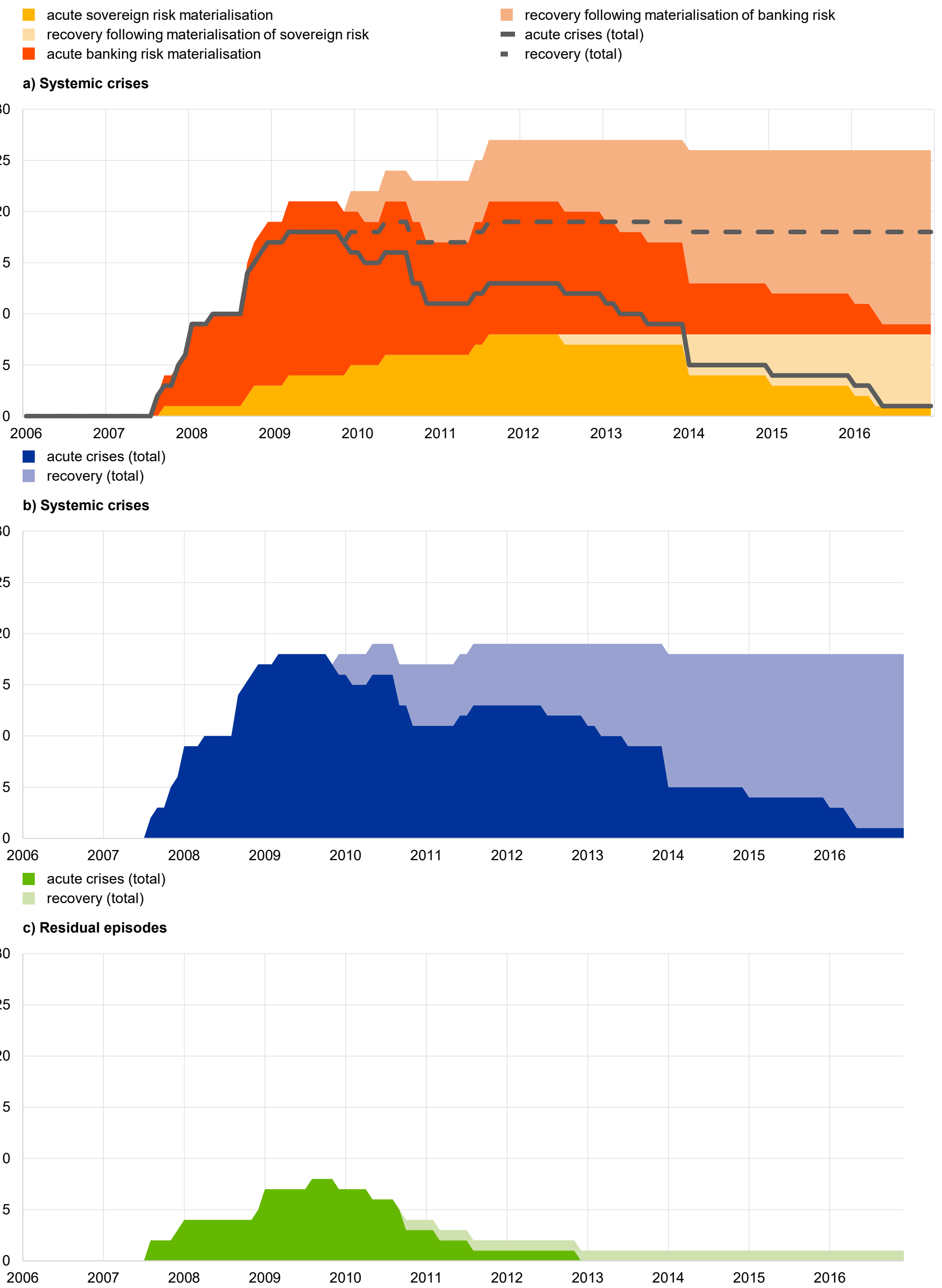
---

[30] The debate in the literature covered the crisis from different angles, including the impact of monetary policy on the financial markets and the macroeconomy (e.g. Fratzscher, Lo Duca and Straub, 2015; Altavilla, Giannone and Lenza, 2016; Altavilla, Carboni and Motto, 2015), the pricing of bond yields and sovereign risk (e.g. Beirne and Fratzscher, 2013; De Santis, 2012; De Grauwe and Ji, 2013), fiscal aspects of the crisis (e.g. Van Riet, 2010) and institutional aspects, including the architecture of the euro area (e.g. the so called "**Five Presidents' Report**").

[31] See European Commission (2009a) for a description of the European Economic Recovery Plan and European Commission (2009b) for an overview of recovery measures by Member States.

Chart
**Materialisation of different types of risks over time since 2006**

(y-axis: absolute frequency)




Notes: The dataset distinguishes between a core set of systemic crises and an additional set of residual episodes (please refer to Sections 4.2.1 and 4.2.2. for definitions) which the paper further divides into (non-) relevant for the purpose of macroprudential analysis. This chart refers to both systemic and residual episodes which are deemed relevant for macroprudential analysis. This chart does not separate complex from single events, e.g. an event where both dummies for sovereign and banking risks are activated is displayed twice in the orange/grey shaded area in the first panel.

# Section 4
# Assessing the properties of standard early warning indicators based on the new crisis dataset

The existing literature has found that various credit and asset price transformations have the best early warning properties for financial crises. In an early contribution to this literature, Borio and Lowe (2002) showed that sustained rapid credit growth combined with large increases in asset prices appears to increase the probability of an episode of financial instability. In particular, they proposed that credit and asset price gaps, calculated as the deviation from a one-sided HP-filtered trend with a large smoothing parameter, have good signalling properties. This insight has been confirmed and refined in various subsequent contributions to the literature.[32] In a study focusing on EU countries, Detken et al. (2014) confirm that various credit-to-GDP gaps are among the best univariate signalling indicators for systemic banking crises. Moreover, the residential property price-to-income ratio, residential and commercial property price gaps, the debt service-to-income ratio for households, real bank and household credit growth and the deviation of the (deflated) broad monetary aggregate M3 from its trend were found to be good univariate signalling indicators. Multivariate models that combine the credit-to-GDP gap with other variables were found to further improve the signalling power (Lo Duca and Peltonen, 2013).

This section provides first preliminary evidence of the signalling performance of various standard early warning indicators and models by using the systemic crises events included in the new crisis dataset. The goal of the analysis is to provide a sense of whether earlier findings of the literature on the performance of indicators and models appear to be validated using the new crisis dataset. A more refined analysis, based on robust criteria for model evaluation to support policy analysis, is left for future research.

Both a univariate signalling and a multivariate logit analysis are performed for Denmark, Sweden, the United Kingdom and all euro area countries for the period 1970 Q1 to 2016 Q4. The remaining EU countries are not included in the analysis, due to data limitations for most of the early warning indicators that are considered. The evaluation of the performance of standard early warning indicators and models for other EU countries in the new dataset is left for future research.

For the baseline results, all systemic crises according to the new dataset described in Section 3 are taken as the relevant set of events. In total, there are 35 systemic crises events since 1970 for the set of countries that are part of the early warning evaluation exercise. A prediction horizon of 12 to 5 quarters before systemic crises is used to define the vulnerability periods for the early warning exercise.[33] The set of relevant early warning indicators that is considered consists of various transformations [34] of bank credit, total credit to the non-financial private sector (NFPS), total credit to households (HHs), total credit to non-financial corporations (NFCs), residential real estate (RRE)

[32] See, for example, Borio and Drehmann (2009), Drehmann et al. (2011), Drehmann and Juselius (2014) and Detken et al. (2014).

[33] As frequently seen in literature, the vulnerability indicator (i.e. the dependent variable) is set to 1 for the 12 to 5 quarters before a systemic crisis, to missing for the 4 to 1 quarters before a systemic crisis and for the crisis period itself (between start date and end of crisis management date, i.e. for the acute phase of the crisis), and to 0 otherwise. See Box 2.

[34] The following transformations were used for these variables: one-quarter, one-year, two-year and three-year growth rates, one-quarter, one-year, two-year and three-year changes in ratios to GDP (for stock variables), one-sided HP-filtered gaps with a smoothing parameter of 400,000 and 26,000, and the levels of the variables if deemed relevant (e.g. for REER or real interest rates). This is in line with transformations used in the early warning literature (e.g. Detken et al. 2014).

prices, RRE price-to-income and price-to-rent ratios, equity prices, M3[35], debt-service ratios (DSR), real GDP growth, consumer price inflation, real effective exchange rate (REER), and real short-term and long-term interest rates. Only indicators that have at least 1,500 country-quarter observations are considered as relevant for the early warning evaluation, which leads to a set of 436 different indicators.[36] In addition, all indicators, except the ones related to interest rates, exchange rates and equity prices are lagged by one quarter to account for publication lags.

Box 2

## A primer on evaluation criteria for early warning models for systemic financial crises

This box provides an overview of the common evaluation criteria for early warning models.[37] Every early warning indicator can be transformed into a discrete crisis warning signal by applying a certain threshold to it, where values above the threshold are classified as signals for vulnerable states and values below the threshold are classified as tranquil periods. These signals can then be compared to the true states of the world and classified into one of four possible outcomes: 1) true positives (signal and true state are vulnerable); 2) false negative (signal is tranquil and true state is vulnerable); 3) true negative (signal and true state are tranquil); 4) false positive (signal is vulnerable, but state is tranquil).

Based on these four possible outcomes, Type I error rates (missed vulnerable states) can be defined as false negatives divided by all vulnerable states, while Type II error rates (false alarms) can be defined as false positives divided by all tranquil states. The true positive rate is defined as 1 – the Type I error rate. Based on this classification system various evaluation criteria can be computed.

In order to decide which threshold should be used to produce vulnerability signals for a given indicator, a loss function approach can be taken (see, for example, Alessi and Detken, 2011), where the optimal signalling threshold minimises a weighted average between Type I (T1) and Type II (T2) errors: $L(\theta) = \theta \cdot T1 + (1 - \theta) \cdot T2$. The policy preference parameter ($\theta$) reflects the relative concern assigned to missing crises (T1) versus issuing false crisis alarms (T2).

One of the advantages of the loss function approach for deriving the optimal signalling threshold is that it makes it possible to evaluate the early warning model in terms of the relative usefulness of the model for the policymaker. The relative usefulness measure represents the difference in the loss that the policymaker would get by using the model compared with ignoring the model, which is expressed as a share of the maximum achievable difference. The measure therefore gives an idea of how close the early warning model is to a perfect model of crisis prediction for a policymaker with preferences represented by ($\theta$). However, relative usefulness depends on the preferences of the policymaker and it is therefore desirable to look at global measures of signalling performance in addition to relative usefulness.

The area under the receiver operating characteristics curve (AUROC) is a global measure of the signalling performance of an early warning indicator independent of the policy preference parameter. It is computed as the area under the receiver operating characteristics (ROC) curve,

35 For euro area countries M3 is measured as the national contribution to euro area M3, while for non-euro area countries M3 refers to the domestic M3 concept.

36 For the early warning exercise, the effective sample can be smaller than 1,500 as immediate pre-crisis and actual crisis quarters are excluded from the evaluation sample.

37 Parts of this box are based on the findings in Detken et al. (2014).

which plots the noise ratio (false positive rate) on the x-axis against the signal ratio (true positive rate) on the y-axis for every possible threshold value that can be applied to an early warning indicator. For a given noise ratio, a higher signal ratio implies that an early warning indicator is better able to differentiate between vulnerable and tranquil states of the world. Usually, there is a trade-off between the noise and the signal ratio, so higher signal ratios are associated with higher noise ratios. The ROC curve is therefore upward sloping. A perfect indicator would imply a noise ratio of 0 and a signal ratio of 1 for the optimal signalling threshold. For other signalling thresholds, the signal ratio would stay at 1, but the noise ratio would start to increase until it also reaches 1. The ROC curve for such a perfect early warning indicator would look like an upside down L and the area under this curve would be equal to 1. Hence, an AUROC value of 1 indicates a perfect early warning indicator, while an AUROC value of 0.5 indicates an uninformative indicator.

The best univariate early warning models are selected based on a combination of their in-sample and out-of-sample signalling performance.[38] First, a univariate in-sample signalling exercise is performed for the entire set of relevant early warning indicators. The in-sample early warning properties are evaluated based on the AUROC, the relative usefulness, and the Type I and Type II errors associated with the optimal signalling threshold for balanced preferences (see Box 2 for details on these measures). In the second step, only models that have an AUROC of at least 0.65, a relative usefulness of 0.25 and Type I and Type II errors below 0.5 and 0.6 respectively are considered relevant for the out-of-sample evaluation.[39] In total 55 univariate signalling indicators are selected for a recursive quasi real-time out-of-sample evaluation, which is performed as follows: starting in 2000 Q1, a univariate signalling model is estimated with data up to 1997 Q1[40], and the resulting optimal in-sample signalling threshold is applied to data from 2000 Q1 to generate a signal. Once the signal is recorded, the same procedure is performed for the next quarter, i.e. 2000 Q2, where the relevant estimation sample for the univariate signalling model now includes one additional quarter of data, i.e. data up to 1997 Q2. This procedure is performed recursively until 2016 Q4. All univariate indicators that have an out-of-sample relative usefulness of at least 0.25 and out-of-sample Type I and Type II errors of no more than 0.5 and 0.6 for balanced preferences are considered for multivariate models.[41]

The best univariate signalling indicators are used to generate a large set of multivariate logit early warning models that are evaluated in-sample and out-of-sample. For this purpose the best

[38] This is one possible approach to identify best-performing indicators and models. It should be noted, however, that a good in-sample signalling performance of an indicator/model does not imply a good out-of-sample signalling performance of the same indicator. From a macroprudential policy perspective, it can be argued that the out-of-sample signalling performance of the indicator should receive more weight on balance. Finding an optimal selection strategy for early warning models and indicators is beyond the scope of this paper and is left for future research.

[39] The cut-off values for the in-sample performance measures are chosen to significantly narrow down the set of relevant early warning indicators for the out-of-sample evaluation, given that the recursive out-of-sample evaluation procedure is computationally much more demanding. Standard early warning indicators that have been found useful in past studies, such as the total or bank credit-to-GDP gaps, were included in the out-of-sample evaluation regardless of their in-sample performance.

[40] A 3-year data lag is used for the estimation sample to mimic real-time information availability: given that the relevant vulnerability period is defined as 12 to 5 quarters before systemic crises, the true vulnerability periods cannot be known for the last 12 quarters of the sample period, unless a systemic crisis materialised during the last 12 quarters. For example, in the second quarter of 2017 it is only possible to define vulnerability periods up to the second quarter of 2014 if no systemic crisis happened in the last three years.

[41] The cut-off values for the out-of-sample performance measures are chosen to significantly narrow down the set of relevant early warning indicators that are used in multivariate early warning models, in order to keep the total number of possible multivariate logit model combinations in a range that is computationally not too costly.

univariate signalling indicators are grouped into four categories and combined into all possible bivariate, trivariate and quadvariate logit models: (i) household credit variables (8), (ii) other credit variables (17), (iii) RRE price variables (6), and (iv) equity price growth and the DSR (2).[42] For all of the resulting possible logit model combinations, an in-sample early warning exercise is performed along the same lines as for the univariate signalling exercise. All of the logit models with an AUROC of at least 0.80, a relative usefulness of at least 0.49, and Type I and Type II errors below or equal to 0.2 and 0.36 respectively are selected as the relevant set of multivariate models.[43] In addition, all models are excluded where at least one of the estimated coefficient signs is not in accordance with economic reasoning. For this set of multivariate models, the same out-of-sample evaluation as for the univariate signalling models is carried out.

Table 8

**Overview of univariate signalling results**

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise-2-signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise-2-signal ratio | Conditional probability | Obs |
| Bank credit-to-GDP (one-year change) | 0.76 | 0.41 | 0.31 | 0.28 | 0.41 | 0.24 | 1,978 | 0.22 | 0.21 | 0.57 | 0.72 | 0.28 | 660 |
| RRE price-to-income (two-year change) | 0.74 | 0.39 | 0.31 | 0.30 | 0.43 | 0.27 | 1,494 | 0.25 | 0.29 | 0.46 | 0.65 | 0.28 | 715 |
| Bank credit-to-GDP (two-year change) | 0.74 | 0.39 | 0.41 | 0.19 | 0.33 | 0.28 | 1,894 | 0.16 | 0.28 | 0.56 | 0.78 | 0.27 | 628 |
| RRE price-to-income (three-year change) | 0.74 | 0.36 | 0.29 | 0.35 | 0.49 | 0.24 | 1,406 | 0.17 | 0.26 | 0.58 | 0.78 | 0.24 | 686 |
| Bank credit-to-GDP (one-quarter change) | 0.73 | 0.36 | 0.32 | 0.32 | 0.47 | 0.21 | 2,041 | 0.22 | 0.30 | 0.48 | 0.69 | 0.28 | 684 |
| HH credit-to-GDP (three-year change) | 0.72 | 0.38 | 0.29 | 0.34 | 0.47 | 0.27 | 1,261 | 0.23 | 0.24 | 0.53 | 0.70 | 0.28 | 604 |
| HH credit-to-GDP (two-year change) | 0.72 | 0.38 | 0.26 | 0.36 | 0.49 | 0.26 | 1,334 | 0.23 | 0.20 | 0.57 | 0.71 | 0.29 | 640 |
| RRE price-to-rent (two-year change) | 0.72 | 0.36 | 0.40 | 0.25 | 0.41 | 0.26 | 1,709 | 0.09 | 0.33 | 0.58 | 0.87 | 0.22 | 715 |
| RRE price-to-rent (three-year change) | 0.72 | 0.39 | 0.43 | 0.18 | 0.32 | 0.30 | 1,623 | 0.12 | 0.30 | 0.58 | 0.83 | 0.23 | 686 |
| Real bank credit (one-year growth) | 0.71 | 0.33 | 0.19 | 0.48 | 0.59 | 0.18 | 2,041 | 0.24 | 0.29 | 0.47 | 0.67 | 0.30 | 660 |

42 The set of variables is as follows: real HH credit (one-year growth), real HH credit (two-year growth), real HH credit (three-year growth), HH credit-to-GDP (one-quarter change), HH credit-to-GDP (one-year change), HH credit-to-GDP (two-year change), HH credit-to-GDP (three-year change), HH credit-to-GDP (gap 400,000), bank credit-to-GDP (one-quarter change), bank credit-to-GDP (one-year change), bank credit-to-GDP (two-year change), real bank credit (one-year growth), real bank credit (two-year growth), bank credit-to-GDP (gap 400,000), NFC credit-to-GDP (one-year change), total credit-to-GDP (one-year change), total credit-to-GDP (gap 400,000), real total credit (one-year growth), real NFC credit (one-year growth), real M3 (one-year growth), real M3 (two-year growth), real M3 (three-year growth), M3-to-GDP (three-year change), real M3 (relative gap 400,000), real M3 (relative gap 26,000), RRE price-to-income (one-year change), RRE price-to-income (two-year change), real RRE prices (two-year growth), real RRE prices (three-year growth), RRE price-to-income (gap 400,000), RRE price-to-rent (gap 400,000), real equity prices (three-year growth), debt service ratio.

43 The cut-off values for the in-sample performance measures are chosen to significantly narrow down the set of relevant logit early warning models for the out-of-sample evaluation, given that the recursive out-of-sample evaluation procedure is computationally much more demanding.

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise -2- signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise -2- signal ratio | Conditional probability | Obs |
| M3-to-GDP (two-year change) | 0.71 | 0.32 | 0.30 | 0.38 | 0.54 | 0.18 | 1,718 | 0.28 | 0.06 | 0.66 | 0.70 | 0.29 | 590 |
| Real M3 (two-year growth) | 0.71 | 0.31 | 0.36 | 0.33 | 0.52 | 0.19 | 1,751 | 0.37 | 0.13 | 0.51 | 0.58 | 0.33 | 590 |
| Real bank credit (two-year growth) | 0.70 | 0.33 | 0.26 | 0.41 | 0.55 | 0.19 | 1,985 | 0.15 | 0.40 | 0.45 | 0.74 | 0.28 | 628 |
| Total credit-to-GDP (one-year growth) | 0.70 | 0.34 | 0.22 | 0.44 | 0.57 | 0.18 | 2,036 | 0.11 | 0.20 | 0.68 | 0.86 | 0.24 | 689 |
| Bank credit-to-GDP (three-year change) | 0.70 | 0.33 | 0.32 | 0.35 | 0.52 | 0.20 | 1,813 | 0.08 | 0.25 | 0.66 | 0.89 | 0.23 | 596 |
| RRE price-to-income (one-year change) | 0.70 | 0.34 | 0.52 | 0.14 | 0.30 | 0.34 | 1,582 | 0.26 | 0.49 | 0.25 | 0.48 | 0.33 | 743 |
| RRE price-to-income (gap 400,000) | 0.70 | 0.31 | 0.40 | 0.29 | 0.48 | 0.23 | 1,670 | 0.29 | 0.28 | 0.43 | 0.60 | 0.28 | 771 |
| HH credit-to-GDP (one-year change) | 0.70 | 0.33 | 0.28 | 0.40 | 0.55 | 0.24 | 1,414 | 0.20 | 0.18 | 0.62 | 0.75 | 0.27 | 676 |
| Real M3 (one-year growth) | 0.70 | 0.29 | 0.46 | 0.24 | 0.45 | 0.21 | 1,839 | 0.31 | 0.30 | 0.39 | 0.56 | 0.33 | 630 |
| Real M3 (three-year growth) | 0.70 | 0.32 | 0.26 | 0.42 | 0.57 | 0.17 | 1,663 | 0.31 | 0.19 | 0.51 | 0.63 | 0.32 | 550 |
| Real M3 (relative gap 26,000) | 0.70 | 0.35 | 0.38 | 0.27 | 0.43 | 0.20 | 1,927 | 0.33 | 0.45 | 0.22 | 0.40 | 0.39 | 667 |
| Real RRE prices (three-year growth) | 0.69 | 0.36 | 0.38 | 0.27 | 0.43 | 0.24 | 1,618 | 0.23 | 0.38 | 0.40 | 0.64 | 0.27 | 617 |
| RRE price-to-rent (gap 400,000) | 0.69 | 0.26 | 0.66 | 0.08 | 0.24 | 0.36 | 1,885 | 0.09 | 0.57 | 0.34 | 0.79 | 0.23 | 771 |
| Bank credit-to-GDP (gap 400,000) | 0.69 | 0.31 | 0.50 | 0.19 | 0.38 | 0.25 | 2,062 | 0.07 | 0.53 | 0.40 | 0.85 | 0.24 | 692 |
| M3-to-GDP (one-year change) | 0.69 | 0.29 | 0.47 | 0.25 | 0.46 | 0.20 | 1,806 | 0.29 | 0.05 | 0.66 | 0.69 | 0.28 | 630 |
| M3-to-GDP (three-year change) | 0.69 | 0.33 | 0.43 | 0.24 | 0.43 | 0.22 | 1,633 | 0.29 | 0.29 | 0.42 | 0.60 | 0.33 | 550 |
| HH credit-to-GDP (gap 400,000) | 0.68 | 0.30 | 0.19 | 0.52 | 0.64 | 0.21 | 1,493 | 0.14 | 0.46 | 0.40 | 0.74 | 0.26 | 712 |
| Total credit-to-GDP (gap 400,000) | 0.68 | 0.28 | 0.39 | 0.33 | 0.55 | 0.18 | 2,120 | 0.03 | 0.49 | 0.49 | 0.95 | 0.21 | 721 |
| Real M3 (relative gap 400,000) | 0.67 | 0.26 | 0.43 | 0.31 | 0.54 | 0.17 | 1,927 | 0.20 | 0.39 | 0.41 | 0.68 | 0.28 | 667 |
| Real RRE prices (gap 400,000) | 0.66 | 0.27 | 0.61 | 0.12 | 0.30 | 0.30 | 1,852 | 0.15 | 0.22 | 0.63 | 0.81 | 0.22 | 698 |
| Real equity prices (three-year growth) | 0.64 | 0.30 | 0.33 | 0.37 | 0.55 | 0.18 | 2,038 | 0.25 | 0.18 | 0.57 | 0.70 | 0.25 | 781 |

Notes: All systemic crises according to the new dataset described in Section 3 are taken as the relevant set of events. Moreover, a prediction horizon of 12 to 5 quarters before systemic crises is used to define the vulnerability periods for the early warning exercise. For definitions of the performance measures, see Box 2. All performance measures, except for the AUROC, are computed for balanced preferences between Type I and Type II errors, i.e. for a policy preference parameter of $\theta = 0.5$. The conditional probability is defined as the share of true signals of a coming crisis whenever the model issues a warning signal.

Various medium-term transformations of bank credit, household credit, RRE prices, M3, and equity prices emerge as the best univariate early warning indicators for systemic crises in the new database. The set of indicators with the best in-sample signalling properties differs to some extent from the set of indicators that have the best out-of-sample signalling properties (see Table 8). For example, the highest in-sample AUROCs for the systemic crises of the new dataset of more than 0.71 are achieved by the one-quarter, one-year, and two-year changes in the bank credit-to-GDP ratio, the two-year and three-year changes in the RRE price-to-income and price-to-rent ratios, the two-year and three-year changes in the HH credit-to-GDP ratio, the two-year change in the M3-to-GDP ratio, the two-year growth rate of real M3 and the one-year growth rate of real bank credit (see Table 8). Many of these variables also have a good out-of-sample relative usefulness of more than 0.20 for balanced preferences. Interestingly, one-year, two-year and three-year growth rates of real M3 and the real M3 gap with a smoothing parameter of 26,000 have the best out-of-sample relative usefulness with values above 0.30. The three-year growth rates of real RRE and equity prices also have good out-of-sample signalling properties, although they are not among the top 15 indicators based on the in-sample AUROC.

Gap measures for different credit and RRE price measures also have good in-sample signalling properties, but the out-of-sample properties are often much weaker. The total credit-to-GDP gap, bank credit-to-GDP gap, HH credit-to-GDP gap, real RRE price gap, and RRE price-to-income and price-to-rent gap all have fairly high in-sample AUROCs of between 0.66 and 0.70 (see Table 8). Moreover, their in-sample usefulness for balanced preferences is between 0.27 and 0.31. However, none of the gap measures is among the ten best univariate models according to either the AUROC or the relative usefulness. Simpler transformations such as one-year, two-year or three-year changes of these underlying variables have similar or even better in-sample signalling properties than gap transformations. In addition, the out-of-sample relative usefulness for these gap measures is often quite low and under 0.1, except for the HH-credit-to-GDP gap (0.14), the real RRE price gap (0.15) and the RRE price-to-income gap (0.29).

Multivariate logit models that combine transformations of credit and asset price indicators can improve the early warning properties for systemic crises in the new database. The in-sample AUROC improves from 0.76 for the best univariate signalling model to 0.83 for the best quadvariate logit early warning model that includes the HH credit-to-GDP gap, the three-year change in the M3-to-GDP ratio, the three-year real RRE price growth rate and the three-year real equity price growth rate (see Table 9). The best out-of-sample usefulness 0.41 is attained by a trivariate model that combines the three-year change in the M3-to-GDP ratio, the two-year real RRE price growth rate and the three-year real equity price growth rate. In general, various combinations of gaps, medium-term changes and growth rates of HH credit, M3, bank credit, RRE prices, equity prices or debt-service ratios have good in-sample and out-of-sample signalling properties (see Table 9).

The results confirm the existing findings in the early warning literature that multivariate models can improve upon univariate signalling models (for example Lo Duca and Peltonen, 2013), although gap variables are found to have slightly less information content for signalling systemic events than more simple transformations, such as changes in ratios relative to GDP or growth rates.

Table 9

**Overview of the performance of multivariate logit models**

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise-2-signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise-2-signal ratio | Conditional probability | Obs |
| **HH credit-to-GDP, M3-to-GDP (3-year change), real RRE prices (3-year growth), real equity prices (3-year growth)** | 0.83 | 0.53 | 0.12 | 0.35 | 0.40 | 0.29 | 1005 | 0.40 | 0.08 | 0.52 | 0.57 | 0.34 | 490 |
| **HH credit-to-GDP (3-year change), M3-to-GDP (3-year change), real RRE prices (2-year growth), real equity prices (3-year growth)** | 0.82 | 0.54 | 0.20 | 0.27 | 0.33 | 0.34 | 966 | 0.35 | 0.14 | 0.52 | 0.60 | 0.33 | 483 |

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise -2-signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise -2-signal ratio | Conditional probability | Obs |
| HH credit-to-GDP (two-year change), M3-to-GDP (3-year change), real RRE prices (3-year growth), real equity prices (3-year growth) | 0.83 | 0.54 | 0.15 | 0.32 | 0.37 | 0.32 | 973 | 0.33 | 0.16 | 0.51 | 0.61 | 0.33 | 482 |
| HH credit-to-GDP (3-year change), M3-to-GDP (3-year change), real RRE prices (3-year growth), real equity prices (3-year growth) | 0.83 | 0.53 | 0.18 | 0.30 | 0.36 | 0.33 | 957 | 0.31 | 0.16 | 0.54 | 0.64 | 0.32 | 478 |
| HH credit-to-GDP (3-year change), real M3 (relative gap 26,000), real RRE prices (3-year growth), real equity prices (3-year growth) | 0.81 | 0.49 | 0.18 | 0.34 | 0.41 | 0.29 | 1027 | 0.31 | 0.30 | 0.39 | 0.56 | 0.32 | 545 |
| HH credit-to-GDP (two-year change), M3-to-GDP (3-year change), real RRE prices (2-year growth), real equity prices (3-year growth) | 0.82 | 0.53 | 0.14 | 0.33 | 0.38 | 0.31 | 982 | 0.29 | 0.20 | 0.51 | 0.63 | 0.32 | 487 |
| real HH credit (3-year growth), M3-to-GDP (3-year change), real RRE prices (2-year growth), real equity prices (3-year growth) | 0.81 | 0.51 | 0.18 | 0.31 | 0.38 | 0.31 | 966 | 0.29 | 0.23 | 0.49 | 0.63 | 0.32 | 483 |
| HH credit-to-GDP, real M3 (rel gap 26,000), RRE price-to-income (2-year change), Debt-service ratio | 0.81 | 0.50 | 0.18 | 0.33 | 0.40 | 0.31 | 1081 | 0.27 | 0.26 | 0.46 | 0.63 | 0.30 | 628 |
| Bank credit-to-GDP (one-year change), RRE price-to-service gap, Debt-service ratio | 0.82 | 0.49 | 0.18 | 0.33 | 0.41 | 0.29 | 1400 | 0.27 | 0.20 | 0.53 | 0.67 | 0.30 | 658 |
| Bank credit-to-GDP (one-year change), RRE price-to-income (gap 400,000), real equity prices (3-year growth) | 0.82 | 0.56 | 0.13 | 0.31 | 0.36 | 0.31 | 1453 | 0.26 | 0.19 | 0.54 | 0.67 | 0.30 | 654 |
| HH credit-to-GDP (3-year change), real M3 (relative gap 26,000), RRE price-to-income gap, real equity prices (3-year growth) | 0.81 | 0.53 | 0.15 | 0.33 | 0.38 | 0.33 | 1032 | 0.25 | 0.29 | 0.46 | 0.64 | 0.31 | 580 |
| Bank credit-to-GDP (one-year change), real RRE prices (3-year growth), real equity prices (3-year growth) | 0.80 | 0.50 | 0.18 | 0.32 | 0.39 | 0.26 | 1528 | 0.25 | 0.24 | 0.51 | 0.67 | 0.28 | 588 |
| HH credit-to-GDP gap, real bank credit (one-year growth), RRE price-to-income gap, Debt-service ratio | 0.81 | 0.50 | 0.16 | 0.35 | 0.41 | 0.31 | 1207 | 0.25 | 0.24 | 0.52 | 0.67 | 0.30 | 649 |

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise -2- signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise -2- signal ratio | Conditional probability | Obs |
| **Bank credit-to-GDP (two-year change), RRE price-to-income gap, real equity prices (3-year growth)** | 0.82 | 0.53 | 0.16 | 0.31 | 0.37 | 0.30 | 1410 | 0.25 | 0.25 | 0.51 | 0.68 | 0.30 | 623 |
| **HH credit-to-GDP gap, Bank credit-to-GDP (two-year change), RRE price-to-income (two-year change), real equity prices (3-year growth)** | 0.83 | 0.53 | 0.15 | 0.32 | 0.37 | 0.34 | 1144 | 0.24 | 0.22 | 0.55 | 0.70 | 0.30 | 614 |
| **HH credit-to-GDP (3-year change), real M3 (3-year growth), RRE price-to-income gap, real equity prices (3-year growth)** | 0.80 | 0.51 | 0.15 | 0.34 | 0.40 | 0.33 | 954 | 0.24 | 0.30 | 0.46 | 0.66 | 0.33 | 505 |
| **Bank credit-to-GDP (gap 400,000), RRE price-to-income (2-year change), Debt-service ratio** | 0.80 | 0.51 | 0.19 | 0.31 | 0.37 | 0.31 | 1342 | 0.24 | 0.23 | 0.53 | 0.69 | 0.28 | 668 |
| **HH credit-to-GDP (3-year change), real M3 (relative gap 26,000), RRE price-to-income (two-year change), Debt-service ratio** | 0.81 | 0.50 | 0.19 | 0.31 | 0.38 | 0.33 | 1006 | 0.24 | 0.27 | 0.49 | 0.68 | 0.29 | 586 |
| **HH credit-to-GDP (3-year change), Bank credit-to-GDP (one-year change), RRE price-to-income gap, real equity prices (3-year growth)** | 0.81 | 0.51 | 0.16 | 0.33 | 0.39 | 0.33 | 1115 | 0.23 | 0.28 | 0.49 | 0.68 | 0.29 | 597 |
| **HH credit-to-GDP gap, real M3 (two-year growth), RRE price-to-income (two-year change), Debt-service ratio** | 0.81 | 0.49 | 0.20 | 0.31 | 0.38 | 0.34 | 1022 | 0.23 | 0.30 | 0.47 | 0.67 | 0.31 | 572 |
| **HH credit-to-GDP (3-year change), real M3 (two-year growth), RRE price-to-income (gap), real equity prices (3-year growth)** | 0.81 | 0.51 | 0.13 | 0.36 | 0.42 | 0.32 | 986 | 0.23 | 0.25 | 0.52 | 0.69 | 0.31 | 537 |
| **HH credit-to-GDP (gap), Bank credit-to-GDP (two-year change), RRE price-to-income (one-year change), real equity prices (3-year growth)** | 0.82 | 0.52 | 0.17 | 0.31 | 0.37 | 0.34 | 1172 | 0.22 | 0.22 | 0.56 | 0.71 | 0.29 | 614 |
| **Bank credit-to-GDP (two-year change), RRE price-to-income (one-year change), real equity prices (3-year growth)** | 0.82 | 0.51 | 0.17 | 0.32 | 0.39 | 0.30 | 1374 | 0.22 | 0.22 | 0.56 | 0.72 | 0.29 | 623 |
| **HH credit-to-GDP (3-year change), real M3 (relative gap 26,000), RRE price-to-income (one-year change), Debt-service ratio** | 0.81 | 0.49 | 0.19 | 0.32 | 0.40 | 0.32 | 1018 | 0.21 | 0.28 | 0.51 | 0.71 | 0.28 | 586 |

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise -2- signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise -2- signal ratio | Conditional probability | Obs |
| HH credit-to-GDP (3-year change), real M3 (rel gap 26,000), RRE price-to-income (two-year change), real equity prices (3-year growth) | 0.81 | 0.49 | 0.16 | 0.35 | 0.42 | 0.31 | 1003 | 0.20 | 0.35 | 0.45 | 0.69 | 0.29 | 580 |
| HH credit-to-GDP (two-year change), real M3 (rel gap 26,000), RRE price-to-income (two-year change), Debt-service ratio | 0.81 | 0.49 | 0.16 | 0.35 | 0.42 | 0.31 | 1045 | 0.20 | 0.33 | 0.47 | 0.71 | 0.28 | 608 |
| HH credit-to-GDP (gap), real M3 (3-year growth), RRE price-to-income (two-year change), Debt-service ratio | 0.80 | 0.51 | 0.17 | 0.32 | 0.39 | 0.33 | 982 | 0.19 | 0.35 | 0.47 | 0.72 | 0.30 | 532 |
| HH credit-to-GDP (gap), Bank credit-to-GDP (one-year change), RRE price-to-income (one-year change), real equity prices (3-year growth) | 0.82 | 0.50 | 0.16 | 0.34 | 0.41 | 0.32 | 1207 | 0.17 | 0.25 | 0.58 | 0.77 | 0.27 | 645 |
| HH credit-to-GDP (3-year change), real M3 (one-year growth), RRE price-to-income (gap 400,000), Debt-service ratio | 0.80 | 0.49 | 0.17 | 0.34 | 0.41 | 0.32 | 1007 | 0.17 | 0.27 | 0.57 | 0.77 | 0.27 | 569 |
| HH credit-to-GDP (gap), Bank credit-to-GDP (two-year change), RRE price-to-income (gap), Debt-service ratio | 0.82 | 0.50 | 0.18 | 0.32 | 0.39 | 0.33 | 1173 | 0.10 | 0.32 | 0.59 | 0.86 | 0.25 | 619 |
| HH credit-to-GDP (3-year change), Bank credit-to-GDP (two-year change), RRE price-to-income (gap), real equity prices (3-year growth) | 0.81 | 0.50 | 0.20 | 0.30 | 0.38 | 0.34 | 1098 | 0.09 | 0.47 | 0.44 | 0.84 | 0.25 | 588 |
| M3-to-GDP (3-year change), real RRE prices (two-year growth), real equity prices (3-year growth) | 0.81 | 0.53 | 0.19 | 0.28 | 0.35 | 0.27 | 1231 | 0.41 | 0.19 | 0.40 | 0.49 | 0.36 | 504 |
| HH credit-to-GDP (gap), M3-to-GDP (3-year change), real RRE prices (3-year growth), real equity prices (3-year growth) | 0.83 | 0.53 | 0.12 | 0.35 | 0.40 | 0.29 | 1005 | 0.40 | 0.08 | 0.52 | 0.57 | 0.34 | 490 |
| HH credit-to-GDP (two-year change), M3-to-GDP (3-year change), real RRE prices (two-year growth), real equity prices (3-year growth) | 0.82 | 0.54 | 0.20 | 0.27 | 0.33 | 0.34 | 966 | 0.35 | 0.14 | 0.52 | 0.60 | 0.33 | 483 |
| HH credit-to-GDP (two-year change), M3-to-GDP (3-year change), real RRE prices (3-year growth), real equity prices (3-year growth) | 0.83 | 0.54 | 0.15 | 0.32 | 0.37 | 0.32 | 973 | 0.33 | 0.16 | 0.51 | 0.61 | 0.33 | 482 |

| | In-sample | | | | | | | Out-of-sample | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | AUROC | Relative usefulness | Type I error rate | Type II error rate | Noise -2-signal ratio | Conditional probability | Obs | Relative usefulness | Type I error rate | Type II error rate | Noise -2-signa l ratio | Conditional probability | Obs |
| **HH credit-to-GDP (3-year change), M3-to-GDP (3-year change), real RRE prices (3-year growth), real equity prices (3-year growth)** | 0.83 | 0.53 | 0.18 | 0.30 | 0.36 | 0.33 | 957 | 0.31 | 0.16 | 0.54 | 0.64 | 0.32 | 478 |
| **HH credit-to-GDP (3-year change), real M3 (rel gap 26,000), real RRE prices (3-year growth), real equity prices (3-year growth)** | 0.81 | 0.49 | 0.18 | 0.34 | 0.41 | 0.29 | 1027 | 0.31 | 0.30 | 0.39 | 0.56 | 0.32 | 545 |
| **HH credit-to-GDP (two-year change), M3-to-GDP (3-year change), real RRE prices (two-year growth), real equity prices (3-year growth)** | 0.82 | 0.53 | 0.14 | 0.33 | 0.38 | 0.31 | 982 | 0.29 | 0.20 | 0.51 | 0.63 | 0.32 | 487 |
| **Real HH credit (3-year growth), M3-to-GDP (3-year change), real RRE prices (two-year growth), real equity prices (3-year growth)** | 0.81 | 0.51 | 0.18 | 0.31 | 0.38 | 0.31 | 966 | 0.29 | 0.23 | 0.49 | 0.63 | 0.32 | 483 |
| **HH credit-to-GDP (gap), real M3 (rel gap 26,000), RRE price-to-income (two-year change), Debt-service ratio** | 0.81 | 0.50 | 0.18 | 0.33 | 0.40 | 0.31 | 1081 | 0.27 | 0.26 | 0.46 | 0.63 | 0.30 | 628 |
| **Bank credit-to-GDP (one-year change), RRE price-to-income (gap), Debt-service ratio** | 0.82 | 0.49 | 0.18 | 0.33 | 0.41 | 0.29 | 1400 | 0.27 | 0.20 | 0.53 | 0.67 | 0.30 | 658 |
| **Bank credit-to-GDP (one-year change), RRE price-to-income (gap), real equity prices (3-year growth)** | 0.82 | 0.56 | 0.13 | 0.31 | 0.36 | 0.31 | 1453 | 0.26 | 0.19 | 0.54 | 0.67 | 0.30 | 654 |
| **HH credit-to-GDP (3-year change), real M3 (rel gap 26,000), RRE price-to-income (gap), real equity prices (3-year growth)** | 0.81 | 0.53 | 0.15 | 0.33 | 0.38 | 0.33 | 1032 | 0.25 | 0.29 | 0.46 | 0.64 | 0.31 | 580 |

Notes: All systemic crises according to the new dataset described in Section 3 are taken as the relevant set of events. Moreover, a prediction horizon of 12 to 5 quarters before systemic crises is used to define the vulnerability periods for the early warning exercise. For definitions of the performance measures see Box 2. All performance measures, except for the AUROC, are computed for balanced preferences between Type I and Type II errors, i.e. for a policy preference parameter of $\theta$=0.5. The conditional probability is defined as the share of true signals of a coming crisis, whenever the model issues a warning signal.

# Section 5
# Conclusions

This occasional paper has presented a new crises database for European countries. It represents an important step towards establishing a common ground for macroprudential oversight and policymaking in the European Union. The database focuses on the delimitation of crisis periods to support the calibration of models in macroprudential analysis. An important contribution of this work is that crises are identified by combining a quantitative approach based on a financial stress index with expert judgement from national and European authorities. In addition, key innovations of the dataset are: (i) a distinction between crisis and post crisis adjustment periods, (ii) the introduction of a broad set of non-exclusive categories to classify events, and (iii) the inclusion of qualitative information about crises periods and policy responses. The overall consistency of the dataset was checked on several levels. First, the editing team ensured that the provided information was in line with the agreed common guidelines, including definitions and criteria. Second, the editing team checked that the overall picture provided by the dataset was consistent across countries and over time. The dataset covers crises from 1970 until 2016, and offers a relatively rich set of information with a particular focus on the delimitation of events and event descriptions, compared to existing crises datasets, e.g. Detken et al. (2014), Babecký et al. (2012) and Laeven and Valencia (2013).

A preliminary assessment of the performance of standard early warning indicators in the new crisis dataset confirms the finding in the early warning literature that multivariate models can improve upon univariate signalling models. However, gap variables are found to have slightly less information content for signalling systemic events than more simple transformations, such as changes in ratios relative to GDP or growth rates.

The dataset will allow researchers to analyse crises along several dimensions. Potential questions for future research relate to the identification of early warning indicators for the materialisation of different type of risks or in the presence of different types of domestic and international imbalances; the determinants of vulnerabilities to external shocks; an assessment of the impact of the post-crisis bias by explicitly modelling the identified recovery periods after the end of the acute phase of the crisis; the estimation of more complex models which describe the transition across different cyclical phases; and an analysis of the determinants of the length and intensity of crisis phases, differentiating between the acute phase of the crisis and the recovery period.

# References


Alessi, L. and Detken, C. (2011), “Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity”, *European Journal of Political Economy*, Vol. 27, No 3, pp. 520-533.

Altavilla, C., Giannone, D. and Lenza, M. (2016), “The financial and macroeconomic effects of the OMT announcements”, *International Journal of Central Banking*, Vol. 12, No 3, pp. 29-57.

Atlavilla, C., Carboni, G. and Motto, R. (2015), “Asset purchase programmes and financial markets: Lessons from the euro area”, *Working Paper Series*, No 1864, ECB, Frankfurt am Main, November.

Babecký, J., Havránek, T., Matějů, J., Rusnák, M., Šmídková, K. and Vašíček, B. (2012), “Banking, debt and currency crises: Early warning indicators for developed countries”, *Working Paper Series*, No 1485, ECB, Frankfurt am Main, October.

Backus, D. K. and Kehoe, P. J. (1992), “International evidence on the historical properties of business cycles”, *The American Economic Review*, Vol. 82, No 4, pp. 864-888.

Beirne, J. and Fratzscher, M. (2013), “The pricing of sovereign risk and contagion during the European sovereign debt crisis”, *Journal of International Money and Finance*, Vol. 34, pp. 60-82.

Berg, A. and Pattillo, C. (2000), “Predicting currency crises: The indicators approach and an alternative”. *Journal of International Money and Finance,* Vol. 18, No 4, pp. 561-586.

Berg, A., Borensztein, E. and Pattillo, C. (2004), “Assessing early warning systems: How have they worked in practice?”, *IMF Working Paper*, No 04/52, Washington DC, March.

Borio, C. and Lowe, P. (2002), “Asset prices, financial and monetary stability: Exploring the nexus”, *BIS Working Papers*, No 114, Basel, July.

Borio, C. and Lowe, P. (2004), “Securing sustainable price stability: should credit come back from the wilderness?”, *BIS Working Papers*, No 157, Basel, July.

Borio, C. and Drehmann, M. (2009), “Assessing the risk of banking crises – revisited”, *BIS Quarterly Review*, pp. 29-46, March.

Bussière, M. and Fratzscher, M. (2006), “Towards a new early warning system of financial crises”, *Journal of International Money and Finance*, Vol. 25, No 6, pp. 953-973.

Bussière, M. and Fratzscher, M. (2008), “Low probability, high impact: Policy making and extreme events”, *Journal of Policy Modeling*, Vol. 30, No 1, pp. 111-121.

De Grauwe, P. and Ji, Y. (2013), “Self-fulfilling crises in the eurozone: An empirical test”, *Journal of International Money and Finance*, Vol. 34, pp. 15-36.

De Santis, R. A. (2012), “The euro area sovereign debt crisis: Safe haven, credit rating agencies and the spread of the fever from Greece, Ireland and Portugal”, *Working Paper Series*, No 1419, ECB, Frankfurt am Main, February.

Demirgüc-Kunt, A. and Detragiache, E. (2000), “Monitoring banking sector fragility: A multivariate logit approach”, *The World Bank Economic Review*, Vol. 14, No 2, pp. 287-307, May.

Detken, C., Weeken, O., Alessi, L., Bonfim, D., Bouchina, M., Castro, C., Frontczak, S., Giordana, G., Giese, J., Jahn, N., Kakes, J., Klaus, B., Lang, J.H., Puzanova, N. and Welz, P. (2014), “Operationalising the countercyclical capital buffer: Indicator selection, threshold identification and calibration options”, *Occasional Paper Series*, No 5, ESRB, Frankfurt am Main, June.

Drehmann, M., Borio, C. and Tsatsaronis, K. (2011), “Anchoring countercyclical capital buffers: The role of credit aggregates”, *BIS Working Papers*, No 355, Basel, November.

Drehmann, M. and Juselius, M. (2014), “Evaluating early warning indicators of banking crises: Satisfying policy requirements”, *BIS Working Papers*, No 421, Basel, August.

Duprey, T., Klaus, B. and Peltonen, T. (2015), “Dating systemic financial stress episodes in the EU countries”, *Working Paper Series*, No 1873, ECB, Frankfurt am Main, December.

Edison, H.J. (2003), “Do indicators of financial crises work? An evaluation of an early warning system”, *International Journal of Finance and Economics*, Vol. 8, No 1, pp. 11-53.

European Commission (2009a), “Economic crisis in Europe: Causes, consequences and responses”, *European Economy*, No 7, Directorate-General for Economic and Financial Affairs, Luxembourg, September.

European Commission (2009b), “The EU’s response to support the real economy during the economic crisis: An overview of Member States’ recovery measures”, *European Economy Occasional Papers*, No 51, Directorate-General for Economic and Financial Affairs, Brussels, July.

Frankel, J. and Rose, A. (1996), “Currency crashes in emerging markets: An empirical treatment”, *Journal of International Economics*, Vol. 41, No 3-4, pp. 351-366.

Fratzscher, M., Lo Duca, M. and Straub, R. (2016), “ECB unconventional monetary policy: Market impact and international spillovers”, *IMF Economic Review*, Vol. 64, No 1, May.

Holló, D., Kremer, M. and Lo Duca, M. (2012), “CISS – A composite indicator of systemic stress in the financial system”, *Working Paper Series*, No 1426, ECB, Frankfurt am Main, March.

Jordà, O., Schularick, M. and Taylor, A.M. (2011), “Financial crises, credit booms, and external imbalances: 140 years of lessons”, *IMF Economic Review*, Vol. 59, No 2, pp. 340-378.

Kaminsky, G. L. and Reinhart, C.M. (1999), “The twin crises: The causes of banking and balance of payments problems”, *The American Economic Review*, Vol. 89, No 3, pp. 473-500.

Laeven, L. and Valencia, F. (2008), “Systemic banking crises: A new database”, *IMF Working Paper*, No 08/224, Washington DC, November.

Laeven, L. and Valencia, F. (2013), “Systemic banking crises database: An update”, *IMF Economic Review*, Vol. 61, No 2, pp. 225-270.

Lo Duca, M. and Peltonen, T. (2013), “Assessing systemic risk and predicting systemic events”, *Journal of Banking and Finance*, Vol. 37, No 7, pp. 2183-2195.

Reinhart, C.M. and Rogoff, K.S. (2008), “Is the 2007 US sub-prime financial crisis so different? An international historical comparison”, *The American Economic Review*, Vol. 98, No 2, pp. 339-344.

Reinhart, C.M. and Rogoff, K.S. (2009), “The aftermath of financial crises”, *The American Economic Review*, Vol. 99, No 2, pp. 466-472.

Schularick, M. and Taylor, A.M. (2011), “Credit booms gone bust: Monetary policy, leverage cycles and financial crises, 1870-2008”, *The American Economic Review*, Vol.102, No 2, pp. 1029-1061.

Tölö, E., Laakkonen, H. and Kalatie, S. (forthcoming), “Evaluating indicators for use in setting the countercyclical capital buffer”, *International Journal of Central Banking*.

Van Riet, A. (2014), “Euro area fiscal policies and the crisis”, *Occasional Paper Series*, No 109, ECB, Frankfurt am Main, April.

# Annex A
# Fields of the crises database

The crisis dataset is enclosed in an excel file with the fields listed below. The systemic crises and the residual events are reported in separate spreadsheets of the excel file containing the crisis dataset. The fields in the spreadsheets are the same.

### Country

The country where the event took place. Format: two-letter ISO country code (for example Germany is DE).

### Event

Event number for each event in one country (starting from 1, first event in time). Events marked with L&V are imported from Laeven and Valencia (2008 and 2013). Format: text/number.

### Start date

Date when the event started. Please refer to the description in Section 2. Format: date (YYYY-MM).

### End of crisis management date

Date when the acute phase of the event ended. Please refer to the description in Section 2. Format: date (YYYY-MM).

### System "back to normal" date

Date when the macro-financial environment had recovered from the event. Please refer to the description in Section 2. Format: date (YYYY-MM).

### Systemic crisis

Indication as to whether the event is systemic according to the guidelines provided (see the main text for details). A crisis is considered systemic when it fulfils the criteria listed in Section 2. Format: number, 0 (not systemic) or 1 (systemic).

### Accelerator and motivation

Indicator of one or more of the five ESRB intermediate macroprudential objectives (excessive credit growth and leverage, mismatches and market illiquidity, exposure concentration, misaligned incentives, infrastructure resilience) – see the Recommendation of the ESRB of 4 April 2013 on intermediate objectives and instruments of macroprudential policy (ESRB/2013/1) (OJ 2013/C 170/01). Format: text.

### Brief description of the identified event

Brief description of the event. For systemic crises it also includes (i) information on the choice of the starting date of the event (when the latter differs from the date identified with the financial stress index) and (ii) information on the choice of the end date of the event (if not evident from the "Crisis management policies" field). Format: text.

### Crisis management policies

Description of crisis management policies. For systemic crises it may include information on the choice of the end date of the event. Format: text.

### External support
Indication as to whether crisis management was externally supported by parties from outside of the domestic economy (for example, the IMF). Format: number: 0 (no external support) or 1 (external support).

### Domestic vs imported
Indication as to whether the event originated in the domestic economy or abroad. Format: number 0 (domestic), 1 (abroad) or 2 (both).

### Date of the first default
Date when the first of from the following occurred: default, debt restructuring, recapitalisation, partial nationalisation, merger or acquisition of a systemic player in financial distress. Systemic player in financial distress can be considered one of following types: bank, other financial corporation, non-financial corporation, sovereign, other systematically important institution.

Format: date (YYYY-MM)/ text.

### Currency / BoP / capital flow
When the dummy "currency / BoP / capital flow" is equal to 1, it indicates that the adjustment of the external position of one country was one of the symptoms of the event (at least during part of the crisis). The "activation" of this dummy does not exclude the "activation" of other categories. Format: number, 0 (no) or 1 (yes).

### Sovereign
When the dummy "Sovereign" is equal to 1, it indicates that the emergence of sovereign risk was one of the symptoms of the event (at least during part of the crisis). The "activation" of this dummy does not exclude the "activation" of other categories. Format: number, 0 (no) or 1 (yes).

### Banking
When the dummy "Banking" is equal to 1, it indicates that the emergence of credit or liquidity risk in the banking sector was one of the symptoms of the event (at least during part of the crisis). The "activation" of this dummy does not exclude the "activation" of other categories. Format: number, 0 (no) or 1 (yes).

### Significant asset price correction
The dummy is set to 1 when during the event under review a significant asset price correction took place in equity, bond, currency or real estate markets, according to the view of NAs. To ensure cross-consistency, this dummy is normally set to 1 for all events that are linked to the recent financial crises. The "activation" of this dummy does not exclude the "activation" of other categories. Format: number, 0 (no) or 1 (yes).

### Transition
The dataset contains a number of events that are marked as "transition" events. This concerns a number of events in central and eastern European countries in the 1990s. Transition events relate to the transformation from centrally-planned economies to market-based economies which also involved complex privatisation processes. The transformation often resulted in profound economic changes as entire economic sectors proved unprofitable, changes in institutions, changes in broad terms and changes in the functioning and governance of the financial system. This often caused the recognition of bank losses, closure of non-viable institutions, assisted mergers, bankruptcies and crisis management interventions. The "activation" of this dummy does not exclude the "activation" of other event categories. Format: number, 0 (no) or 1 (yes).

### Macropru relevant
This field is relevant only for residual episodes of financial stress. Macroprudential relevance

indicates whether the NAs believe that the identified residual event was severe enough for consideration in the dataset, although the event does not fulfil the specified criteria for systemic crises. This could be the case when (i) financial turmoil persisted for at least some months, (ii) financial turmoil is perceived to have caused or amplified some negative macroeconomic outcomes, (iii) some non-systemic financial intermediaries experienced distress, and/or (iv) according to the NA's macroprudential policy, tools could have been used for attenuating the impact of the event. This is when the event was associated with vulnerabilities that could have been addressed by macroprudential policy instruments, if available. By default, this variable is set to 1 to for systemic crises. [44] Format: 0 (no) or 1 (yes).

### Macropru relevance explanation

Explanation of the choice for the dummy "Macropru relevant" when it is set to 0 (i.e. not relevant). Format: text.

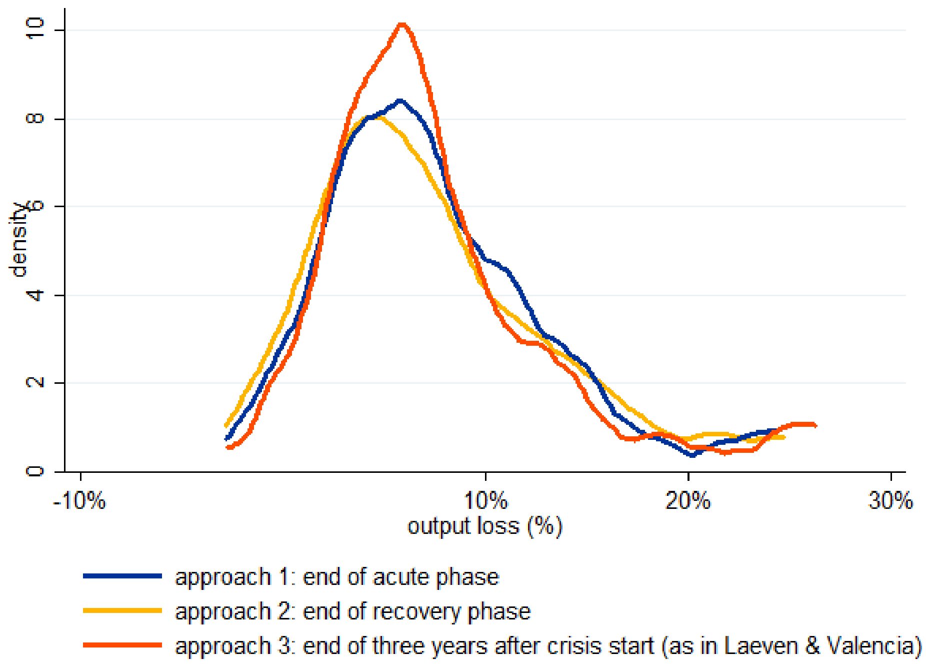
[44] It is assumed that systemic crises are, by definition, relevant for macroprudential policy analysis. The only exceptions are some crises episodes related to the transition to market-based economies in some central and eastern European countries.

# Annex B
# Comparison of loss distribution and computational details

Annex B provides more detail on the underlying computational methods and presents choices for the comparison of output losses and increases in government debt as presented in Section 5.3.

Chart B1
**Comparison of loss distribution across systemic crises for the three selected approaches towards end-date selection**

(x-axis, output loss estimate, percentages; y-axis, kernel density estimate)




Sources: World Bank and ECB ESRB calculations.

Table B1
**Three methods deliver relatively close estimates of output losses**

(percentages)

| Crisis type | Output loss as % of GDP, end of acute phase | | | Output loss as % of GDP, end of recovery phase | | | Output loss as % of GDP, crisis end three years after crisis start (as in Laeven and Valencia, 2013) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Mean | Median | Skewness | Mean | Median | Skewness | Mean | Median | Skewness |
| Total | 8% | 6% | 1.07 | 9% | 7% | 1.13 | 8% | 7% | 1.35 |
| Currency | 9% | 7% | 0.96 | 9% | 7% | 1.06 | 9% | 7% | 1.20 |
| Sovereign | 12% | 12% | 0.50 | 11% | 12% | 0.62 | 11% | 11% | 0.91 |
| Banking | 9% | 7% | 1.02 | 9% | 8% | 1.10 | 9% | 7% | 1.27 |
| Asset price correction | 9% | 7% | 0.93 | 9% | 8% | 0.99 | 9% | 7% | 1.22 |
| External origination | 6% | 5% | 0.76 | 6% | 5% | 0.61 | 8% | 7% | 0.56 |
| Domestic and external origination | 11% | 10% | 0.58 | 11% | 9% | 0.66 | 11% | 8% | 0.89 |

Sources: World Bank and ECB ESRB calculations.

The general approach for calculating output loss follows the method applied in Laeven and Valencia (2013), and is based on computing the cumulative difference between trend and observed GDP over the crisis period. In order to test the robustness of the calculated results, the computation includes, on one hand, three different approaches for selecting the end-date for the time window over which the loss is calculated, and, on the other hand, two different approaches for selecting the formula used for calculation. This yields a total of six sets of results.

The time window for computing the potential output loss can be determined by each of the following dates, the first of which represents the baseline scenario presented in the main analysis in Section 3:

- end of acute crisis phase, i.e. the end of crisis management policies (please refer to Section 2.3.2)
- end of recovery period, i.e. the date by which the system is back to normal (please refer to Section 2.3.3)
- a general time window of three years following the start of a crisis which is in line with the approach chosen by Laeven and Valencia (2013).

Furthermore, the absolute output losses are put in relation to both the trend GDP and the observed GDP:

$$\frac{\text{GDP\_trend} - \text{GDP\_observed}}{\text{GDP\_trend}} \times 100 \quad (1)$$

$$\frac{\text{GDP\_trend} - \text{GDP\_observed}}{\text{GDP\_observed}} \times 100 \quad (2)$$

With regard to the estimation of the GDP trend, this paper uses a Hodrick-Prescott filter with a smoothing parameter (λ) of 100, an approach widely used in the literature[45] for annual data and also applied in Laeven and Valencia (2013). The time window is set to ten years, due to limited data availability. For three crisis events in central and eastern European countries (BG 1996, CZ 1997, RO 1996), the starting year of the trend estimation window was fixed at 1992, due to unique nature of GDP developments related to the economic transition process in the early 1990s.

GDP data is gathered from the World Bank using its World Development Indices. The data is provided at market prices in constant 2010 US dollars. The following events are not covered by this source: EE 1992, EE 1994, HU 1991, LT 1995, LV 1995, PL 1981, RO 1981, SI 1991.

The debt-to-GDP data refers to the general government consolidated gross debt as a share of GDP. Data from European Commission's AMECO is mainly used for this series except for Croatia and Norway, for which the IMF's World Economic Outlook was used.

[45] For example, see Backus and Kehoe (1992).

# Annex C
# Overview crises database and comparison with Laeven and Valencia (2008 and 2013) per country

Annex C provides an overview of all the identified systemic crises and residual events in Tables C.1 and C.2. It follows an illustration in Table C.3 of this dataset compared with the one by Laeven and Valencia (2008 and 2013).

Table C1
**Overview of systemic crises in the dataset**

(crises risk materialisation dummy abbreviations: C = currency/BoP/capital flow; S = sovereign; B = banking; AP = significant asset price correction; T = transition; MP = macroprudential relevance)

| Country | Event | Start date | End of crisis management date | System "back normal" date | Systemic crisis | Domestic vs imported | C | S | B | AP | T | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 1 | 2007-12 | 2016-04 | ongoing | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| BE | 1 | 2007-11 | 2012-12 | ongoing | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| BG | 1 | 1996-05 | 1997-07 | 1997-07 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| CY | 1 | 2000-01 | 2001-03 | 2001-03 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| CY | 2 | 2011-06 | 2016-03 | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| CZ | 1 | 1997-05 | 2000-06 | 1999-01 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 1 |
| DE | 1 | 1974-06 | 1974-11 | 1975-08 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| DE | 2 | 2001-01 | 2003-11 | 2004-12 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 |
| DE | 3 | 2007-08 | 2013-06 | ongoing | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| DK | 1 | 1987-03 | 1995-01 | 1995-01 | 1 | 2 | 1 | 0 | 1 | 1 | 0 | 1 |
| DK | 2 | 2008-01 | 2013-12 | 2013-12 | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| EE | 1 | 1992-11 | 1993-03 | 1994-01 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| EE | 2 | 1994-08 | 1994-09 | 1995-03 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| EE | 3 | 1998-06 | 1998-10 | 1999-04 | 1 | 2 | 0 | 0 | 1 | 0 | 0 | 1 |
| ES | 1 | 1978-01 | 1985-09 | 1985-09 | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| ES | 2 | 2009-03 | 2013-12 | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| FI | 1 | 1991-09 | 1996-12 | 1998-12 | 1 | 2 | 1 | 0 | 1 | 1 | 0 | 1 |
| FR | 1 | 1991-06 | 1995-03 | 1999-06 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |
| FR | 2 | 2008-04 | 2009-11 | ongoing | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 |
| GR | 1 | 2010-05 | ongoing | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| HR | 1 | 1998-04 | 2000-01 | 2001-07 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| HR | 2 | 2007-09 | 2012-06 | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| HU | 1 | 1991-01 | 1995-12 | 1996-12 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| HU | 2 | 2008-09 | 2010-08 | 2010-08 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| IE | 1 | 2008-09 | 2013-12 | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| IT | 1 | 1991-09 | 1997-12 | 1997-12 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 |
| IT | 2 | 2011-08 | 2013-12 | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| LT | 1 | 1995-01 | 1996-12 | 1996-12 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 |
| LT | 2 | 2008-12 | 2009-11 | ongoing | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| LU | 1 | 2008-01 | 2010-10 | ongoing | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| LV | 1 | 1995-05 | 1996-06 | 1996-06 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| LV | 2 | 2008-11 | 2010-08 | ongoing | 1 | 2 | 1 | 0 | 1 | 1 | 0 | 1 |
| NL | 1 | 2008-01 | 2013-02 | ongoing | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| NO | 1 | 1988-09 | 1993-11 | 1994-05 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |

| Country | Event | Start date | End of crisis management date | System "back normal" date | Systemic crisis | Domestic vs imported | C | S | B | AP | T | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| NO | 2 | 2008-09 | 2009-10 | 2009-10 | 1 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| PL | 1 | 1981-03 | 1994-10 | 1994-10 | 1 | 2 | 1 | 1 | 0 | 0 | 1 | 1 |
| PL | 2 | 1992-01 | 1994-12 | 1996-12 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 |
| PT | 1 | 1983-02 | 1985-03 | 1985-03 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 1 |
| PT | 2 | 2008-10 | 2015-12 | ongoing | 1 | 2 | 1 | 1 | 1 | 1 | 0 | 1 |
| RO | 1 | 1981-11 | 1989-12 | 1989-12 | 1 | 2 | 0 | 1 | 0 | 0 | 0 | 1 |
| RO | 2 | 1996-01 | 2000-12 | 2000-12 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 |
| RO | 3 | 2007-11 | 2010-08 | 2010-08 | 1 | 2 | 1 | 0 | 0 | 1 | 0 | 1 |
| SE | 1 | 1991-01 | 1997-06 | 1997-06 | 1 | 2 | 1 | 0 | 1 | 1 | 0 | 1 |
| SE | 2 | 2008-09 | 2010-10 | ongoing | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 |
| SI | 1 | 1991-06 | 1994-07 | 1994-02 | 1 | 2 | 0 | 0 | 1 | 0 | 1 | 1 |
| SI | 2 | 2009-12 | 2014-12 | ongoing | 1 | 2 | 0 | 1 | 1 | 1 | 0 | 1 |
| SK | 1 | 1997-12 | 2002-04 | 2002-04 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 |
| UK | 1 | 1973-11 | 1975-12 | 1977-08 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 |
| UK | 2 | 1991-07 | 1994-04 | 1994-04 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 |
| UK | 3 | 2007-08 | 2010-01 | ongoing | 1 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |

Notes: Section 2 and Annex A provide detailed field explanations.

## Table C2
## Overview of residual events (episodes of elevated financial stress) in the database

(crises risk materialisation dummy abbreviations: C = currency/BoP/capital flow; S = sovereign; B = banking; AP = significant asset price correction; T = transition; MP = macroprudential relevance)

| Country | Event | Start date | End of crisis management date | System "back normal" date | Systemic crisis | Domestic vs imported | C | S | B | AP | T | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| AT | 1 | 1973-09 | 1975-09 | NA | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| AT | 2 | 1981-02 | 1983-05 | NA | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| AT | 3 | 1991-03 | 1993-09 | NA | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| BE | 1 | 1990-08 | 1993-11 | 1993-11 | 0 | NA | 1 | 0 | 0 | 1 | 0 | 1 |
| BG | 1 | 2007-12 | 2011-02 | NA | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| CZ | 1 | 2007-08 | 2010-08 | NA | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 |
| DE | 1 | 1980-03 | 1982-03 | NA | 0 | NA | 0 | 0 | 0 | 1 | 0 | 0 |
| DE | 2 | 1992-07 | 1994-10 | NA | 0 | NA | 0 | 0 | 0 | 0 | 1 | 0 |
| DK | 1 | 1974-06 | 1975-01 | 1975-01 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| DK | 2 | 1978-07 | 1981-03 | 1981-03 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| EE | 1 | 2009-01 | 2010-04 | 2010-04 | 0 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| ES | 1 | 1993-09 | 1994-09 | 1994-09 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 1 |
| FI | 1 | 1975-01 | 1979-02 | 1979-02 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| FI | 2 | 2001-03 | 2001-11 | 2001-11 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| FI | 3 | 2008-12 | 2010-09 | ongoing | 0 | NA | 0 | 0 | 0 | 1 | 0 | 1 |
| FR | 1 | 1973-12 | 1978-07 | NA | 0 | NA | 0 | 0 | 0 | 1 | 0 | 0 |
| FR | 2 | 1981-01 | 1983-04 | 1983-04 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| FR | 3 | 2002-07 | 2003-08 | 2003-08 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| FR | 4 | 2011-03 | 2013-10 | ongoing | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |
| GR | 1 | 1983-01 | NA | NA | 0 | NA | 1 | 0 | 0 | 0 | 0 | 0 |
| GR | 2 | 1993-01 | 1994-03 | NA | 0 | NA | 1 | 0 | 0 | 0 | 0 | 0 |
| IT | 1 | 1973-07 | 1979-01 | NA | 0 | NA | 1 | 0 | 0 | 1 | 0 | 0 |
| IT | 2 | 1981-07 | 1983-06 | NA | 0 | NA | 1 | 0 | 0 | 1 | 0 | 0 |
| IT | 3 | 2008-01 | 2011-08 | ongoing | 0 | NA | 0 | 0 | 0 | 1 | 0 | 1 |

| Country | Event | Start date | End of crisis management date | System "back normal" date | Systemic crisis | Domestic vs imported | C | S | B | AP | T | MP |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **LT** | 1 | 1992-01 | 1993-06 | NA | 0 | NA | 1 | 0 | 0 | 0 | 1 | 0 |
| **LT** | 2 | 1999-01 | 1999-12 | 1999-12 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 |
| **LV** | 1 | 1992-01 | 1993-03 | NA | 0 | NA | 0 | 0 | 0 | 0 | 1 | 0 |
| **LV** | 2 | 1998-08 | 1999-03 | 1999-03 | 0 | 2 | 0 | 0 | 1 | 0 | 0 | 1 |
| **MT** | 1 | 2009-08 | 2012-11 | 2012-11 | 0 | NA | 0 | 0 | 0 | 1 | 0 | 1 |
| **NL** | 1 | 1973-09 | 1975-12 | NA | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 0 |
| **NL** | 2 | 1980-03 | 1983-09 | 1985-01 | 0 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| **NL** | 3 | 2002-06 | 2004-08 | NA | 0 | NA | 0 | 0 | 0 | 1 | 0 | 1 |
| **NO** | 1 | 2002-10 | 2003-10 | 2003-10 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 |
| **PL** | 1 | 2007-08 | 2009-11 | NA | 0 | NA | 0 | 0 | 0 | 1 | 0 | 1 |
| **PT** | 1 | 1977-06 | 1978-12 | 1979-07 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| **PT** | 2 | 1992-04 | 1995-03 | 1995-03 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |
| **RO** | 1 | 1990-01 | 1992-12 | NA | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| **SE** | 1 | 1974-09 | 1975-11 | NA | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| **SE** | 2 | 1976-10 | 1976-10 | 1979-03 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 |
| **SE** | 3 | 1980-01 | 1983-08 | NA | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| **SE** | 4 | 2000-10 | 2001-10 | 2001-10 | 0 | 2 | 0 | 0 | 0 | 1 | 0 | 1 |
| **SK** | 1 | 2009-01 | 2010-09 | 2010-09 | 0 | 2 | 0 | 0 | 1 | 1 | 0 | 1 |
| **UK** | 1 | 1979-03 | 1981-12 | 1981-12 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |

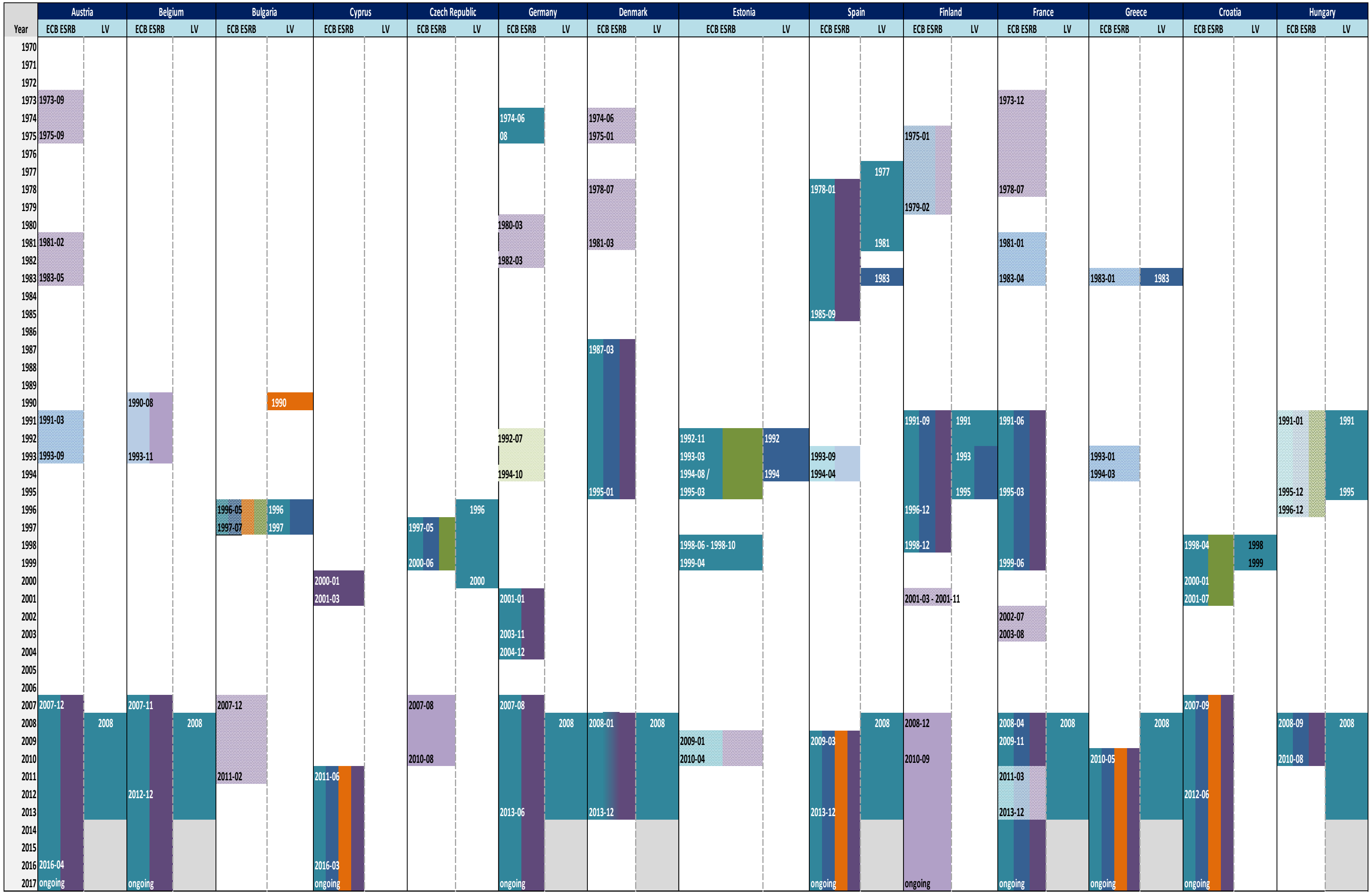
Notes: Section 2 and Annex A provide detailed field explanations.

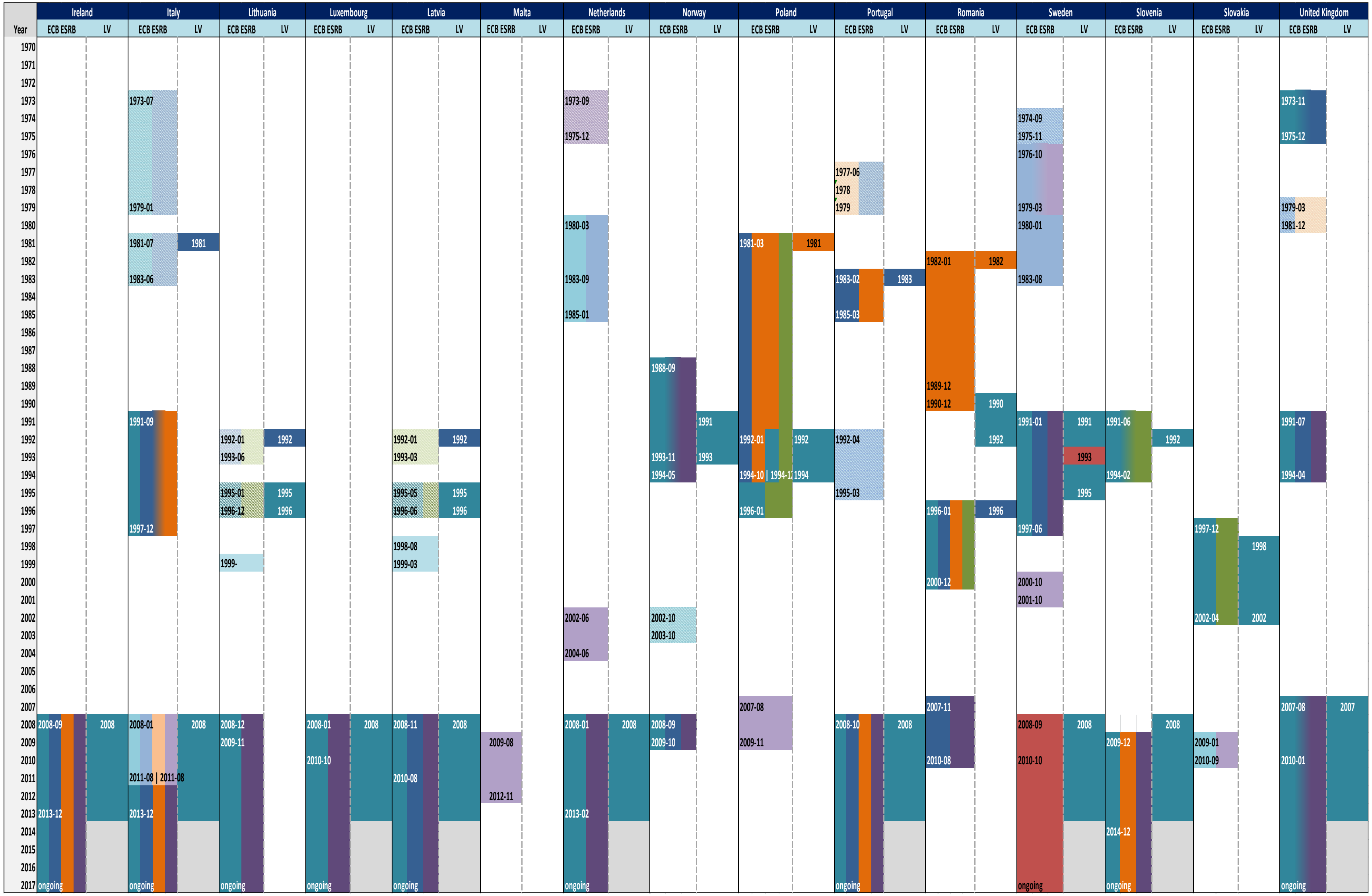
## Table C3
**Comparison with Laeven and Valencia (2008 and 2013) per country**

(absolute frequency; percentages)

| systemic | residual | |
|---|---|---|
| | | Complex crisis: multiple crises types |
| | | Banking crisis |
| | | Currency crisis / BoP / capital flow |
| | | Sovereign debt crisis |
| | | Significant asset price correction |
| | | Transition |
| | | For crisis events of Laeven and Valencia that were described as ongoing in 2013 (latest update) |
| pattern | pattern | Not relevant for macroprudential analysis |

Note: The colours illustrate the types of risk which materialise during an episode of financial stress, but do not provide any time-relevant information.


Year
Austria
ECB ESRB
LV
1973-09
1975-09
1981-02
1983-05
1991-03
1993-09
2007-12
2008
2016-04
ongoing
Belgium
1990-08
1993-11
2007-11
2008
2012-12
ongoing
Bulgaria
1990
1996-05
1997-07
1996
1997
2007-12
2011-02
Cyprus
2000-01
2001-03
2011-06
2016-03
ongoing
Czech Republic
1996
1997-05
2000-06
2000
2007-08
2010-08
Germany
1974-06
08
1980-03
1982-03
1992-07
1994-10
2001-01
2003-11
2004-12
2007-08
2008
2013-06
ongoing
Denmark
1974-06
1975-01
1978-07
1981-03
1987-03
1995-01
2008-01
2008
2013-12
Estonia
1992-11
1992
1993-03
1994-08 /
1994
1995-03
1998-06 - 1998-10
1999-04
2009-01
2010-04
Spain
1977
1978-01
1981
1983
1985-09
1993-09
1994-04
2008
2009-03
2013-12
ongoing
Finland
1975-01
1979-02
1991-09
1991
1993
1995
1996-12
1998-12
2001-03 - 2001-11
2008-12
2010-09
ongoing
France
1973-12
1978-07
1981-01
1983-04
1991-06
1995-03
1999-06
2002-07
2003-08
2008-04
2008
2009-11
2011-03
2013-12
ongoing
Greece
1983-01
1983
1993-01
1994-03
2008
2010-05
ongoing
Croatia
1998-04
1998
1999
2000-01
2001-07
2007-09
2012-06
ongoing
Hungary
1991-01
1991
1995-12
1995
1996-12
2008-09
2008
2010-08
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017



Year
Ireland
Italy
Lithuania
Luxembourg
Latvia
Malta
Netherlands
Norway
Poland
Portugal
Romania
Sweden
Slovenia
Slovakia
United Kingdom
ECB ESRB
LV
1970
1971
1972
1973
1974
1975
1976
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2008-09
2013-12
ongoing
2008
1973-07
1979-01
1981-07
1981
1983-06
1991-09
1997-12
2008-01
2011-08 | 2011-08
2013-12
ongoing
2008
1992-01
1992
1993-06
1995-01
1995
1996-12
1996
1999-
2008-12
2009-11
ongoing
2008-01
2008
2010-10
ongoing
1992-01
1992
1993-03
1995-05
1995
1996-06
1996
1998-08
1999-03
2008-11
2008
2010-08
ongoing
2009-08
2012-11
1973-09
1975-12
1980-03
1983-09
1985-01
2002-06
2004-06
2008-01
2008
2013-02
ongoing
1988-09
1991
1993-11
1993
1994-05
2002-10
2003-10
2008-09
2009-10
1981-03
1981
1992-01
1992
1994-10 | 1994-1
1994
1996-01
2007-08
2009-11
1977-06
1978
1979
1983-02
1983
1985-03
1992-04
1995-03
2008-10
2008
ongoing
1982-01
1982
1989-12
1990-12
1990
1992
1996-01
1996
2000-12
2007-11
2010-08
1974-09
1975-11
1976-10
1979-03
1980-01
1983-08
1991-01
1991
1993
1995
1997-06
2000-10
2001-10
2008-09
2008
2010-10
ongoing
1991-06
1992
1994-02
2008
2009-12
2014-12
ongoing
1997-12
1998
2002-04
2002
2009-01
2010-09
1973-11
1975-12
1979-03
1981-12
1991-07
1994-04
2007-08
2007
2010-01
ongoing

# Abbreviations

## Countries

| | |
|---|---|
| **BE** | Belgium |
| **BG** | Bulgaria |
| **CZ** | Czech Republic |
| **DK** | Denmark |
| **DE** | Germany |
| **EE** | Estonia |
| **IE** | Ireland |
| **GR** | Greece |
| **ES** | Spain |
| **FR** | France |
| **HR** | Croatia |
| **IT** | Italy |
| **CY** | Cyprus |
| **LV** | Latvia |
| **LT** | Lithuania |
| **LU** | Luxembourg |
| **HU** | Hungary |
| **MT** | Malta |
| **NL** | Netherlands |
| **AT** | Austria |
| **PL** | Poland |
| **PT** | Portugal |
| **RO** | Romania |
| **SI** | Slovenia |
| **SK** | Slovakia |
| **FI** | Finland |
| **SE** | Sweden |
| **UK** | United Kingdom |
| **NO** | Norway |
| **US** | United States |

## Other

| | |
|---|---|
| **BIS** | Bank for International Settelements |
| **ECB** | European Central Bank |
| **ERM** | exchange rate mechanism |
| **ESCB** | European System of Central Banks |
| **ESRB** | European Systemic Risk Board |
| **EU** | European Union |
| **EUR** | euro |
| **GDP** | gross domestic product |
| **IMF** | International Monetary Fund |
| **NA** | National Authority |
| **NCA** | National Competent Authority |
| **NCB** | National Central Bank |

# Imprint and acknowledgements

**Marco Lo Duca**
European Central Bank, Frankfurt am Main, Germany; email: marco.lo_duca@ecb.europa.eu

**Anne Koban**
European Central Bank, Frankfurt am Main, Germany; email: anne.koban@ecb.europa.eu

**Marisa Basten**
ESRB Secretariat; email: marisa.basten@ecb.europa.eu

**Elias Bengtsson**
ESRB Secretariat; email: elias.bengtsson@ecb.europa.eu

**Benjamin Klaus**
European Central Bank, Frankfurt am Main, Germany; email: benjamin.klaus@ecb.europa.eu

**Piotr Kusmierczyk**
ESRB Secretariat; email: piotr_kornel.kusmerczyk@ecb.europa.eu

**Jan Hannes Lang**
European Central Bank, Frankfurt am Main, Germany; email: jan-hannes.lang@ecb.europa.eu

**Carsten Detken**
European Central Bank, Frankfurt am Main, Germany; email: carsten.detken@ecb.europa.eu

**Tuomas Peltonen**
ESRB Secretariat; email: tuomas.peltonen@ecb.europa.eu

The 2021 update of the financial crises database and the revision of the “back to normal” date definition have been conducted by:

**Ludivine Berret**
ESRB Secretariat, email: ludivine.berret@ecb.europa.eu

**Frederik Ledoux**
ESRB Secretariat, email: frits.ledoux@ecb.europa.eu

This paper and the crises database have benefited from contributions from MPAG and AWG members and further contributors.

**Sampo Tapio Alhonsuo**
ESRB Secretariat

**Ayman el-Dahrawy**
ESRB Secretariat

**Peter Sarlin**
European Central Bank, Frankfurt am Main, Germany

**Alexandre Francart**
Nationale Bank van België/Banque Nationale de Belgique

**Mara Pirovano**
Nationale Bank van België/Banque Nationale de Belgique

**Thomas Schepens**
Nationale Bank van België/Banque Nationale de Belgique

**Mihail Mihaylov**
Българска народна банка (Bulgarian National Bank)

**Silvia Prokopieva**
Българска народна банка (Bulgarian National Bank)

**Kalina Hadjinedelcheva**
Bulgarian Financial Supervision Commission

**Hana Hejlová**
Česká národní banka

**Miroslav Plašil**
Česká národní banka

**Theis Jørgensen**
Danmarks Nationalbank

**Ianna Georgieva Yordanova**
Danmarks Nationalbank

**Frank Heid**
Deutsche Bundesbank

**Sebastian Wider**
Deutsche Bundesbank

**Peer Osthoff**
Bundesanstalt für Finanzdienstleistungsaufsicht (German Federal Financial Supervisory Authority)

**Taavi Raudsaar**
Eesti Pank

**Mari Tamm**
Eesti Pank

**Siim Rahu**
Finantsinspektsioon (Estonian Financial Supervisory Authority)

**Martin O'Brien**
Central Bank of Ireland

**Maria Woods**
Central Bank of Ireland

**Vicky Nidrioti**
Bank of Greece

**Javier Mencia**
Banco de España

**Julien Idier**
Banque de France

**Stéphanie Tristram**
Banque de France

**Emmanuel Point**
Banque de France Autorité de contrôle prudentiel et de resolution (French Prudential Supervision and Resolution Authority)

**Véronique Janod**
Autorité des marchés financiers (AMF)

**Ivana Herceg**
Hrvatska narodna banka

**Alessio De Vincenzo**
Banca d'Italia

**Stefano Neri**
Banca d'Italia

**Constantinos Trikoupis**
Central Bank of Cyprus

**Anna Kasjanova**
Latvijas Banka

**Olga Lielkalne**
Latvijas Banka

**Irina Ivanova**
Finanšu un kapitāla tirgus komisija (Latvian Financial and Capital Market Commission)

**Andrius Škarnulis**
Lietuvos Bankas

**John Theal**
Banque centrale du Luxembourg

**Jean-François Carpantier**
Commission de Surveillance du Secteur Financier (Luxembourgish Financial Sector Supervisory Commission)

**Louay Kheder**
Commission de Surveillance du Secteur Financier (Luxembourgish Financial Sector Supervisory Commission)

**Istvan Papp**
Magyar Nemzeti Bank

**Wendy Zammit**
Central Bank of Malta

**Ian Buttigieg**
Malta Financial Service Authority

**Shahin Kamalodin**
De Nederlandsche Bank

**Remco Van der Molen**
De Nederlandsche Bank

**Gernot Ebner**
Oesterreichische Nationalbank

**Eleonora Endlich**
Oesterreichische Nationalbank

**Timo Broszeit**
Finanzmarktaufsicht (Austrian Financial Market Authority)

**Alice Mladenka**
Finanzmarktaufsicht (Austrian Financial Market Authority)

**Adam Głogowski**
Narodowy Bank Polski

**João Oliveira**
Banco de Portugal

**Ana Pereira**
Banco de Portugal

**Ana Ramos Estrela**
Banco de Portugal

**César Henriques**
Autoridade de Supervisão de Seguros e Fundos de Pensões (Portuguese Insurance and Pension Funds Supervisory Authority)

**Irina Mihai**
Banca Naţională a României

**Marius-Cristian Acatrinei**
Autoritatea de Supraveghere Financiară (Romanian Financial Supervisory Authority)

**Eveline Turturescu**
Autoritatea de Supraveghere Financiară (Romanian Financial Supervisory Authority)

**Meta Ahtik**
Banka Slovenije

**Vidosava Bukatarević**
Banka Slovenije

**Ján Klacso**
Národná banka Slovenska

**Paavo Miettinen**
Suomen Pankki – Finlands Bank

**Mervi Toivanen**
Finanssivalvonta (Finnish Financial Supervisory Authority)

**David Farelius**
Sveriges Riksbank

**Roland Nilsson**
Finansinspektionen (Swedish Financial Supervisory Authority)

**Heleen Hofmans**
Bank of England

**Katrine Godding Boye**
Norges Bank

**Bent Vale**
Norges Bank



Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website **www.esrb.europa.eu**



ISSN 2467-0669 (pdf)
ISBN 978-92-95210-64-6 (pdf)
DOI 10.2849/119019 (pdf)
EU catalogue No DT-AC-17-002-EN-N (pdf)