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Macroprudential oversight, risk communication and visualization

Macroprudential Research Network

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Macroprudential Research Network
This paper presents research conducted within the Macroprudential Research Network (MaRs). The network is composed of economists from the European System of Central Banks (ESCB), i.e. the national central banks of the 27 European Union (EU) Member States and the European Central Bank. The objective of MaRs is to develop core conceptual frameworks, models and/or tools supporting macro-prudential supervision in the EU.
The research is carried out in three work streams: 1) Macro-financial models linking financial stability and the performance of the economy; 2) Early warning systems and systemic risk indicators; 3) Assessing contagion risks.
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Abstract: This paper discusses the role of risk communication in macroprudential oversight and of visualization in risk communication. Beyond the soar in data availability and precision, the transition from firm-centric to system-wide supervision imposes vast data needs. Moreover, in addition to internal communication as in any organization, broad and effective external communication of timely information related to systemic risks is a key mandate of macroprudential supervisors. This further stresses the importance of simple representations of complex data. The present paper focuses on the background and theory of information visualization and visual analytics, as well as techniques within these fields, as potential means for risk communication. We define the task of visualization in risk communication, discuss the structure of macroprudential data, and review visualization techniques applied to systemic risk. We conclude that two essential, yet rare, features for supporting the analysis of big data and communication of risks are analytical visualizations and interactive interfaces. For visualizing the so-called macroprudential data cube, we provide the VisRisk platform with three modules: *plots*, *maps* and *networks*. While VisRisk is herein illustrated with five web-based interactive visualizations of systemic risk indicators and models, the platform enables and is open to the visualization of any data from the macroprudential data cube.

Keywords: Macroprudential oversight, risk communication, visualization, analytical visualization, interactive visualization, VisRisk

JEL codes: G01, G15, F37, F38, F47

Non-technical summary

The policy objective of safeguarding financial stability, which is addressed through macroprudential oversight of the financial system, is currently being accepted and implemented within governmental authorities and supervisors. Beyond the soar in availability and precision of data, the transition from firm-centric to system-wide supervision imposes obvious data needs when analyzing a large number of entities and their constituents as a whole. As central tasks ought to be timely and accurate measurement of systemic risks, big data and analytical models and tools become a necessity. While analytics might aid in automated modeling, one approach to dealing with complex data and modeling problems is to improve end users' understanding of them in order to tap into their expertise. This points towards means that support disciplined and structured judgmental analysis based upon policymakers' experience and domain intelligence. Further, the mandates of macroprudential supervisors have to date been stressing or even limited to communication, issuing warnings and giving recommendations, which boils down to an emphasis on broad and effective communication of timely information related to systemic risks.

Systemic risk has commonly been distinguished into three categories: (*i*) build-up of widespread imbalances, (*ii*) exogenous aggregate shocks, and (*iii*) spillover and contagion. With the aim of mitigating system-wide risks, macroprudential oversight is commonly comprised into a process, where key tasks include (*i*) risk identification, (*ii*) risk assessment, and (*iii*) policy assessment, implementation and follow-up. As a soft policy intervention, risk communication concerns the overall task of spreading broadly and effectively timely information related to systemic risks, as well as other vulnerabilities concerning the financial system and its macro-financial environment. Fortunately, policymakers and regulators have access to a broad toolbox of analytical models to measure and analyze system-wide threats to financial stability. The tasks of these tools can be mapped to the above listed three forms of systemic risk: (*i*) early-warning models and indicators, (*ii*) macro stress-test models, and (*iii*) contagion and spillover models. While the first aids in risk identification, the second and third approaches provide means for risk assessment. Yet, this points out a mismatch between the current objectives and needs and the available tools: while a key task is the communication of risks, the toolbox of analytical models lacks a focus on approaches that support human understanding.

The term visualization has a wide meaning and relates to a number of interdisciplinary topics, in particular information visualization and visual analytics. The rationale behind the use of visual representations and their usefulness relates to traits of the human visual system. Visualization can be seen as a type of cognitive support or amplification, which leads to a focus on strengths and weaknesses of human perception. This highlights the importance of principles for designing visuals that meet the demands of the human visual system. Next, the utilized techniques for visualization can be divided into two types: graphical representations of data and means for interaction. While the former can be summarized in various categories of visualization techniques, such as per output and data, the latter refer to how the user can interact with or manipulate the displayed data, such as zooming or panning, which often has its basis in one or more graphical displays for enabling more flexibility to explore data. This invokes two questions: *1. (2. how) would tapping into visualization support risk communication in macroprudential oversight?*

This paper discusses the role of visualization in macroprudential oversight at large, especially for the purpose of risk communication. Risk communication comprises two tasks. Internal communication concerns spreading information about systemic risks within but at various levels of the organization, such as among divisions, groups or analysts, whereas external communication refers to the task of disseminating information about systemic risks to the general public. In this paper, we mainly focus on the background and theory of information visualization and visual analytics, as well as techniques provided within these disciplines, as potential means for risk communication. The topic of visualization is in this paper discussed from three viewpoints: (*i*) we define the task of visualization in risk communication, (*ii*) present a so-called macroprudential data cube and discuss its structure, and (*iii*) review visualization techniques applied to systemic risk. This provides an overview of which tasks should be supported by visualization and the underlying data to be visualized. Eventually, the discussion boils down to two essential, but to date rare, features for supporting the analysis of big financial data and the communication of risks: analytical visualizations and interactive interfaces.

For visualizing the macroprudential data cube through analytical and interactive visualization, we provide the VisRisk platform with three modules: *plots*, *maps* and *networks*. The platform can be accessed here: http://vis.risklab.fi/. *Plots* focuses on interactive interfaces for representing large amounts of data. While *maps* provides analytical means for representing the three standard dimensions of a data cube in simple formats, *networks* aims at visualization of the fourth data cube dimension of interlinkages.

While VisRisk enables and is open to the visualization of any data from a macroprudential data cube, the platform is herein illustrated with five web-based interactive visualizations of systemic risk indicators and models, of which three make use of analytical visualizations. First, we make use of analytical techniques for data and dimension reduction to explore high-dimensional systemic risk indicators and time-varying networks of linkages. Second, this paper adds interactivity to not only dashboards of standard risk indicators and early-warning models, but also to the analytical applications. The ultimate aim of VisRisk, and this paper at large, is to provide a basis for the use of visualization techniques, especially those including analytical and interactive features, in macroprudential oversight in general and risk communication in particular.

"In the absence of clear guidance from existing analytical frameworks, policy-makers had to place particular reliance on our experience. Judgement and experience inevitably played a key role. [...] But relying on judgement inevitably involves risks. We need macroeconomic and financial models to discipline and structure our judgemental analysis. How should such models evolve?"
– Jean-Claude Trichet, President of the ECB, Frankfurt am Main, 18/11/2010

1 Introduction

Macroprudential oversight refers to surveillance and supervision of the financial system as a whole. As can be exemplified by recently founded supervisory bodies with the mandate of safeguarding financial stability, a system-wide perspective to financial supervision is currently being accepted and implemented as a common objective of governmental authorities and supervisors. To this end, the European Systemic Risk Board (ESRB) in Europe, the Financial Policy Committee (FPC) in the UK, and the Financial Stability Oversight Council (FSOC) in the US were founded in the aftermath of the financial instabilities of 2007–2008. Beyond the soar in availability and precision of data, the transition from firm-centric to system-wide supervision imposes obvious data needs when analyzing a large number of entities and their constituents as a whole (see e.g. Flood and Mendelowitz, 2013). As central tasks ought to be timely and accurate measurement of systemic risks, big data and analytical models and tools become a necessity. While analytics might aid in automated modeling, one approach to dealing with complex data and modeling problems is to improve end users' understanding of them in order to tap into their expertise. As above noted by Mr. Trichet, we need means supporting disciplined and structured judgmental analysis based on policymakers' experience and domain intelligence – and not only models but also means to understand their output and underlying data. Further, the mandates of macroprudential supervisors have to date been stressing (or even limited to) communication, issuing warnings and giving recommendations, which boils down to an emphasis on broad and effective communication of timely information related to systemic risks.

Financial systems, described by the three pillars of financial intermediaries, markets and infrastructures, have been shown to be recurringly unstable due to limitations related to market imperfections (de Bandt and Hartmann, 2002; Carletti, 2008). Underlying systemic risk, while having no unanimous definition, has commonly been distinguished into three categories (de Bandt et al., 2009; ECB, 2009): (*i*) build-up of widespread imbalances, (*ii*) exogenous aggregate shocks, and (*iii*) spillover and contagion. With the aim of mitigating system-wide risks, macroprudential oversight is commonly comprised into a process, where key tasks include (*i*) risk identification, (*ii*) risk assessment, and (*iii*) policy assessment, implementation and follow-up. As a soft policy intervention, risk communication concerns the overall task of spreading broadly and effectively timely information related to systemic risks, as well as other vulnerabilities concerning the financial system and its macro-financial environment. Fortunately, policymakers and regulators have access to a broad toolbox of analytical models to measure and analyze system-wide threats to financial stability. The tasks of these tools can be mapped to the above listed three forms of systemic risk (e.g., ECB (2010)): (*i*) early warning of the build-up of widespread vulnerabilities and imbalances, (*ii*) stress-testing the resilience of the financial system to a wide variety of exogenous aggregate shocks, and (*iii*) modeling contagion and spillover to assess how resilient the financial system is to cross-sectional transmission of financial instability. While the first approach aids in risk identification and the second and third provide in risk assessment, risk communication relates to all of the above approaches.

Despite macroprudential bodies have only recently been mandated with macroprudential oversight, central bank communication is far from a new task. As reviewed by Blinder et al. (2008), over the past 20 years central banks have started placing a larger weight on communication and overall become more transparent. That said, the role of communication related to financial stability and overall macroprudential tasks is more recent (e.g., Cihák et al., 2012; Born et al., 2013). Accordingly, this points out a mismatch between the current objectives and needs and the available tools: while a key task is the communication of risks, the toolbox of analytical models lacks a focus on approaches that support human understanding.

The term visualization has a wide meaning and relates to a number of interdisciplinary topics, in particular information visualization and visual analytics. The rationale behind the use of visual representations and their usefulness relates to traits of the human visual system (see, e.g., Ware (2004)). Card et al. (1999) assert visualization as a type of cognitive support or amplification, which leads to a focus on strengths and weaknesses of human perception. This highlights the importance of principles for designing visuals that meet the demands of the human visual system. Although the computer age has brought visuals, and even the design of them, to the desks of ordinary people, including policymakers, the most influential literature on data graphics design still today dates back to work by Tufte (1983) and Bertin (1983). Rather than an exact theory, Tufte and Bertin provide a set of principles and rules of thumb to follow. Techniques supporting visualization can be divided into two types: graphical representations of data and means for interaction. While the former can be summarized in various categories of visualization techniques, such as per output and data, the latter refer to how the user can interact with or manipulate the displayed data, such as zooming or panning, which often has its basis in one or more graphical displays for enabling more flexibility to explore data. This invokes two questions: *1. (2. how) would tapping into visualization support risk communication in macroprudential oversight?*

This paper discusses the role of visualization in macroprudential oversight at large, especially for the purpose of risk communication. Risk communication comprises two tasks. Internal communication concerns spreading information about systemic risks within but at various levels of the organization, such as among divisions, groups or analysts, whereas external communication refers to the task of disseminating information about systemic risks to the general public. In this paper, we mainly focus on the background and theory of information visualization and visual analytics, as well as techniques provided within these disciplines, as potential means for risk communication. The topic of visualization is in this paper discussed from three viewpoints. First, based upon the needs for internal and external risk communication, we define the task of visualization in macroprudential oversight. Second, we present the so-called macroprudential data cube, by discussing the type of available data for identifying and assessing systemic risk, including their structure and its potential implications for analysis and visualization. Third, we review the current state of the art in visualization techniques applied to the analysis of systemic risk. This provides an overview of which tasks should be supported by visualization and the underlying data to be visualized. Eventually, the discussion boils down to two essential, but to date rare, features for supporting the analysis of big financial data and the communication of risks: analytical visualizations and interactive interfaces.

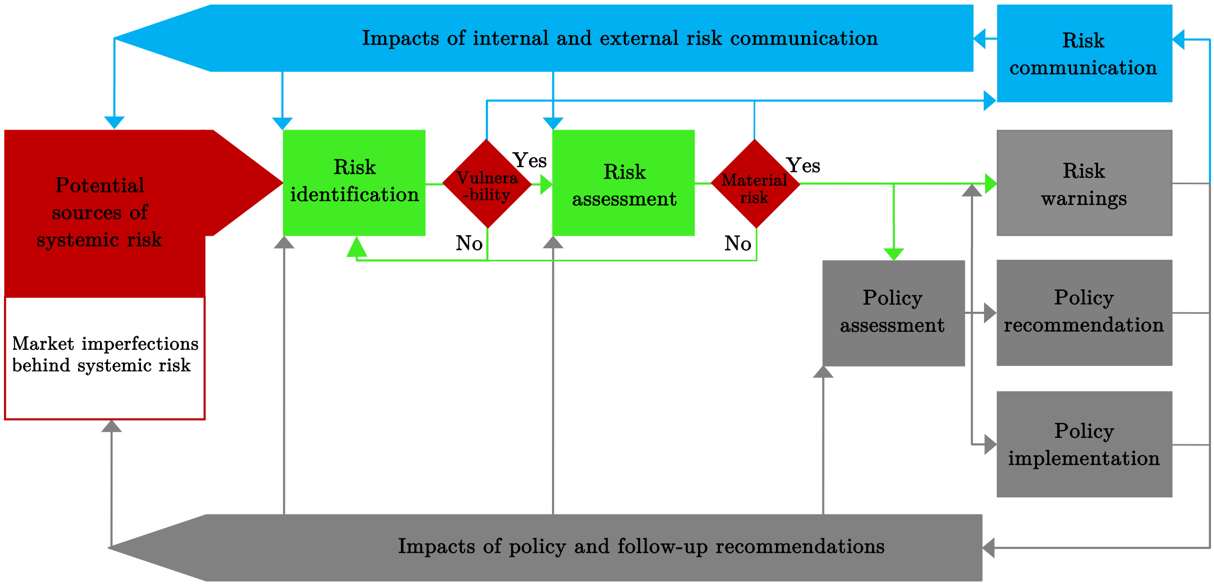
For visualizing the macroprudential data cube through analytical and interactive visualization, we provide the VisRisk platform with three modules: *plots*, *maps* and *networks*.[1] *Plots* focuses on interactive interfaces for representing large amounts of data, but does not make use of analytical techniques for reducing complexity. While *maps* provides analytical means for representing the three standard dimensions of a data cube in simple formats, *networks* aims at visualization of the fourth data cube dimension of interlinkages. As VisRisk enables and is open to the visualization of any data from a macroprudential data cube, we aim at providing a basis with which systemic risk indicators and models can be widely communicated. It is herein illustrated with five web-based interactive visualizations of systemic risk indicators and models, of which three make use of analytical visualizations. First, we make use of analytical techniques for data and dimension reduction to explore high-dimensional systemic risk indicators and time-varying networks of linkages. Second, this paper adds interactivity to not only dashboards of standard risk indicators and early-warning models, but also to the analytical applications. The ultimate aim of VisRisk, and this paper at large, is to provide a basis for the use of visualization techniques, especially those including analytical and interactive features, in macroprudential oversight in general and risk communication in particular.

The present paper is organized as follows. While Section 2 discusses macroprudential oversight and risk communication, Section 3 focuses on information visualization and visual analytics. In Section 4, we present an overview of visualization techniques in risk communication and macroprudential oversight and the macroprudential data cube. Section 5 introduces VisRisk as a general platform for visualizing the macroprudential data cube, and illustrates it with five web-based interactive visualizations of systemic risk indicators and models, of which three make use of analytical visualizations. Section 6 concludes.

2 Macroprudential oversight and risk communication

Since the date when the still ongoing global financial crisis broke out, the notion of a macroprudential approach to safeguarding financial stability has grown consensus among the academic and policymaking communities alike. Yet, it is by no means a new concept. The Bank for International Settlements (BIS) applied the term to describe a system-wide orientation of regulatory frameworks already in the 1970s, and the term appeared in publicly available material in the mid-1980s (see BIS (1986) as discussed in Borio

[1] The VisRisk platform for interactive and analytical applications can be found here: http://vis.risklab.fi/



Notes: The figure illustrates the macroprudential oversight process. The red components represent risks and vulnerabilities and the green components represent the need for risk identification and assessment, the gray components represent policy assessment and implementation, as well as risk warnings, policy recommendations and to follow-up, and the blue components represent overall risk communication. The figure is adapted from ECB (2010).

Figure 1: The macroprudential oversight process.

(2011)). The series of recently established macroprudential supervisory bodies obviously also motivates understanding and disentangling their specific tasks and functions.

This section attempts to provide a holistic view of a so-called macroprudential oversight process. As mentioned in the introduction, the starting point ought to be acknowledging the existence of underlying market imperfections, which might cause systemic risks in the financial system. This section discusses the tasks within the process, and relates the concept of risk communication to macroprudential oversight.

2.1 The macroprudential oversight process

The previously described market imperfections, and thereby caused systemic risks, are a premise for macroprudential oversight. Accordingly, the above described three analytical approaches aim at signaling these systemic risks at an early stage. In terms of a process, Figure 1 puts forward the steps of the process that a macroprudential supervisory body follows. As described in ECB (2010), macroprudential oversight can be related to three steps: (*i*) risk identification, (*ii*) risk assessment, and (*iii*) policy assessment, implementation and follow-up, as well as giving risk warnings and policy recommendations. The process in Figure 1 deviates from that in ECB (2010) by explicitly introducing a fourth task of risk communication and its feedback loop. In the figure, the red components represent risks and vulnerabilities, the green components represent the need for risk identification and assessment, the gray components represent policy assessment and implementation, as well as risk warnings, policy recommendations and follow-up, and the blue components represent overall risk communication. Moreover, following Bundesbank (2013), we can distinguish the final instruments into different levels of organization: (*i*) soft (communication), intermediate (warnings and recommendations) and hard (interventions).

In the *first step* of the supervisory process, the key focus is on identifying risks to stability and potential sources of vulnerability. The vulnerabilities and risks could exist in any of the three pillars of the financial system: financial intermediaries, financial markets and financial infrastructure. The necessary analytical tools to identify possible risks, vulnerabilities and triggers come from the set of early-warning models and indicators, combined with the use of market intelligence, and expert judgment and experience. This involves ranking risks and vulnerabilities as per intensity, as well as for assigning probabilities to specific shocks or future systemic events.

In the *second step* of the process, the rankings and probabilities may be used to assess the identified risks. Beyond market intelligence, as well as expert judgment and experience, risk assessment makes use of analytical tools mainly from the set of macro stress-testing models and contagion models. In macro stress-testing, simulations of most plausible risk scenarios show the degree of impact severity on the overall financial system, as well as its components. Contagion models, on the other hand, might be used through counterfactual simulations to assess the impact of specific failures on the entire financial system and individual institutions. The first and the second step of the process should not only provide a list of risks ordered according to possible severity, but also contain their materialization probabilities, losses given their materialization, and real losses in output and welfare, as well as their possible systemic impact. Hence, these two initial steps in the process aim at early risk identification and assessment and provide means for safeguarding financial stability.

The *third step* of the process involves the assessment, recommendation and implementation of policy actions as early preventive measures. Based upon the identified and assessed risks, a macroprudential supervisory body can consider giving a wide variety of risk warnings and recommendations for other parties to use policy instruments, as well as implementations of policies given the instruments at hand. To steer their decisions, the policy assessment step can make use of the same analytical tools used for risk identification and assessment. Likewise, analytical tools may support assessment prior to issuing risk warnings and giving policy recommendations. While the use of policy tools is beyond the mandate of some macroprudential supervisory bodies, actions tailored to the needs of a system-wide orientation are becoming a key part of financial regulation and supervision.[2] As illustrated in Figure 1, policies have an impact on not only the assessment of policy and identification and assessment of risks, but obviously also directly on market imperfections and the accumulation of systemic risks.

The *fourth step*, while not always being the last task to be performed, concerns risk communication, and its own feedback loop, which is a central part of this paper and is thus the topic of the following subsection.

2.2 Risk communication

The above discussion untangled overall risk communication as a separate step in the macroprudential oversight process. Although the tasks of overall risk communication is inherently different, a integral part of warnings, and policy recommendations and implementations also makes use of the communication channel, in which the overall task concerns disseminating information. The above subsection positioned risk communication within the macroprudential oversight process, yet did not provide a detailed discussion. This subsection brings up the role and possible forms of risk communication.

Risk communication describes the task of disseminating broadly and effectively timely information related to systemic risks and other vulnerabilities of the pillars of the financial system. Moreover, macro-financial imbalances and risks at the sector level (i.e., household, corporate, foreign and government). From the viewpoint of risk communication of a macroprudential supervisory body, Figure 2 simplifies the macroprudential oversight process into three key steps: risk identification, risk assessment and risk communication. The simplification refers to a focus on the soft type of intervention. However, with only the three distinct steps, the figure enables a more detailed description of tasks. Following the discussion thus far, the figure also summarizes the key tasks and available tools in each of the process steps. Building upon Figure 1, where risk communication was shown to feed into both underlying systemic risks and the tasks of risk identification and assessment, Figure 2 disentangles the two types of feedback depending on whether one communicates internally or externally. Internal communication concerns spreading information about systemic risks within, but at various levels of, the organization, such as among divisions, groups or analysts, whereas external communication refers to the task of disseminating information about systemic risks to the general public. As shown in Figure 1, it is worth to note that the information to be communicated might derive directly from the risk identification or assessment steps or then feed back only after recommendations, warnings and implementations in step three.

Internal communication refers to a range of activities at different levels of the organization. Despite that communication of macroprudential supervisors like central banks commonly refers to disseminating information externally, Mohan (2009) stresses that they, particularly policy and research wings, ought to pay attention to and play a pro-active role in the dissemination and effective communication of policy and analysis to internal staff. Borrowing from Mitchell (2001), this necessitates to *"sell the brand inside"*. This is further exemplified by Mohan, as *"internal communication could act as a conduit for external communication"*, where staff oftentimes play a key role as ambassadors of the institution.

[2]For instance, as interest rate policy may be a too blunt and powerful tool with material impact on other parts of the economy, the policies could take the form of tighter standards – e.g., requirements on capital adequacy, provisioning, leverage ratios, and liquidity management – for individual financial institutions with larger contributions to systemic risk and calibrated to address common exposures and joint failures. Macroprudential regulation and tools may also be used for accumulating buffers or reserves in good economic times to be used during worse times.

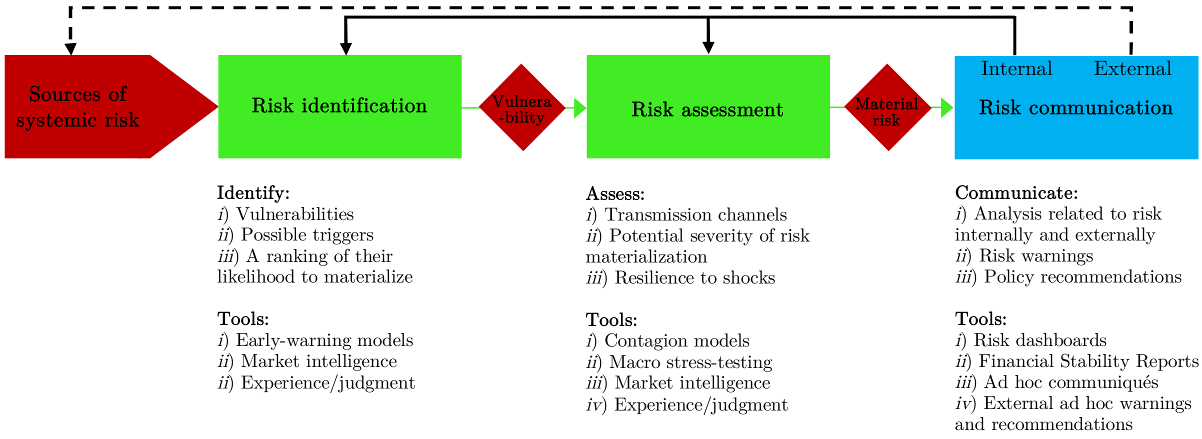


Figure 2: Risk communication in macroprudential oversight.

We relate internal communication to three levels of organization. At the lowest level, it relates to the use of means for communicating information to support individual analysts, which in the information age mainly relates to human-computer interaction (see, e.g., Dix et al. (2004)). In this case, communication relates to the interaction between a computer and interface with an analyst or policymaker overall. The second level of organization concerns the task of communicating among and within smaller groups, teams or divisions. Within the limits of a small, specialized audience, this involves not only supporting knowledge crystallization, but also supporting the dissemination of knowledge. While the former relates to communication within groups of analysts and policymakers, the latter concerns communicating the results or insights of one member or team to another. At the final, third level of an organization, communication relates to disseminating the information gathered within the specialized teams, groups or divisions to high-level management or the rest of the organization. As the audience becomes broader, the means for disseminating information, as well as the information itself, need also to be of a more general nature for the message to be digestible. At each of these levels, while the means for internal communication are various communiqués and announcements, a policymaker can tap into the tools and expertise, such as analytical models, market intelligence and expert judgment and experience, available at the supervisory body.

Beyond stressing the importance of it, Mohan (2009) pinpoints four suggestions that support internal communication: (*i*) arranging internal seminars in all regional offices and training colleges after external policy announcements and report publications (*ii*) the publication of FAQs (frequently asked questions) on the internet and intranet on each policy matter, as well as the provision of educational resources, (*iii*) the publication of a working paper series with a clear disclaimer that ascribes research findings and overall opinions to the authors, and (*iv*) internal notes of various divisions should be easily accessible for the entire organization, as they are of immense analytical value.

External communication refers to conveying information about systemic risks to the general public, including other authorities with responsibility for financial stability and overall financial-market participants, such as laymen, professional investors and financial intermediaries. An obvious difference in relation to internal communication relates to a comparatively larger heterogeneity in the audience. Yet, while a voluminous literature supports internal communication within organizations, one needs to look to a different direction in order to answer why a macroprudential supervisory body ought to communicate risk externally. Paraphrasing the role of communication in monetary policy, Born et al. (2013) argue that communication aims at (*i*) improving credibility of central banks (relating communication to transparency and reputational purposes), (*ii*) enhancing effectiveness of policy (relating communication to financial stability contributions), and (*iii*) to make central banks accountable (relating to explicit communication of identified risks and vulnerabilities).

By means of an example, a key channel for such communication is through quarterly or biannual Financial Stability Reports, a recent phenomenon that has quickly spread to a large number of central banks. With the aim of understanding the overall purpose of communication, a survey among central bankers by Oosterloo and de Haan (2004) pinpoints three main reasons for publishing Financial Stability Reports: (*i*) to contribute to overall financial stability, (*ii*) to increase the transparency and accountability, and (*iii*) to strengthen co-operation between authorities with financial stability tasks. At the same time, Allen et al. (2004) were consulted to study the effectiveness of communication related to financial stability at Sveriges Riksbank, the first central bank to publish a Financial Stability Report in 1997. Their external evaluation focused on Financial Stability Reports in 2003 and overall analytical framework and other work on financial stability. This resulted in ten recommendations, such as having and making objectives explicit and precise in the Financial Stability Reports, also covering other sectors than banks, such as the insurance sector, and making charts and underlying data easily downloadable. Although the case study focuses solely on the Riksbank, its conclusion of *"the Riksbank is doing a very good job in fulfilling its financial stability responsibilities"* seems justified, as they were indeed forerunners in the tasks at that point in time. Further, Cihák (2006) systematically reviews Financial Stability Reports, and documents a considerable increase in sophistication over time and improvements in not only their scope, but also the analytical tools with which analysis is conducted.

In a recent study focusing on communication, the overall finding by Born et al. (2013) was that Financial Stability Reports, as well as ad hoc speeches and interviews, affect financial markets by creating news (i.e., co-occurring jumps in stock returns) and reducing noise (i.e., decreasing market volatility). Further, Ekholm (2012) – the Deputy Governor of the Riksbank – notes that there is a strive for not only openness and transparency, but also clear external communication. In particular, Ekholm notes that during times of crisis "*a "negative" but reliable announcement can [...] be better for confidence than a "positive" but uncertain announcement*". Along these lines, the means for external communication concern the use of not only Financial Stability Reports published at regular intervals, but also risk warnings and recommendations communicated through various ad hoc public announcements. A recent addition to the toolbox of communication approaches is the publication of a risk dashboard, which essentially involves developing and publishing a set of indicators to identify and measure systemic risk.[3] Like in internal communication, a policymaker communicating externally also ought to tap into not only analytical models and tools at hand, but also market intelligence and expert judgment and experience when representing and judging the current state of risks and vulnerabilities. The latter becomes an obvious input when drafting any types of textual policy communiqués.

Thus far, we have taken the analytical models as given – both those used in risk identification and assessment and those used in risk communication. Yet, whereas analytical tools have clearly been designed to address the tasks in risk identification and assessment, they are in no, or little, explicit focus in the task of risk communication. In particular, there is a clear lack of integration of tools for the common objective of a macroprudential supervisory body, whose one key focus is to communicate identified and assessed risks. This paper asks the question: *is there something to be gained by tapping into the fields of information visualization and visual analytics when communicating systemic risk?*

3 Information visualization and visual analytics

The visualization of complex data has lately emerged as one of the key aids to support exploratory data analysis (EDA), though the task of EDA dates back to Tukey's early work in the 1970s (e.g., Tukey (1977)). Whereas advanced visual representations of data are common in a wide range of disciplines and domains, the use of these types of representations are rare in the communication of macroprudential bodies or supervisory authorities at large. The key aim of this section is to discuss the rationale behind the usefulness of visual representations, how visuals should be designed to meet the demands of the human visual system and categorizations of approaches to visualization. At a higher level, this section covers the discipline of information visualization – and its more recent derivative, visual analytics – in order to support a later discussion of their merits in macroprudential oversight.

Information visualization as a discipline has its origin in the fields of human-computer interaction, computer science, graphics and visual design. A more precise definition of it is *"the use of computer-supported, interactive, visual representations of abstract data to amplify cognition"* (Card et al., 1999), which highlights improving human understanding of data with graphical presentations or graphics. Tools for information visualization are mainly and best applied for EDA tasks, and most commonly aim at browsing a large space of information. While being in a highly common and general setting, Lin (1997) lists browsing to be useful when: (*i*) there is a good underlying structure and when related items can be located close by; (*ii*) users are unfamiliar with the contents of the collection; (*iii*) users have little understanding of the organization of a system and prefer to use a method of exploration with a low

[3] While the risk dashboard of the European Systemic Risk Board has been published since September 2012, the European Banking Authority published its first risk dashboard in October 2013.

cognitive load; (*iv*) users have difficulty in articulating or verbalizing the specific information need; and (*v*) users search for information that is easier to recognize than describe.

The above list relates to situations when visualization is useful, yet we still need to discuss the elements of information visualization in-depth. The rest of this section focuses on three subtopics of information visualization – human perception and cognition, data graphics design and visualization techniques – in order to end with a discussion of visual analytics, which combines analytical models with visual representations.

3.1 Human perception and cognition

Much attention is given to the design of visual representations of data. While being important, a discussion about information visualization cannot start from the colors, shapes and other features used for representing data. Instead, a starting point to visual communication ought to be to understand and acknowledge the capabilities and limits of the human information and visual system. The visual system comprises the human eye and brain, and can be seen as an efficient parallel processor with advanced pattern recognition capabilities (see, e.g., Ware (2004)). The focus of human perception is the understanding of sensory information, where the most important form is visual perception. The final intelligence amplification of information visualization can be viewed as a type of cognitive support. The mechanisms of cognitive support are, however, multiple. Hence, visualization tools should be targeted to exploit advantages of human perception.

Mostly, arguments about the properties and perception capabilities of the human visual system rely on two grounds: (*i*) information theory (Shannon and Weaver, 1963), and (*ii*) psychological findings. *Information theory* states that the visual canal is best suited to carry information to the brain as it is the sense that has the largest bandwidth. Ware (2004) asserts that there are two main *psychological theories* for explaining how to use vision to perceive various features and shapes: preattentive processing theory (Triesman, 1985) and gestalt theory (Koffa, 1935). Prior to focused attention, preattentive processing theory relates to simple visual features that can be perceived rapidly and accurately and processed effectively at the low level of the visual system. Whereas more complex visual features require a much longer process of sequential scanning, preattentive processing is useful in information visualization as it enables rapid dissemination of the most relevant visual queries through the use of suitable visual features, such as line orientation, line length or width, closure, curvature and color (Fekete et al., 2008). At a higher cognitive level, gestalt theory asserts that our brain and visual system follow a number of principles when attempting to interpret and comprehend visuals (for brevity, a more formal description of these can be found in Appendix A.1).

The principles of gestalt theory can easily be related to some more practical concepts. For instance, most projection methods, when aiming at visualizing data, may be seen to relate to the proximity principle, as they locate high-dimensional data with high proximity close to each other on a low-dimensional display, whereas others are pushed far away. Likewise, a time trajectory may be paired with continuity. More related to the cognition of visualization, Fekete et al. (2008) relate the core benefit of visuals to their functioning as a frame of reference or temporary storage for human cognitive processes. They assert that visuals are external cognition aids in that they augment human memory, and thus enable allocating a larger working set for thinking and analysis. In the above stated definition of information visualization by Card et al. (1999), visuals are presented as a means to "amplify cognition". The same authors also list a number of ways how well-perceived visuals could amplify cognition: (*i*) by increasing available memory and processing resources; (*ii*) by reducing the search for information; (*iii*) by enhancing the detection of patterns and enabling perceptual inference operations; (*iv*) by enabling and aiding the use of perceptual attention mechanisms for monitoring; and (*v*) by encoding the information in an interactive medium.

Not to disturb legibility of this section, examples of the five ways to amplify cognition are given Appendix A.1. Yet, while visualization provides ample means to amplify cognition, it is also worth looking into matters concerning human perception and cognition that may hinder, disturb or otherwise negatively affect how visualizations are read. An essential part of visualization is to take into account the deficiencies and limitations of human perception. More detailed exemplifications are provided in Appendix A.2. Accordingly, an understanding of the functioning of the human visual system aids in producing effective displays of information, where emphasis is on presented data such that the patterns are likely to be correctly perceived.

3.2 Data graphics design

Based upon features of the human visual system, and avenues for supporting perception and cognition, the literature on data graphics design has its focus on the principles for visual representations of data. Herein, the focus is on the early, yet still today influential, work by Tufte (1983) and Bertin (1983). Their works, while being principles for graphics design, are also valid for overall computer-based visualization. Tufte's set of principles are called a theory of data graphics, whereas Bertin's work is most often denoted a framework of the planar and retinal variables. Yet, rather than an exact theory, Tufte and Bertin provide a set of rules of thumb to follow.

The following overview is included to provide concrete guidelines, in addition to the higher-level discussion of perception and cognition. Herein, we will only focus on the key components of frameworks and theories by Bertin and Tufte. We start from Bertin's (1983) framework called the Properties of the Graphic System, which consists of two planar and six retinal variables. The two planar variables are the x and y dimensions of a visual, whereas the six retinal variables describe the following visual marks on the plane: size, value, texture, color, orientation and shape. Each variable is defined to have specific perceptual properties. We refer to Appendix A.3 for an in-depth discussion of the variables, as well as their properties.

A complement to Bertin's framework is the Theory of Data Graphics by Tufte (1983), which consists of a large number of guidelines for designing data graphics. The two key, broad principles are graphical excellence and graphical integrity.

Tufte (1983) defines *graphical excellence* as a graphic that "*gives to the viewer the greatest number of ideas in the shortest time with the least ink in the smallest space*". The principle of graphical excellence summarizes a number of his guidelines that encourage graphical clarity, precision, and efficiency: (*i*) avoid distortions of what the data have to say; (*ii*) aid in thinking about the information rather than the design; (*iii*) encourage the eye to compare the data; (*iv*) make large data sets coherent; (*v*) present a large number of data in a small space; (*vi*) reveal data at multiple levels of detail ranging from a broad overview to fine detail; (*vii*) and closely integrate statistical and verbal descriptions of the data. The second of Tufte's (1983) principles, *graphical integrity*, relates to telling the truth about data. To follow this principle, Tufte provides six key guidelines: (*i*) visual representations of numbers should be directly proportional to the quantities which the visuals represent; (*ii*) clear and detailed labeling should be used to avoid ambiguity; (*iii*) show data variation, not design variation; *iv*) deflate and standardize units when dealing with monetary values; (*v*) the number of dimensions depicted should not exceed the number of dimensions in data; and (*vi*) data should not be showed out of context. The overall aim of principles related to graphical integrity is to avoid deception and misinterpretation. This provides a brief overview of Tufte's rules of thumb, whereas interested readers are referred to Appendix A.3 as well as the original sources.

Bertin's and Tufte's principles provide a guiding set of rules of thumb to follow when spanning the space of two-dimensional visualizations. Yet, visualizations, not the least interactive visualizations, go beyond a static two-dimensional space by including additional visual variables, such as depth and time. This highlights requirements on the visualization techniques and tools, where interaction is essential.

3.3 Visualization techniques and interfaces

The literature has provided a long list of techniques for creating visual representations and interfaces, with the aim of supporting human perception and cognition. This subsection focuses mainly on a rough overview, as well as a brief and simple taxonomy, of methods, rather than a detailed survey. Obviously, a key issue of information visualization is what formats and features the methods will help to organize and visualize, as well as how that relates to the use of the capabilities of the human visual system. Techniques supporting information visualization can be divided into two types: graphical representations of data and interaction techniques. The former type refers to the visual form in which the data or model is displayed, such as standard bar and line charts. Yet, visualization may often refer to the use of manipulable graphical displays of data. The latter type of techniques refer to how the user can interact with or manipulate the graphical displays, such as zooming or panning. These oftentimes have their basis in one or more graphical displays such that they enable more freedom and flexibility to explore the data.

From the viewpoint of the underlying data, rather than the formats of visual displays, Zhang et al. (2012) categorize visualization techniques into four groups: numerical data, textual data, geo-related data and network data. Yet, a categorization of visualization techniques as per the types of data does not differentiate all possibilities of techniques. While being some years old, Keim and Kriegel (1996) provide a five-category grouping of techniques by the visualization output that still today holds merit: geometric, icon-based, pixel-oriented, hierarchical, and graph-based techniques. In addition, Keim and Kriegel also illustrate the existence of a wide range of hybrids that make use of multiple categories. While a description of each category and examples of techniques can be found in Appendix A.4, it only highlights the large number and wide variety of available techniques. The categorization of visualizations as per data and display, while highlighting challenges in choosing the correct technique for the data and the task at hand, provides guidance in the choice. For instance, one obvious factor to define the nature of the chosen visualization technique is the properties of the data, such as the form of data, dimensionality of data, data structures and size of data. Further, another factor is the expected output and purpose of use, such as predictive *vs.* exploratory, temporal *vs.* cross-sectional, and univariate *vs.* multivariate analysis and similarity *vs.* dissimilarity matching, as well as other purposes related to a focus on geo-spatial visualization and network relationships, for instance. While there obviously is no one way to choose the correct technique, considering the two dimensions of data and display, as well as other restrictions, demands and needs for the task, provides an adequate basis.

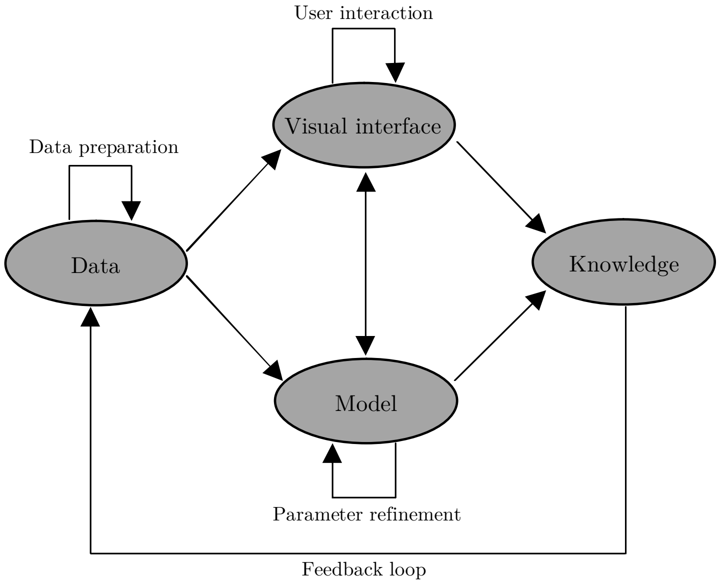
Given a technique, a critical factor of information visualization is, however, the possibility to interact with the visuals. A common guideline for interactions with visualizations is the visual information seeking mantra (Shneiderman, 1996): "*Overview first, zoom and filter, then details-on-demand*". Whereas Shneiderman (1996) characterizes the mantra with seven abstract tasks, we focus only on the following four explicitly mentioned ones: First, a user should gain an *overview* of the entire collection through a high-level representation. Second, users should have the possibility to *zoom* in on a portion of items that are of particular interest. Third, there should exist the possibility to *filter* out or to eliminate uninteresting and unwanted items, such as allowing users to specify which items to display. Fourth, the user should have the option to select an item or group of items to get further *details-on-demand*, such as clicking a group or individual items to browse descriptive information.

This provides a starting point to data visualization and user interaction, but does still not address the role of analytical techniques in visualization. The next step is to combine graphical representations of data and interaction techniques with analytical methods.

3.4 Visual analytics

A recent, rapidly growing discipline is that of visual analytics. By adding analytics to the ingredients of information visualization, we end up with the original definition of visual analytics (Thomas and Cook, 2005): "*the science of analytical reasoning facilitated by interactive visual interfaces*". Hence, the field of visual analytics has strong roots in information visualization. Likewise, visual analytics is obviously strongly related to overall data analytics. The term visual data mining descends from the integration of the user in the data mining (or analytics) process through visualization techniques and interaction capabilities (see, e.g., Keim (2001)). This has taken visual analytics to be applied in areas with challenging problems that were unsolvable using standalone automatic or visual analysis (see, e.g., Keim et al. (2009)). In particular, while automated computational processing enables scaling to larger and more challenging tasks, humans exhibit traits that enable a deeper understanding (Risch et al., 2008). This highlights the importance of coupling the strengths of computational and human information processing. When also including the interaction with analytical parameters, visual analytics is not only helpful in applications involving large, complex data, but also those involving complex analytical processes requiring monitoring and interaction.

Since we derive visual analytics from three above presented concepts – graphical representations of data, interaction techniques and analytical techniques – there is no need to repeat the discussion of each component. Further, the above presented information seeking mantra only mentions visualization, yet does not integrate it with analytics. Keim et al. (2006) propose combining an analytics process and the information seeking mantra for a visual analytics mantra: "*Analyze first, show the important, zoom, filter and analyze further, details on demand*". The authors exemplify the visual analytics mantra with analysis of large network security data. As graphical representations of raw data is infeasible and seldom reveals deep insights, the data need to first be analyzed, such as by computing changes and performing intrusion detection analysis. Then, the outcome of the automated analysis is visualized. Out of the displayed results, the user filters out and zooms in to choose a suspicious subset of all recorded intrusion incidents for further, more careful analysis. Thus, the mantra involves automated analysis before and after the use of interactive visual representations. Following the mantra, the visual analytics



Notes: The figure represents the visual analytics process. The figure is adapted from Keim et al. (2010).

Figure 3: The visual analytics process.

process discussed in Keim et al. (2010) is presented in Figure 3. The key steps in the process are data preparation, visual and automatic analysis, and knowledge consolidation. After the step of data preprocessing and transformations, the user selects between visual or automatic analysis methods. The user might prefer to start from whichever of the two tasks, and might then iterate multiple times in between the two components of data visualization and interaction and automatic analysis. Finally, after alternating between visual and automatic methods, the thus far gained knowledge is not only gathered, but also transferred through a feedback loop to support future analysis.

To be more general, the viewpoint we take on visual analytics relates more to human-computer cooperation. Relying on data as an input, this concerns the combination of various forms of computational and human processing, in order to support the knowledge crystallization process. Beyond aids for visualization and interaction, which support the development of a mental model, this includes advanced analytical techniques as a means to rigorous formal models. It is the interplay between formal and mental models that is the basis for knowledge creation, including tasks ranging from sensemaking to reasoning to decisionmaking.

4 Visualization in macroprudential oversight

The discussion thus far has concerned macroprudential oversight, in particular the role of risk communication, and the visualization of data, in particular the fields of information visualization and visual analytics. It is obvious that what follows now is their coupling: *how can visualization be used to support macroprudential oversight in general and risk communication in particular?*

This section starts by defining the task of visualization in internal and external risk communication. Then, we turn to a discussion about the type of available data for measuring and assessing systemic risk in macroprudential oversight. Finally, we relate the above discussed topics in visualization to the tasks of macroprudential oversight, including current use of various categories of visualizations as per the three types of systemic risk models.

4.1 Visual risk communication

Data visualization can serve multiple purposes in macroprudential oversight overall and risk communication in particular. As was already discussed in Section 2, visual representations can generally be classified to serve the purpose of communicating information to two audiences: (*i*) internal and (*ii*) external.

The purpose of use in *internal communication* relates to enhancing the understanding of policymakers on various levels. Accordingly, it is key to account for the fact that various stakeholders have different information needs, and thus only cater to their specific demands. One obvious task is to support analysts themselves, and within other groups of active participants in the process of collecting data and deriving indicators and analytical models. This particularly concerns human-computer interaction, as visual interfaces are used as interactive tools to better understand complex phenomena with no one known message to be communicated. Whereas the more common setting is likely to involve collecting data and deriving indicators, which could be supported by information visualization, there is also a focus on analytical approaches and understanding derived models, which points more towards visual analytics. This provides input to two purposes: data analysis and decisionmaking. An essential part of data analysis, particularly predictive analytics, involves data understanding and preparation, which indeed benefits from the use of visual interactive interfaces. Likewise, visualizing the output of data analysis provides ample means to support in making better decisions. This provides a range of internal communication tasks.

Beyond supporting individuals, one may want to communicate to other involved parties, for which visuals would be used to communicate a particular message or result to entire divisions, the the management and even at the level of the entire organization. At the lower level, the key task is to provide means for interaction with visuals in order to amplify cognition, which supports a better understanding and modeling of the task at hand. As above noted, the case of data analysis by low-level analysts is a standard setting, and mainly involves the task of human-computer interaction. In the context of low-level internal communication of systemic risk modeling, Flood and Mendelowitz (2013) note that data exploration is an area where visualization tools can make a major contribution. They point to the fact that certain tasks of classification, analysis and triage can be automated, whereas many require a human analyst, such as the difficulty to train a well-performing machine to analyze anomalous financial market activity. This follows the very definition of visual analytics. At the higher level, the focus is more on reporting and presentation of information by means of visuals. An example could be the dissemination of identified risks by a risk identification division for further analysis at a risk assessment division, or even to the board or president of an organization. Moreover, disseminating results of analytical models within and among divisions provides scrutiny, which is likely to improve either model credibility or quality.

In the use of visuals, a key issue is to strike an adequate balance between the complexity and volume of visual for specific audiences. An excessive use of visualizations or over-complexified representations may only function as a communication hinder or otherwise have unintended effects. Issues may relate to triggers of information overload or deter stakeholders from carefully analyzing the visuals. For example, laymen are likely to require different visuals and type of information than other categories of stakeholders. Thus, to sum up, a major concern is how results of the risk identification and assessment tasks are communicated to a wide range of stakeholders in easily understandable formats, with the ultimate aim of achieving transparency and accountability at an internal level.

A possible criticism is that visual inspection of complex data leaves room for human judgment, particularly when used for the support of decisionmaking. Contrary to the concept of economic "rationality", human adjustment is asserted to make visual analysis prone to a so-called personal forecast bias, which has been associated with traits like prejudice, undue conservatism and unfounded optimism, as among others postulated by Armstrong (1985): "Don't trust your common sense." Yet, it is more than common sense that every policy decision relies at least partly on judgment, which might or might not be biased. And it is also worth noting that the decisions are not made by statistical models, but rather by humans, who are also eventually accountable for them. A number of works have, however, shown that judgmental adjustments to macroeconomic model-based forecasts improve accuracy more often than not. For instance, McNees (1990) shows that judgmental adjustments to macroeconomic forecasts resulted in a 15% improvement in accuracy.

On a more general note, which points towards all levels of organization, Mohan (2009) suggests that central banks can do much more to improve internal communication due to *"the increasing availability of electronic communication at low cost"*. Mohan further stresses the importance of innovative ways as means to accomplish this, as the management's time to devote to these issues is unavoidably limited. Contrasting lengthy written reports, turning to Information Visualization and Visual Analytics can be seen as supportive means for internal communication. While the former supports spreading knowledge, the latter has a focus better aligned with creating knowledge.

External communication, on the other hand, refers to conveying information to other authorities with responsibility for financial stability and overall financial-market participants, such as laymen, professional investors and financial intermediaries. So, how do visual means aid in the task? Along the lines of the conclusions in Born et al. (2013), even though they rely on effects of mainly textual communication, providing improved means for communication is expected to increase effectivity and certainty of financial markets, particularly through adjustments in stock returns (i.e., creating news) and reductions in market volatility (i.e., reducing noise). Whereas this mainly relates to communication of readily processed and finalized data products, such as on the higher levels of internal communication, it obviously is a comparatively more challenging task due to the large heterogeneity in the audience.

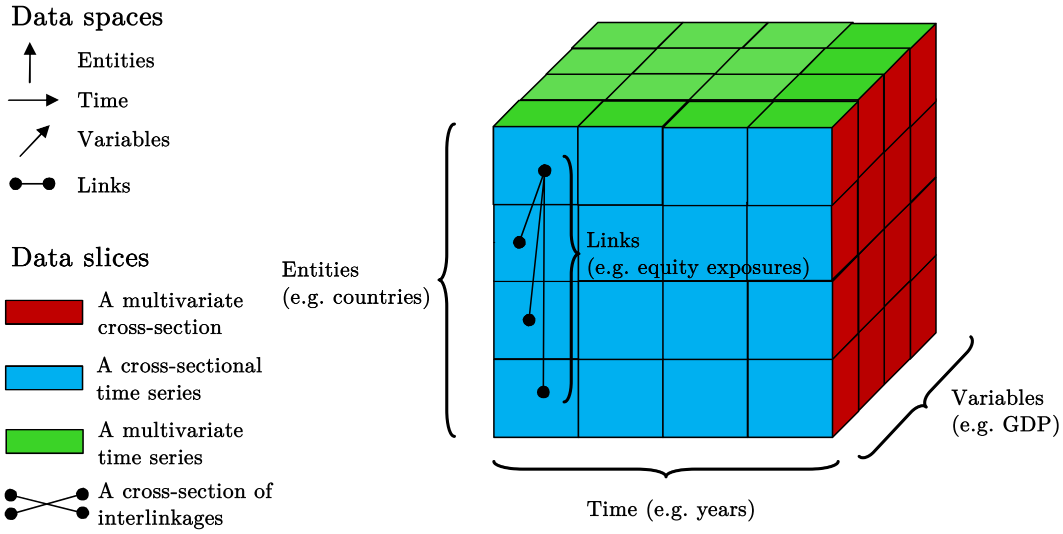
A direct example of such communication is Financial Stability Reports, which indeed can, and already to some extent do, make use of visual representations to communicate the state of financial stability. Relating to the study of the Riksbank's financial stability work by Allen et al. (2004), the last exemplified recommendation highlighted the importance of providing the underlying data and making charts easily downloadable. Beyond transparent data and visuals, the discussion also stresses overall guidelines in presenting data in a graphical fashion and overall communication through visuals. Most importantly, the authors highlight that Financial Stability Reports do and should contain a wealth of data and indicators, the data ought to be presented through graphical means and the graphical means ought to be presented in an easily accessible and understandable fashion, which is not "too busy". This somewhat paradoxical conclusion may also be seen as a call for interaction techniques, with which large amounts of data can be explored but filtered in ways that support understanding.

The most common representation of multidimensional data, yet not interactive, is based upon work by International Monetary Fund (IMF) staff on the Global Financial Stability Map (GFSM) (Dattels et al., 2010), which has sought to disentangle the sources of risks by a mapping of six composite indices with a radar-chart visualization. The aim of the GFSM coincide well with those of external risk communication: *"a summary tool for communicating changes in the risks and conditions [...] in a graphical manner [...] to improve the understanding of risks and conditions [...] and ultimately to warn policymakers and market participants about the risks of inaction."* Relating to the use of judgment, the GFSM not only leaves it to the eyes of the beholder, but goes even further by making use of judgment and technical adjustment to the data prior to visualization. Again, one key task is to achieve transparency and accountability, but obviously this time at an external level. Relating to Information Visualization and Visual Analytics, the task of external communication clearly focuses on spreading rather than creating knowledge, and is hence better aligned with the former approach to visualization.

4.2 Macroprudential data

To arrive at the data used for macroprudential oversight, we need to recall that Section 2.1 related analytical tools in macroprudential oversight to risk identification and assessment. Along these lines, Borio (2009) illustrates how a macroprudential approach to financial regulation and supervision is best thought of as consisting of two respective dimensions: the time and cross-sectional dimensions. First, the time dimension refers to how systemic risk evolves over time and relates to the procyclicality of the financial system. Second, the cross-sectional dimension refers to how systemic risk is distributed in the financial system at a given point in time and relates to common exposures across financial intermediaries and the systemic risk contribution of each institution. This relates data needs to entities and time. Moreover, early-warning exercises most often also make use of a wide range of indicators, measuring various dimensions of risks, vulnerabilities and imbalances. In particular, macroprudential data can be related to three different categories of indicators: (*i*) macroeconomic data, (*ii*) banking system data, and (*iii*) market-based data.

Generally, the key three sources of macroprudential data measure the behavior of three low-level entities: households, firms and assets. By grouping data for the entities, we may produce data on various levels of aggregation. While firm-level data may be of interest in the case of systemically important financial institutions, data for macroprudential analysis oftentimes refers to high-level aggregations of three kinds (see, e.g., Woolford (2001)): macroeconomic, banking system, and financial market behavior. Accordingly, the low-level entities may be aggregated as follows: from data on individual households' actions to the macroeconomic, from data on banks to the banking system, and from data on individual assets to the financial market. For instance, an entity could be a country, which would be described by country-level aggregates of macroeconomic, banking system, and financial market behavior. Despite the importance of the banking sector, sectoral aggregation may likewise be defined in broader terms (e.g. financial intermediaries in general) or some other type of financial intermediaries (e.g., insurers or shadow banks). It is still worth to note that a system-wide approach does not always necessitate aggregation, as a system may also be analyzed from the viewpoint of its more granular constituents, such as characteristics of a network of entities and the overall emergence of system-wide patterns from micro-level data. For instance, Korhonen (2013) links the importance of micro-level data in macroprudential analysis to



Notes: The figure represents the macroprudential data cube. It represents four spaces: entities (e.g., country), time (e.g., year), variables (e.g., gross domestic product (GDP)), and links (e.g., debt and equity exposures). Likewise, it illustrates four data slices: a multivariate cross section (red side), a cross section of time series (blue side), a multivariate time series (green side), and a cross section of interlinkage matrices (**black edges**).

Figure 4: A macroprudential data cube.

a number of possibilities, such as flexibility and information to determine appropriate subsectors, timelier pre-assessment of impacts, more granular composition of different exposures and different scopes of consolidation based upon the same data.

Though we have concluded that we have three dimensions in data, entities, time and indicators, the discussion thus far has provided little structure on the form and complexity of the data. Independent of the aggregation level, macroprudential oversight is most commonly utilizing structured data that come from a so-called macroprudential data cube (henceforth data cube). Yet, rather than three, the data cube in Figure 4 is described by four dimensions: (*i*) entities (e.g., countries); (*ii*) time (e.g., years); (*iii*) indicators (e.g., credit-to-GDP gap); (*iv*) links (e.g., debt and equity exposures). Each cell is hence defined by a specific entity, a specific time unit and a specific variable, as well as its specific set of interlinkages. The value for each cell is the value for that particular variable and the related vector of links. Yet, this representation specifies little about the size of the dataset. Beyond the hazy notion of 'big data', this gives at hand a common setting with large-volume (cf. entities), high-dimensional (cf. indicators) and high-frequency (cf. time) data, where overall size of data is mostly limited by the detail level at which each dimension of the data cube is explored. Hence, for the three more standard dimensions of the cube, a big data problem may arise from increases in size in any of the dimensions. Likewise, the size of the fourth dimension largely follows entities, time and variables, where entities refer to the number of nodes, time to time-varying networks and variables to multi-layer networks.

Following the four dimensions, the data cube can be described according to four types of slices. First, a multivariate cross section (red side) provides a view of multiple entities described by multiple variables at one point in time. Second, a cross section of time series (blue side) is a univariate view of multiple entities over time. Third, a multivariate time series (green side) provides a view of multiple variables over time for one entity. Finally, the fourth view is a cross section of interlinkage matrices (**black edges**) that represent links between multivariate entities at one point in time. While links oftentimes refer to direct linkages and exposures between entities, it is also common to estimate links from interdependence in the variable dimension (e.g., stock returns). By means of a simple example of a macroprudential dataset in the data cube representation, the four dimensions could be defined as follows: countries as entities, quarterly frequency as time, indicators of various sources of risk and vulnerability as variables, and equity and debt exposures between economies as links.

This provides a starting point to data visualization, as it ought to be viewed from the viewpoint of the underlying data.

4.3 Macroprudential visualization: A review

This section provides first a brief overview of used visualization tools for the above discussed three types of analytical tools: (*i*) early-warning models, (*ii*) macro stress-testing models, and (*iii*) contagion and spillover models. Whereas the first type deals with the time dimension (i.e., risk identification), the second and third types deal with the cross-sectional dimension (i.e., risk assessment). To conclude the section, we discuss a categorization of visualization methods based upon the needs for macroprudential oversight.

First, standard *early-warning indicators and models* may be complemented by the use of visualization tools for amplifying cognition. Due to the complexity of financial systems, a large number of indicators are often required to accurately assess the underlying risks and vulnerabilities, and these are oftentimes compressed into a single vulnerability measure of an early-warning model. As with statistical tables, standard two- and three-dimensional visualizations have, of course, their limitations for high dimensions, not to mention the challenge of including a temporal or cross-sectional dimension or assessing multiple countries over time. In particular, capturing the time dimension of systemic risk is a key aim of early-warning models (e.g., Borio, 2009). Although composite indices of leading indicators and predicted probabilities of early-warning models enable comparison across countries and over time, these indices fall short in describing the numerous sources of distress.

Some recent approaches make use of techniques for multidimensional visualization to assess sources of risk and vulnerability. To start with the GFSM, it falls short in reducing dimensionality of the problem, as similarity comparisons of high-dimensional observations is left to be performed by the human eye. In addition, familiar limitations of radar charts are, for example, the facts that area does not scale one-to-one with increases in variables and that the area itself depends on the order of dimensions. This can be illustrated by means of an example, where two countries have an equal amount of aggregated risk in three subdimensions, but one has these as neighboring axes and the other a risk in every second axis. In this case, the former has a significantly (or infinitely) different size but the same aggregate risks (i.e., mean value). Indeed, the GFSM comes with the following caveat: *"given the degree of ambiguity and arbitrariness of this exercise the results should be viewed merely illustrative"*.[4]

Mapping techniques with the aim of data reduction and dimension reduction have also been used to represent these complex data. In terms of Fuzzy c-means (FCM) clustering, a combination of clustering models and the reasoning of fuzzy logic have been introduced to the early-warning literature by finding risky clusters and treating relationships in data structures as true or false to a certain degree (Marghescu et al., 2010). Beyond signaling a crisis in a timely manner, this type of analysis has the benefit of signaling the type and degree of various sorts of financial imbalances (in terms of memberships to clusters). In an exploratory study, Arciniegas Rueda and Arciniegas (2009) found, with the help of the Self-Organizing Map (SOM), strong associations between speculative attacks' real effects and 28 indicators, yet did neither focus on visualizing individual data nor on early-warning performance.

Turning to SOM based papers focusing on visualization, Sarlin (2010) presents the first exploratory study of the SOM as a display of crisis indicators with a focus on the Asian currency crises in 1997–1998. Sarlin and Marghescu (2011) extend the work by using the SOM as an early-warning model, including an evaluation in terms of predictive performance, and with a larger sample of indicators. In Sarlin (2011), the SOM is applied to a wide range of indicators of sovereign default. Further, Sarlin and Peltonen (2013) create the Self-Organizing Financial Stability Map (SOFSM) that lays out a more general framework of data and dimension reduction for mapping the state of financial stability, and visualizing potential sources of systemic risks. As an early-warning model, the SOFSM is shown to perform on par with a statistical benchmark model and to correctly call the crises that started in 2007 in the United States (US) and the euro area. All of these works highlight the usefulness of the SOM for the task.

Second, *macro stress-testing models*, to the best of my knowledge, make no use of advanced visualization techniques for representing the results of the tests, including the processing of data at the input, interim and output stage. Visualization seldom goes beyond a framework or schematic structure for the designed transmission mechanisms in the model and plots of loss distributions in various formats.

[4]The use of adjustment based on market and domain intelligence, especially during crises, and the absence of a systematic evaluation gives neither a transparent data-driven measure of financial stress nor an objective anticipation of the GFSM's future precision. The authors state that the definitions of starting and ending dates of the assessed crisis episodes are somewhat arbitrary. The assessed crisis episodes are also subjectively chosen. Introduction of judgment based upon market intelligence and technical adjustments are motivated when the GFSM is *"unable to fully account for extreme events surpassing historical experience"*, which is indeed an obstacle for empirical models, but also a factor of uncertainty in terms of future performance since nothing assures manual detection of vulnerabilities, risks and triggers.

Obviously, standard visualization techniques from graph theory may be used in representing networks, if such are used in the models. For instance, the macro stress-testing model by Boss et al. (2006), which integrates satellite models of credit and market risk with a network model for evaluating default probabilities of banks, enable one to make use of concepts from graph theory in visualizing the network structure. Network visualizations are, however, more common in contagion models.

As said, the third group of *contagion and spillover models* commonly make use of concepts from graph or network theory to visualize the structure of linkages in the models (see, e.g., Estrada (2011)). This provides means to represent entities as nodes (or vertices) and their links as edges (or arcs). The combination of nodes and edges provide all constituents for a network, where the edges may be directed *vs.* undirected and weighted *vs.* unweighted. However, rather than a visualization, a network is a data structure. The interpretability of networks has been enhanced by the means of various methods. For instance, positioning algorithms, such us force-directed layout methods, are commonly used for locating nodes with similar edges close to each other, as well as ring and chord layouts for more standardized positioning. Yet, the so-called hairball visualization, where nodes and edges are so large in number that they challenge the resolution of computer displays, not to mention interpretation, is not a rare representation of complex financial networks (see, e.g., Bech and Atalay (2010)). By including dynamics, there exists also work on visualizing how shocks cascade in networks, which directly relates to the contagion literature (e.g., von Landesberger et al., 2014). It is worth noting that recent advances in financial network analysis, particularly software, hold promise in bringing aesthetics and the ease of use of visualizations into the financial domain. An additional essential feature, not the least to deal with hairballs, is the use of interaction techniques with visualizations.

4.4 The need for analytical and interactive visualizations

This section has so far defined the task of visualization in risk communication, the structure and properties of macroprudential data and visualizations used to date to represent systemic risk. Beyond the indications of previous works and standards in the policymaking community, as highlighted in the state-of-the-art overview, the notions of risk communication and the underlying data highlight the need for two features: (*i*) interactive and *ii*) analytical visualizations. While analytical techniques enable the visualization of big data, interactivity answers the needs set by communication as it enables extracting large amounts of information through the interaction with a graphic.

The need for *analytical techniques* refers to the complexity of data used in systemic risk measurement. Visual analytics refers often to the coupling of visual interfaces to analytics, which supports in building, calibrating and understanding models (e.g., early-warning models). Yet, the notion of an analytical technique for visualization differs by rather using analytics for reducing the complexity of data, with the ultimate aim of visualizing underlying data structures. These techniques provide means for drilling down into the data cube. For instance, mapping techniques provide a projection of high-dimensional data into two dimensions through dimension reduction, whereas clustering methods enable reducing the volume of data into fewer groups (or mean profiles). Likewise, the analysis of time might also be supported by the use of analytical techniques, as compressing the temporal dimension would enable representations of only relevant points in time.

The coupling of visual interfaces with *interaction techniques* goes to the core of information visualization and visual analytics. This has largely been overlooked in the policymaking community. One key task of macroprudential supervisors has been to publish risk dashboards, such as that of the ESRB, yet none of these have been truly interactive. For instance, the sixth issue of the dashboard was a static 30 page document, in addition to 11 pages of annexes. While the initiative has merit in that it promotes transparency and knowledge among the general public, it is not clear why the dashboard is lacking interactivity and true data sharing in an age when the single most used distribution channel is digital format.[5] Even though one could argue that formal reports, such as Fed's Annual Report to Congress, require static visuals to support transparency, accountability and record-keeping, the property of exporting a static screenshot is a common property of interactive interfaces. To the other extreme, if accountability and common knowledge is of utmost importance and limits the design of reports, then one could ask whether any visuals should be utilized. Another example is when a systemic risk model (e.g., early-warning model) has been built and calibrated. It would be an intuitive first step to circulate it (at least internally) with possibilities to explore all examples of potential interest, rather than only being

[5]It is still worth to note that ESRB's risk dashboard has been paired with the ECB Statistical Data Warehouse. Yet, data for far from all indicators is shared in the data warehouse.

presented with cases selected by its authors. While this could function as a type of review or scrutiny at an early development stage, this would also support transparency, and thus possibly credibility, of internally developed approaches to identify and assess systemic risk. Further, relating to the previous topic, a natural extension to analytical visualization techniques would obviously be means to interact with them.

5 Visualization applications and the VisRisk platform

This section moves from previous abstractions to concrete applications. With the two features pinpointed in the previous section and the macroprudential data cube in mind, this section provides a range of examples both relating to analytical and interactive visualizations in macroprudential oversight. First, we make use of analytical techniques for data and dimension reduction to explore high-dimensional systemic risk indicators and time-varying networks of linkages. Second, we add interactivity to not only dashboards of standard risk indicators and early-warning models, but also to the analytical applications. Hence, we illustrate applications of three analytical visualizations and five interactive web-based visualizations to systemic risk indicators and models. From the viewpoint of the data cube in Figure 4, we provide visual means to explore all four dimensions.

Beyond the applications herein, it is worth remembering that the ultimate aim of the paper is to provide a platform or basis for the use of visualization techniques, especially those including analytical and interactive features, in macroprudential oversight in general and risk communication in particular. Hence, we end this section by presenting the VisRisk platform that enables and is open to the visualization of any data from the macroprudential data cube.

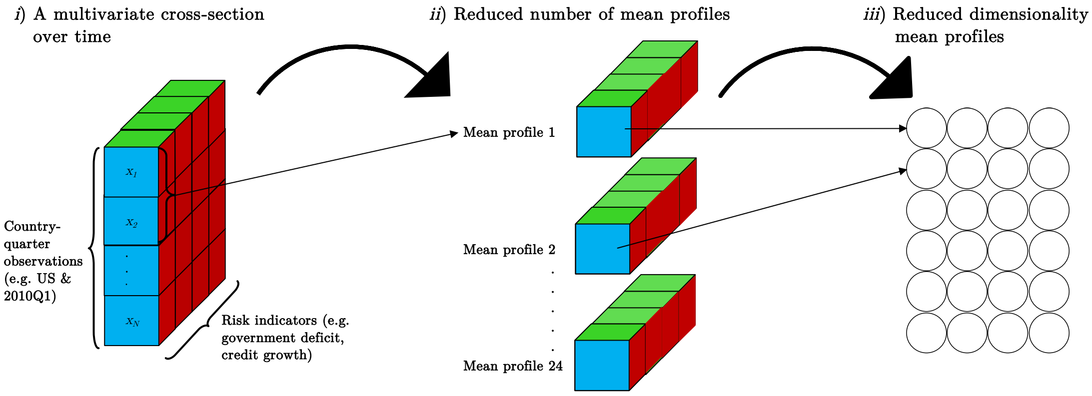
5.1 Analytical visualizations

This subsection presents three cases where data and dimension reduction techniques are used for representing large-volume and high-dimensional data in simpler formats. Further, we also present an application of a force-directed layout algorithm to the visualization of network data. Even though we address systemic risk, it is a deliberate choice not to make use of data that would be overwhelmingly extensive along any of the dimensions of the data cube. This is mainly due to the illustrative nature of the examples, as the main function of this section is to demonstrate the usefulness of analytical and interactive visualizations in macroprudential oversight. Nevertheless, the applications make use of real-world data targeted at systemic risk.

The problem setting described in Section 4.2, particularly the combination of large-volume and high-dimensional data, has been addressed in machine learning, a subfield of computer science. One common approach to reducing large-volume data (i.e., many high-dimensional observations) is to represent a set of points P by a smaller, but representative, set of equidimensional points A. These representative points constitute partitions or clusters and may be called reference vectors, mean profiles or cluster centroids, mostly with an aim to approximate the probability density functions of data. Data reduction is a necessity, and thus common practice, in application areas like speech recognition, computational linguistics, and computational genomics, and is addressed by means of clustering algorithms, or so-called data reduction techniques (see, e.g., Jain (2010)). While both P and A still live in the high-dimensional space $\mathbb{R}^n$, machine learning also provides approaches for reducing the dimensionality of data. Dimension reduction provides low-dimensional overviews of similarity relations in high-dimensional data, where data are represented in two dimensions such that similar high-dimensional data are nearby and dissimilar distant. The task of projecting observations $p_j \in \mathbb{R}^n$ to an equisized set of $l_j \in \mathbb{R}^2$ goes also by the name of manifold learning, embedding and mapping (see, e.g., Lee and Verleysen (2007)), but can as well be considered to cover force-directed layout algorithms for positioning nodes of networks. A recent focus has been to also involve the third dimension – time. This refers to the task of visual dynamic clustering, where *clustering* refers to reducing data, *visual* refers to reducing dimensionality and *dynamic* refers to changes in clusters over time. Hence, it provides means for visualizing how cross-sectional structures (i.e., clusters) evolve over time.

Financial Stability Map

This part describes the application of the (Self-Organizing) Financial Stability Map (FSM), as originally described in Sarlin and Peltonen (2013). The underlying data come from the three standard dimensions



Notes: The figure uses the data structure presented in the data cube to describe how the SOM-based data and dimension reduction is performed. By pooling the cross-sectional and temporal dimensions, the red side represents a multivariate cross section over time, in which the blue side represents time-entity observations and the green side common indicators.

Figure 5: Creating the Financial Stability Map.

of the data cube: quarterly observations for a global set of 28 economies from 1990–2011 and 14 macro-financial indicators. The FSM is based upon the Self-Organizing Map (SOM), which has two aims: (i) to reduce large amounts of high-dimensional data to fewer mean profiles, and (ii) to provide a low-dimensional representation of the high-dimensional mean profiles. As described in Figure 5, using a pooled panel data (i.e., time is not taken into account) in step (i), the FSM follows two subsequent steps: (ii) to group high-dimensional observations to a smaller set of equidimensional mean profiles based upon similarity, and iii) to project the mean profiles to an equisized but low-dimensional grid such that similar profiles are located close by.

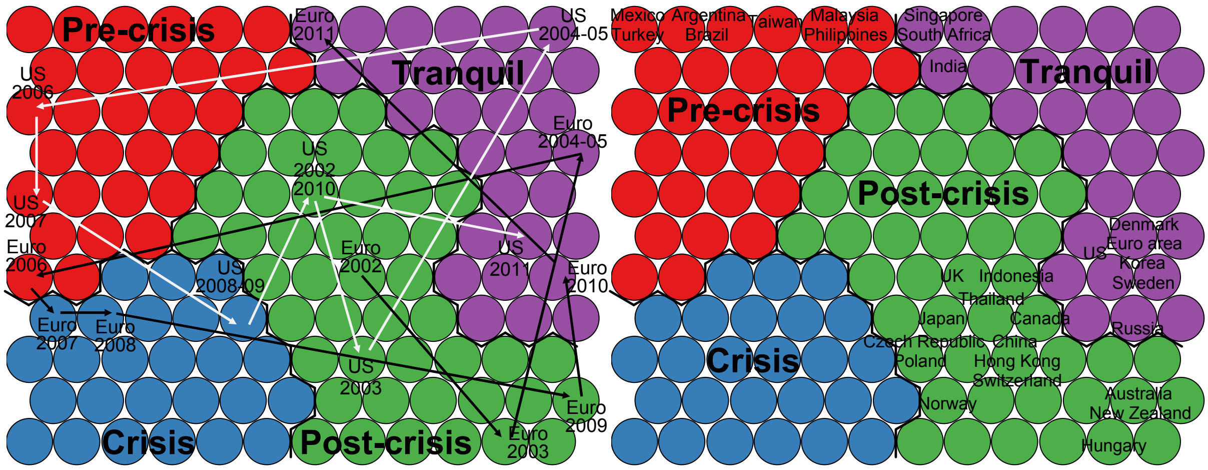
In this application, the motivation for using the SOM for mapping financial stability over alternative techniques relates mainly to the following properties (for a further discussion see Sarlin (2014a)): (i) its simultaneous clustering and projection capabilities, (ii) the pre-defined grid structure for linking visualizations, (iii) computational efficiency, and iv) flexibility for missing data. For a description of the technical details, readers are referred to Appendix B.1 and Kohonen (1982, 2001).

The procedure described in Figure 5 creates the FSM, and provides hence a low-dimensional basis or display with two tasks: (i) to function as a display for visualizing individual data concerning entities and their time series, and (ii) to use the display as a basis to which additional information can be linked. As the nodes of the grid are high-dimensional mean profiles, the high-dimensional observations can be located with their most correct position using any similarity measure. In Figure 6, we illustrate the evolution of macro-financial conditions (14 indicators) for the United States and the euro area (2002–2011, first quarter), and a cross section of macro-financial conditions in key advanced and emerging market economies in 2010Q3. As the figure shows, the map captures a so-called financial stability cycle for both economies. It is true that Europe is classified to be tranquil in midst of the European crisis, but it is worth remembering that this, as most other early-warning models, are built for boom-bust phases, not prolonged periods of financial stress, which might be transmitted from other types of risks (e.g. from banking sector to sovereign). Beyond these temporal and cross-sectional applications, the FSM could be paired other approaches and applications, such as aggregated data (e.g., world conditions), scenario analysis by introducing shocks to current conditions, assessing linkages by connecting linked economies with edges, etc. (see Sarlin (2014b) for further examples).

Yet, this map does not provide means for understanding how the cross sections change over time.

Financial Stability Map over Time

To understand how cross sections are evolving, we need to tap into approaches for visual dynamic clustering. The recently introduced Self-Organizing Time Map (SOTM) (Sarlin, 2013b) is unique in that it provides means for visualizing how cross-sectional structures (i.e., clusters) evolve over time. Although the only difference to the above approach is the addition of a time dimension to the mapping, it provides an approach that truly represents the three dimensions of the data cube. Hence, it addresses large-volume data by reducing the number of entities to clusters and high-dimensional data by reducing dimensionality the clusters, as well as represents changes in clusters over time. Based upon the SOTM, this part



Notes: The figure displays the two-dimensional FSM that represents a high-dimensional financial stability space. The lines that separate the map into four parts are based on the distribution of the four underlying financial stability states. Data points are mapped onto the grid by projecting them to their best-matching units (BMUs) using only macro-financial indicators. Consecutive time-series data are linked with arrows. In the left figure, the data for both the US and the euro area represent the first quarters of 2002–2011 as well as the second quarter of 2011. In the right figure, the data for all economies represent the third quarter of 2010.

Figure 6: Evolution in the US and euro area and a cross section on the FSM.

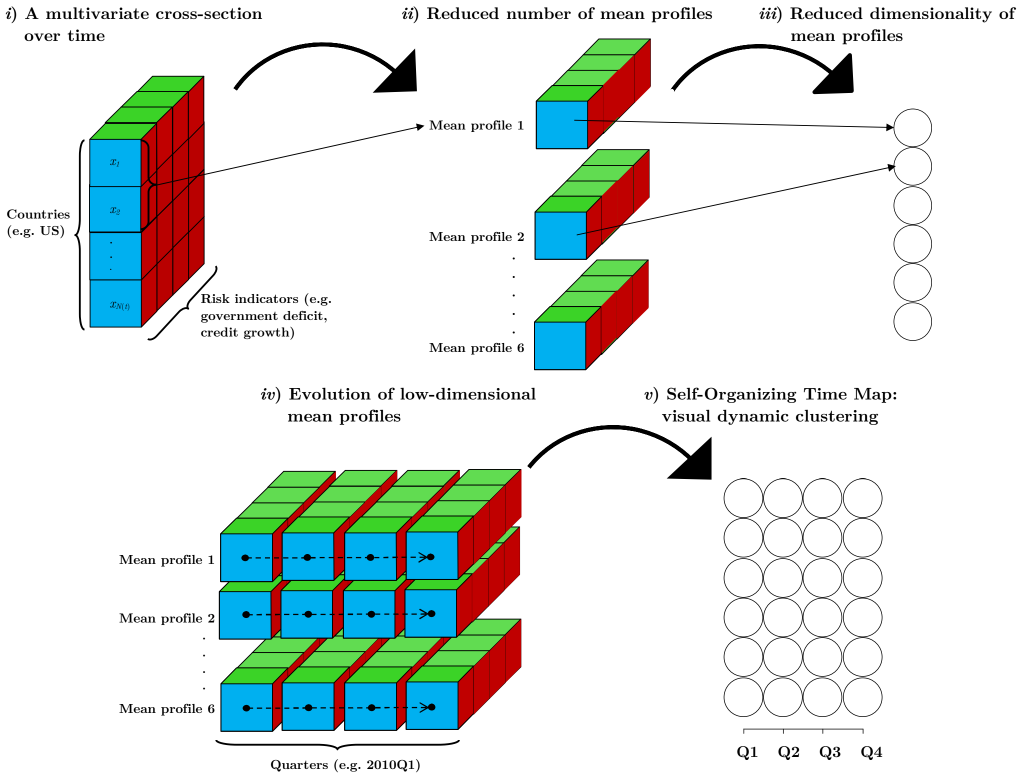
describes the application of the Financial Stability Map over Time (FSM-t), as originally described in Sarlin (2013a). In contrast to the above application, we do not pool the panel data, but rather follow the first three steps as described in the upper part of Figure 7: (i) starting from a multivariate cross section, (ii) high-dimensional observations are grouped to a smaller set of equidimensional mean profiles and (iii) the mean profiles projected to a one-dimensional grid such that similar profiles are close by. Next, as this concerns only an individual point in time, steps (iv) and (v) in the lower part of Figure 7 describe performing the three former steps on all time points, including a number of initialization techniques to preserve orientation, in order to create a two-dimensional grid representing the spaces of both time and data. For technical details on the SOTM, readers are referred to Appendix B.2 and Sarlin (2013b).

The procedure described in Figure 7 creates the FSM-t. Although the FSM-t can also function as a display for visualizing individual data concerning entities and their evolution, its key task is to focus on how the high-dimensional structures are evolving over time. In Figure 8, the upper figure illustrates the evolution of macro-financial conditions (i.e., 14 indicators) in the cross section from 2005Q3–2010Q4. In terms of all 14 indicators, similarity in the mean profiles is represented by similarity in color (from blue to yellow). Further, as the nodes of the grid are high-dimensional mean profiles, one particularly interesting view is to explore how individual variables have evolved in the cross section over time. The lower part of Figure 8 shows how leverage is increasing over time, even after the crisis of 2007–2008, and the increases in government deficits after the first wave of the crisis. The FSM-t can also be created and exploited in various different ways, such as focusing on cross-sectional changes before, during and after crises (e.g., $t-8, t-7, ..., t+8$) and by projecting individual economies on top of it.

Now, we have tackled the three standard dimensions of the data cube, but what about the linkages?

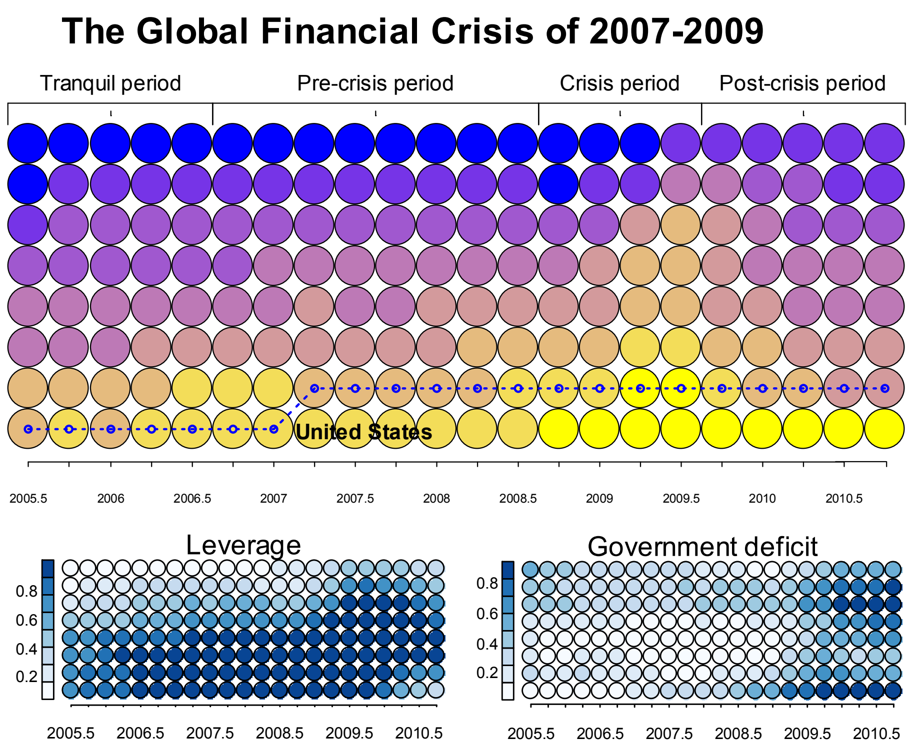
Bank Interrelation Map

Like high-dimensional risk indicators, networks constitute an inherently complex source of information. Network analysis, or link analysis, can be seen as the exploration of crucial relationships and associations between a large set of objects, also involving emergent properties, which may not be apparent from assessing isolated data. Networks of relationships are mostly expressed in matrix form, where the link between entities g and l in a matrix A is represented by element a_{gl}. The matrix is of size n^2, where n is the number of entities. Matrices of directed graphs can be read in two directions: rows g of A represent the relationship of g to l and columns l of A represent the relationship of l to g. Each entity g is thus described by its relationship to each other entity l, and hence $g \in \mathbb{R}^n$. Yet, except for the rare completely connected networks, dense networks comprise for each node an edge number close to the total number of nodes. On the contrary, the nodes in sparse networks comprise only a low number of links, which can also be called scale-free networks if their degree distribution follows a power law. The latter type of networks are predominant in the real world, where the network structure is formed through natural processes and



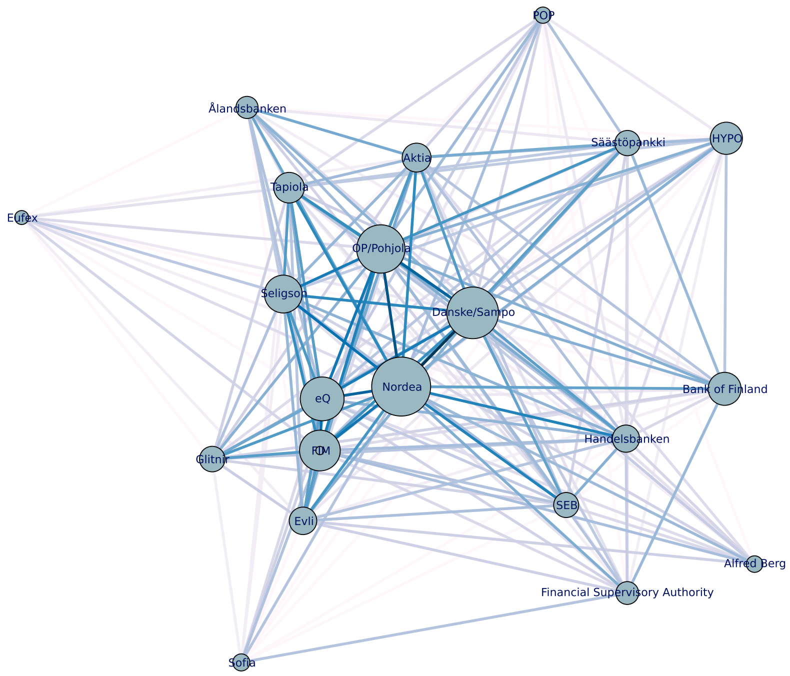
Notes: The figure uses the data structure presented in the data cube to describe how the SOTM-based data and dimension reduction is performed. Instead of pooling data, the SOTM applies one-dimensional SOMs to individual high-dimensional (red side) cross sections (blue side). As this is performed over time (green side), in conjunction with techniques for initialization and a short-term memory, the orientation of the one-dimensional SOMs is preserved.

Figure 7: Creating the Financial Stability Map over Time.



Notes: The figure represents a Self-Organizing Time Map (SOTM) of the global financial crisis, where the cluster coloring shows changes in multivariate cluster structures. Labels above the figure define the classes in data, i.e., the stages of the financial stability cycle, and the trajectory on the SOTM represents the evolution of macro-financial conditions in the US.

Figure 8: A SOTM of the global financial crisis.



Notes: The figure shows one solution of a bank co-occurrences map with the Fruchterman-Reingold algorithm. Node size is proportional to the individual bank occurrence count, while connection darkness is logarithmically scaled to co-occurrence count.

Figure 9: A bank co-occurrence network from financial discussion.

central hubs naturally emerge. In the vein of the above defined task of dimension reduction, this describes the challenge of drawing low-dimensional graphs from complex networks.

There is a range of approaches for visualizing network data. One popular category is that of force-directed layout algorithms. They provide means for representing network centrality and connectivity (i.e., dependency structures) in low dimensions, by optimizing node positions according to some of the following criteria, among others: few crossing edges, straight edges, long enough edges and uniform edge length for non-weighted networks. Based upon work in Rönnqvist and Sarlin (2014b), this part describes the use of financial discussion for creating bank interrelation maps. Most analysis of interdependencies among banks has been based on numerical data. By contrast, this study attempts to gain further insight into bank interconnections by tapping into financial discussion. The approach is illustrated using a case study on Finnish financial institutions, based on discussion in 3.9M posts spanning 9 years in an online discussion forum belonging to a major Finnish web portal dedicated to financial and business information. Based upon these data, co-occurrences of bank names are turned into a network, which can be visualized. For the purpose of data exploration, particularly visualization, the usage of textual data holds an additional advantage in the possibility of gaining a more qualitative understanding of an observed interrelation through its context.

Figure 9 shows a bank interrelation map (BIM) based upon a co-occurrence network from financial discussion. The network depicts counts of bank names co-occurring in forum posts for the entire period 2004–2012. Node size is proportional to the individual bank occurrence count, while connection darkness is logarithmically scaled to co-occurrence count. Nodes are positioned by the Fruchterman-Reingold algorithm (Fruchterman and Reingold, 1991). The message of the figure is that the largest nodes in the center of the graph are also the most centrally connected in the network. Yet, textual data being a rich data source, there is plenty of descriptive information to be explored behind the linkages and nodes, something that could easily be conveyed through interaction possibilities.

Further relating to the limits of a single, static overview is the shortcoming of force-directed layout algorithms when processing large-volume data. Not only are they computationally costly, but they also often find locally optimal solutions. While there is a range of solutions to decrease computational cost, such as multilevel (Hu, 2006) and parallel (Tikhonova and Ma, 2008) extensions, the problem of local optima derives from the complexity of projecting high-dimensional data to low-dimensional displays. One cure may, however, be the possibility to interact with node positions, as well as other techniques improving representation, which takes us to the following topic.

5.2 Interactive interfaces

This section, while still exemplifying visualizations in macroprudential oversight, shifts the focus towards interaction with the visual interfaces. Rather than an ending point, the visual interface or visualization is a starting point for data exploration, to which interactivity is an ideal support. Beyond interactive interfaces, it is worth noting, as above discussed, that screen captures (i.e., pdf, svg and png formats) and URL outputs (i.e., a permalink with chosen parameters) are available to support common-information sharing.[6]

Following Shneiderman's (1996) visual information seeking mantra of "*Overview first, zoom and filter, then details-on-demand*", the visualization provides merely a high-level overview, which should be manipulated through interaction to zoom in on a portion of items, eliminate uninteresting items and obtain further information about requested items. To this end, a large share of the revealed information descends from manipulating the medium, which not only enables better data-driven communication of information related to risk, but also facilitates visual presentation of big data.

Risk dashboard

In recent years, risk dashboards have become essential tools for both internal and external risk communication among macroprudential supervisors. While central banks commonly have their own internal risk dashboards, supervisory bodies like ESRB and EBA publish dashboards also available for external assessment of prevailing risks and vulnerabilities. As an alternative to static documents, this part introduces an interactive data-driven document (D3) based risk dashboard of 14 systemic risk indicators. The dashboard includes quarterly data for a global set of 28 economies and ranges from 1990 to 2011. The dataset is based upon that in Sarlin and Peltonen (2013), of which further details are available in Sarlin (2014b), and which to a large extent descends from Lo Duca and Peltonen (2013).

The dashboard in Figure 10 focuses on time series of univariate indicators for a cross section. As an *overview*, it presents a time-series plot for one chosen indicator and all economies, where the indicator and its transformation can be chosen from the drop-down menu and radio buttons, respectively. The transformation scales the indicators to country-specific percentiles, which enables a view of the data in relation to their own economy's distribution. *Zooming and filtering* involves highlighting individual economies by hovering, showing only one individual economy by selection (which highlights their events), dropping an economy from the graph by deselecting it, and choosing a time span to be shown. *More details* can be obtained about the historical occurrence of crises in economies, more precise information about highlighted data points (value, year and country) and through any of the zooming or filtering options as the entire graph (x and y axes) adapts to changes. Moreover, with the same functionality, the dashboard also allows for focusing on country-level time-to-event plots, which illustrates crisis dynamics for all economies.

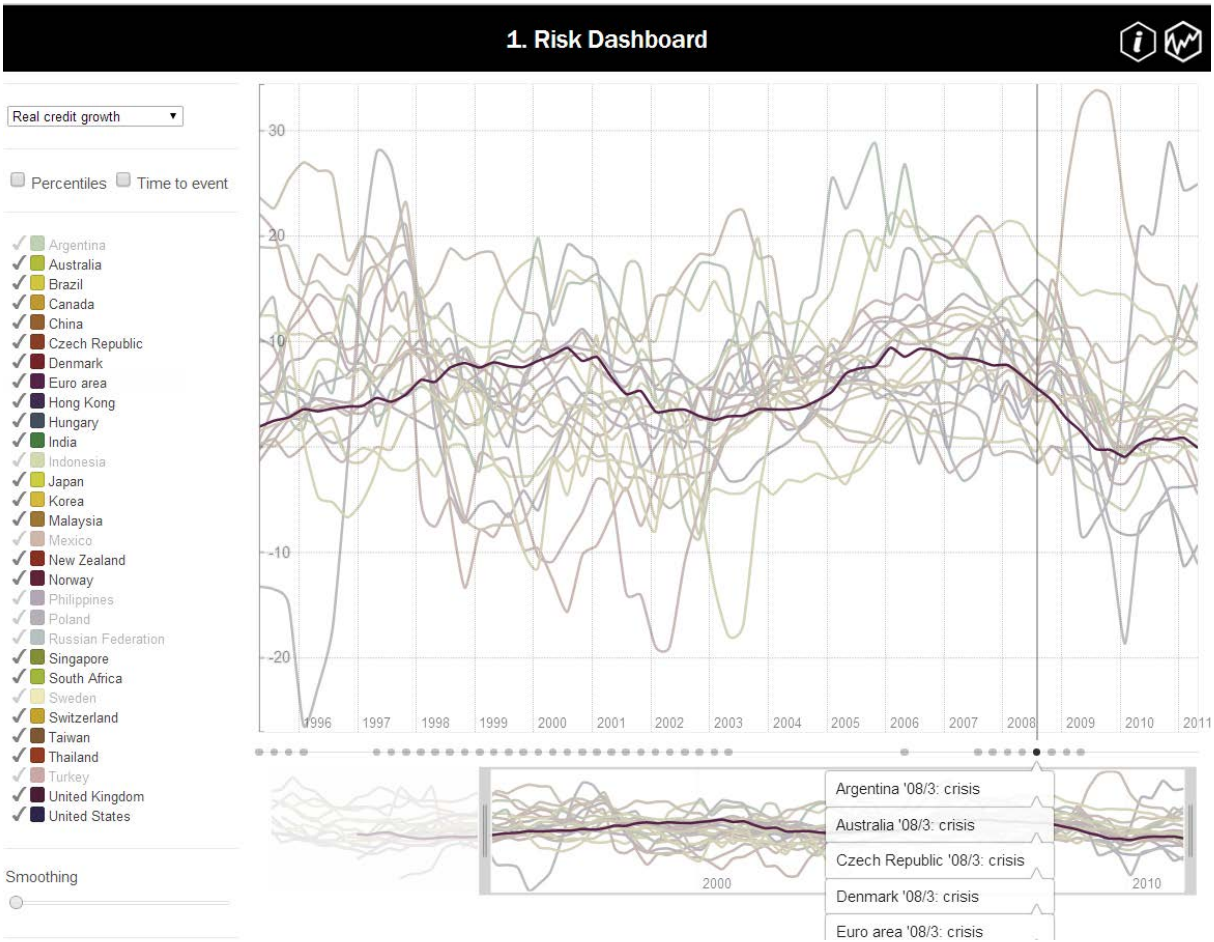
While this provides an interface to time series of a large number of indicators, these are oftentimes combined into a single composite indicator through various analytical techniques, which likewise would benefit from a visual interface.

Early-warning model

This risk dashboard of 14 systemic risk indicators provides a view of individual indicators and their percentile transformations. These indicators could, however, be an input to an early-warning model, to which a visual interface would provide ample means for better understanding the performance and characteristics of the model. Visual means also allows for better scrutiny, which is likely to impact model credibility.

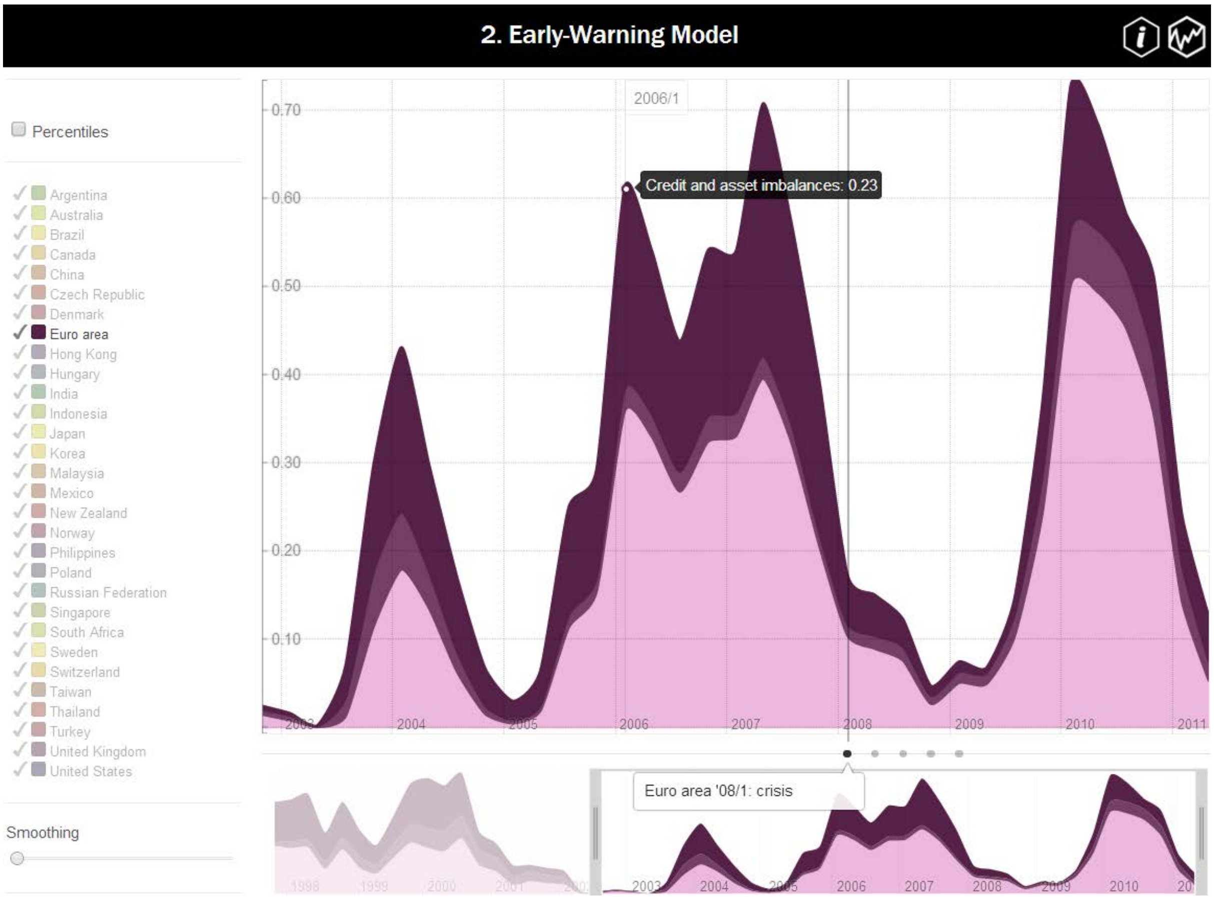
In this part, we provide a similar interface as that for the risk dashboard, but instead visualize the output of an early-warning model with the previously explored early-warning indicators as an input. The *overview* illustrates how systemic risk or vulnerability has evolved in all economies over time. While the

[6] Interested readers can explore the interactive and analytical applications online: http://vis.risklab.fi/.



Notes: The interactive risk dashboard can be found here: http://vis.risklab.fi/. In the screenshot, credit growth is shown for economies selected in the left panel and hovering over the label of the euro area dims the time series for all other economies. The time brush below the figure is used to focus on a specific time span, whereas a drop-down list of events is chosen to be shown from the event line between the two displays, which also adds a vertical line to the above plot. The data are shown in non-transformed format.

Figure 10: An interactive risk dashboard.



Notes: The interactive early-warning model can be found here: http://vis.risklab.fi/. In the screenshot, estimated probabilities of systemic risk are shown for the euro area for a specific time span, as is selected in the left panel and the below time brush, and hovering over a specific data point shows that the contribution, variable category and time point are 0.23, credit and asset imbalances and 2006Q1, respectively. The event for the euro area are chosen to be shown from the event line above the time brush, which also adds a vertical line to the above plot. The data are shown in non-transformed format.

Figure 11: An interactive early-warning model.

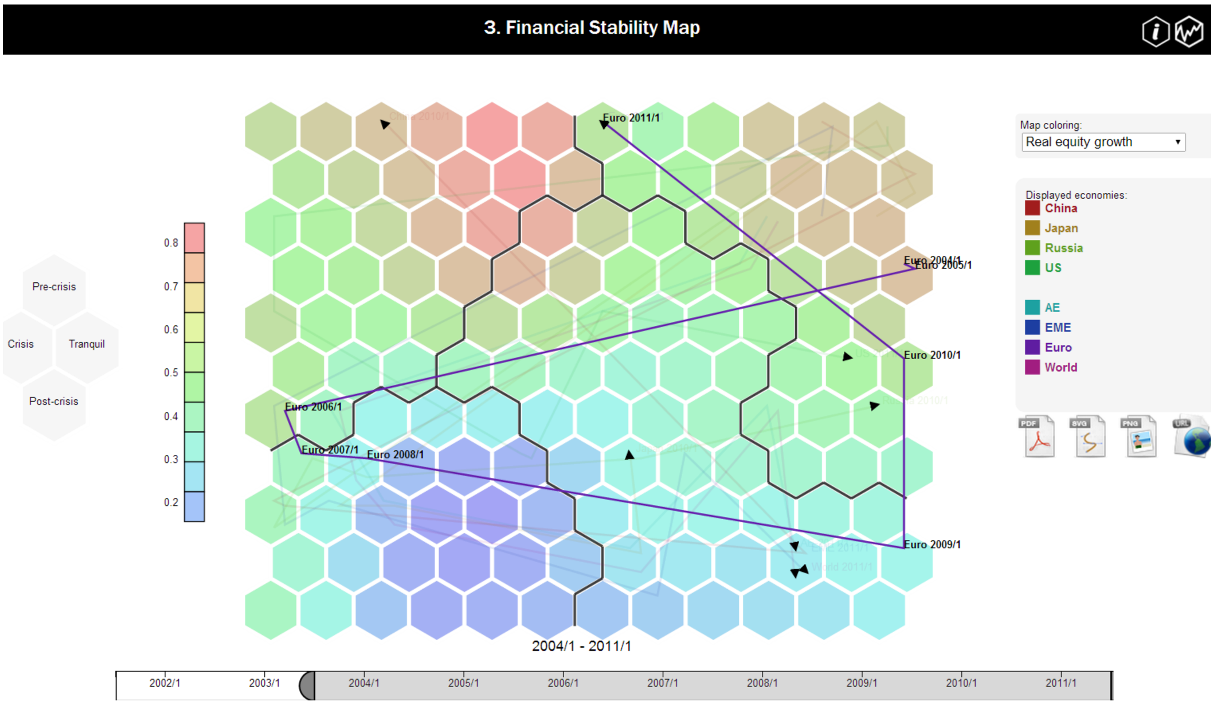
percentile transformation aids in interpreting the severity of the measure in its historical distribution, we can make use of the same features for *zooming and filtering* and retrieving more *details on demand* to better understand the aggregate risk measure. As is shown in Figure 11, a further interaction capability is that the line graph is changed into a stacked graph when a single economy has been chosen, which shows the contribution of three variable groups: domestic macroeconomic and credit and asset imbalances and global imbalances.

The importance of visualizing these types of analytical models derives from their complexity and lack of transparency, as they are often the result of extensive computations, within which it might not always be easy or possible to track the quality of the output. While not being a substitute for more formal evaluations of signaling quality and other quantitative performance measures, this provides a means for a more detailed and general exploration of model outputs. Moreover, one essential task ought to be to improve transparency of analytical projects and models within an organization, by enabling other analysts, groups and divisions to interact with derived models, which could function as an internal model audit.

Early-warning models do not, however, provide a more detailed view of what is driving results and where in a financial stability cycle an economy might be located. They give a mere probability of a crisis, which turns our attention to the FSM and the potential to interact with it.

Financial Stability Map

Building upon the above presented FSM application that uses analytical techniques for visualization, this subsection brings interactivity into the picture. An interactive implementation of the FSM can be found in Figure 12. The implementation uses the same map as an *overview*, but goes beyond Figure 6 by enabling



Notes: The interactive Financial Stability Map can be found here: http://vis.risklab.fi/. In the shown screenshot, the states of financial stability are shown by location on the map for economies highlighted in the right panel, and hovering over the label of the euro area dims the time series for all other economies. The time brush below the figure is used to visualize trajectory for the chosen economies. The left-hand side class legend and scale refer to the financial stability states (or clusters) and the distribution of values for individual indicators, respectively. These indicators can be used for coloring through the drop-down menu on the right side.

Figure 12: An interactive Financial Stability Map.

various forms of interaction. *Zooming and filtering* refers to choosing the labels and trajectories to be plotted, including both the cross-sectional (adjusted through right-side panel) and the time dimensions (adjusted through time brush and left/right arrows), rather than showing all labels at once. More over, hovering labels highlights chosen economies and their trajectories. Further *details on demand* is provided by the possibility to use the underlying dimensions or layers of the map for coloring. Through the drop-down menu (and up/down arrows), the graph shows the distribution of an indicator or the probability of being a member of one of the financial stability states with heatmap color coding.

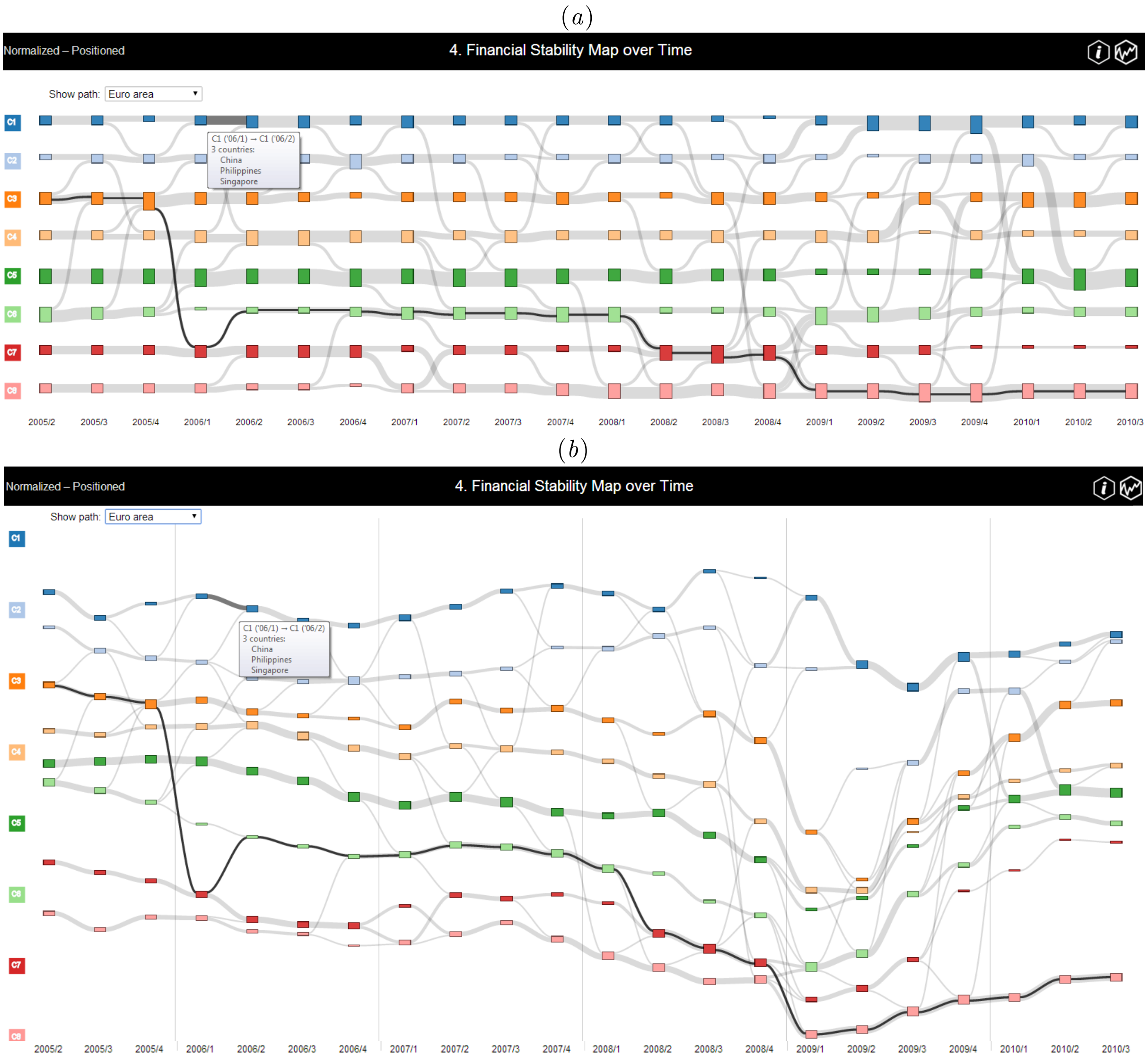
This illustrates the state of individual countries, but how can we understand the evolution of the entire cross section?

Financial Stability Map over Time

The FSM-t, as above shown, provides means for exploring the evolution of the cross section, yet it would undeniably benefit from similar interaction. The visualization design presented herein is based upon an implementation of alluvial diagrams for representing the SOTM (see Rönnqvist and Sarlin, 2014a). As an *overview*, the alluvial SOTM goes beyond the previous representation by encoding cluster size by node height, depicting transitions between clusters from a cross section to the next through links and using a planar visual variable (y-axis) to encode structural changes in data. Figure 13 shows this combined view, where *(a)* shows a standard grid representation and *(b)* distorts positioning along the vertical dimension.

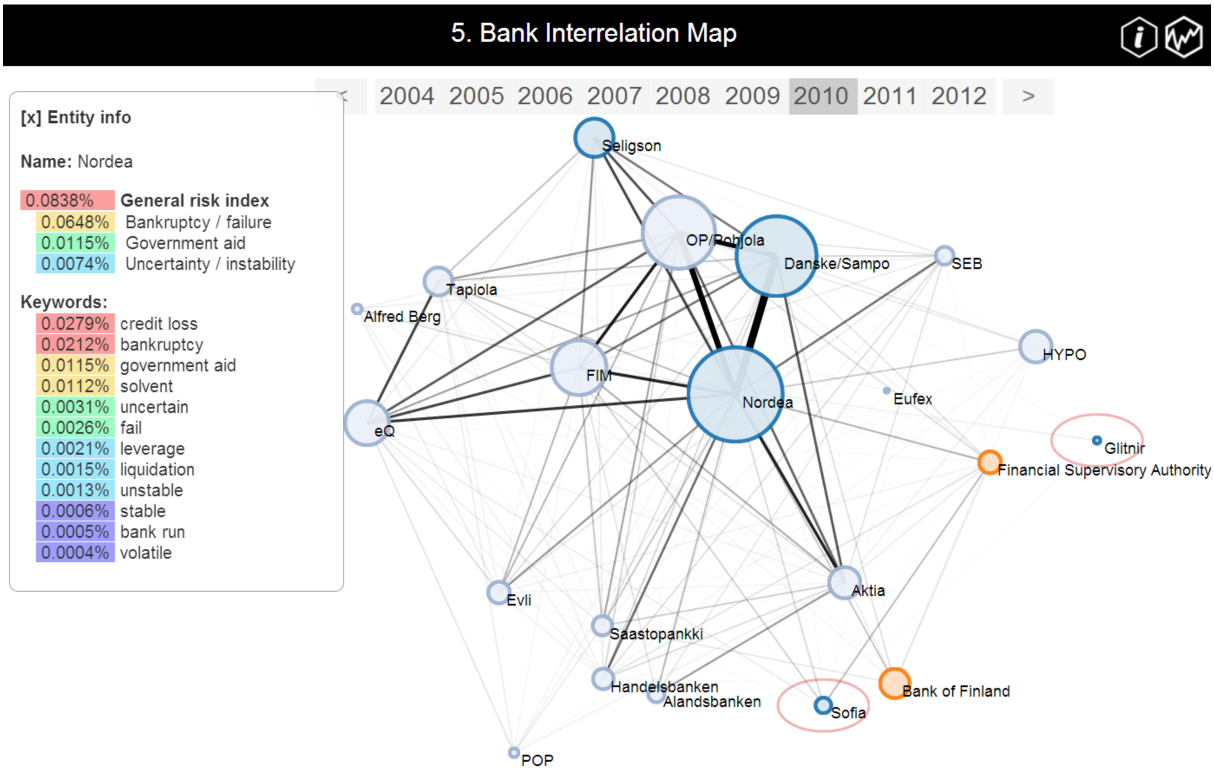
The implementation supports interaction through various means. Beyond possibilities to zoom in on an important or dense part and panning for moving to areas of interest, *zooming and filtering* is supported through the possibility to drag nodes to better understand linkages between overlapping or closely neighboring nodes. Also, selecting individual economies provides means for a more focused view of individual transitions paths. Further *details on demand* is provided when hovering over transition links, which provides a list of all switching economies. One could also see moving from (a) and (b) as a an approach to move from a baseline representation to further details on structural changes.

Now we have provided means for exploring and interacting with the three more standard dimensions of the data cube, but how could we interact with graphics of network data?



Notes: The interactive Financial Stability Map over Time can be found here: http://vis.risklab.fi/. In chart (a), we illustrate a SOTM in a standard grid representation and in (b) we distort positions to represent changes in cluster structures. Further, both charts also show a list of economies staying in cluster 1 between 2006Q1 and 2006Q2, as well as the path for the euro area.

Figure 13: An interactive Financial Stability Map over Time.



Notes: The interactive Bank Interrelation Map can be found here: http://vis.risklab.fi/. In the shown screenshot, a network of bank co-occurrences is drawn with the Fruchterman-Reingold algorithm. Location on the map represents centrality and overall dependency structure. Highlighting nodes provides on the left-hand side statistics measuring the share of discussion relating to risks and distress. The time brush above the figure is used to choose the time span that the network refers to, as well as to support exploration of temporal evolution. The red circles indicate distressed banks during the current crisis (Glitnir, 2008; Sofia; 2010).

Figure 14: An interactive Bank Interrelation Map.

Bank Interrelation Map

Interaction with network models is an inherently important task. Despite the popularity of stand-alone force-directed layout algorithms, coupling them with interaction possibilities, while oftentimes missing, is essential for not only better data exploration, but also possible remedies for improving sub-optimal solutions. Moreover, given the rarity of reaching a global optima, pulling nodes from equilibria, only to let them migrate back to a new sub-optimal position, increases our understanding of network properties.

The *overview* of the bank interrelation map is shown in Figure 14. *Zooming and filtering* is supported by possibilities to zoom in on an important or dense part and panning enables moving to areas of interest, whereas dragging nodes enables both to adjust the current optimum of the layout algorithm and to alter the orientation of the graph and to better understand linkages to overlapping or closely neighboring nodes. Moreover, a time brush enables also varying the time span to range from all years to one year and exploring the evolution of the network over time. Further, the up-down arrow keys enable filtering out the linkages and re-running the algorithm with a random initialization. The variation caused by different initial values highlights the importance of interaction, as two suboptimal solutions may significantly differ. While the richness of textual data would enable a wide range of various further queries, in this application we showcase the feature of *details on demand* by coupling highlighting of nodes with a panel on the left side showing the share of discussion relating to risks and distress.

The use of layout algorithms, while providing means to low-dimensional representations of complex data, is no panacea for visualization. In particular, they lack general-purpose solutions to representing densely connected networks and populated areas. To move beyond the exploration features that are enabled by interaction, layout algorithms can be coupled with other approaches. Entirely different methods may in some cases provide better features for simple representation. For instance, Minimum Spanning Trees provide a simplified skeleton of large networks. Other approaches facilitating the representation of cluttered networks include node and dimension grouping and filtering (see, e.g., Ma and Muelder, 2013), circular and chord diagrams with hierarchical edge bundling (see, e.g., Holten, 2006) and edge lenses and magnifiers (see, e.g., Wong et al. (2003)). Likewise, if that data can be split into smaller and meaning-

Table 1: The applications in relation to the platform and analytical and interactive visualizations

	Analytical visualization	Interactive visualization
plots		1. Risk dashboard 2. Early-warning model
maps	3. FSM 4. FSM-t	3. FSM 4. FSM-t
networks	5. BIM	5. BIM

ful groups, the Hive Plot (Krzywinski et al., 2012) provides ample means for a pure representation of relationships between entities, as well as in communicating system-wide connectedness.

5.3 VisRisk: A visualization platform for macroprudential analysis

So far, this section has presented applications of analytical and interactive visualizations. Now, we move one step further by putting forward a general platform for visualizing the macroprudential data cube. Consisting of analytical and interactive visualizations, the VisRisk platform comes with three modules: *plots*, *maps* and *networks*.[7] *Plots* focuses on interactive interfaces for representing large amounts of data, but does not make use of analytical techniques for reducing complexity. While *maps* provides analytical means for representing the three standard dimensions of a data cube in simple formats, *networks* aims at visualization of the fourth data cube dimension of interlinkages. In this section, we have illustrated applications of five web-based interactive visualizations to systemic risk indicators and models, of which three make use of analytical visualizations. First, we made use of analytical techniques for data and dimension reduction to explore high-dimensional systemic risk indicators and time-varying networks of linkages. Second, we added interactivity to not only dashboards of standard risk indicators and early-warning models, but also to the analytical applications. This spanned the spectrum of the three modules: *plots*, *maps* and *networks*. Table 1 summarizes the relations of the applications to the modules and analytical and interactive features. Interested readers can explore the above illustrated applications, among many others, in the VisRisk platform.

From the viewpoint of the data cube in Figure 4, VisRisk's three modules provide visual means to explore all four dimensions. The tasks of the modules can be described as follows:

1. *plots*: To make use of interactive interfaces to standard two-dimensional graphs for representing large amounts of data from the macroprudential data cube without the use of any analytical approaches for reducing complexity.
2. *maps*: To couple analytical data and dimension reduction techniques with interactive visualizations for reducing complexity of the three standard dimensions of the macroprudential data cube, in order to represent large-volume, high-dimensional and/or high-frequency data in simpler formats.
3. *networks*: To couple analytical data and dimension reduction techniques with interactive visualizations for reducing complexity of the fourth, network dimension of the macroprudential data cube, in order to represent large-volume, multi-layer and/or time-varying networks in simpler formats.

Beyond the applications herein, the ultimate aim of this paper is to provide VisRisk as a platform and basis for the use of visualization techniques, especially those including analytical and interactive features, in macroprudential oversight in general and risk communication in particular. Hence, the platform enables and is open to the visualization of any data from the macroprudential data cube. This aims at supporting the understanding and value of analytical and interactive visualizations, in addition to which the consolidation of systemic risk indicators and models can be seen as a support for assessing and comparing systemic risk indicators and models. Possibilities to graphically explore and compare a wide variety of risk measures strives to broadly support macroprudential analysis and the development of new measures.

[7] Interested readers can explore the VisRisk platform for interactive and analytical applications here: http://vis.risklab.fi/.

6 Conclusions

Macroprudential oversight concerns surveillance and supervision of the financial system as a whole. This paper has brought the topic of visualization to the discussion of risk communication in macroprudential oversight. Communicating timely information related to systemic risks broadly and effectively is a key mandate of macroprudential supervisory bodies. Likewise, while the mandate of multiple macroprudential supervisors imposes a need to analyze a large number of entities and their constituents as a whole, the soar in availability and precision of data further stresses the importance of simple representations of complex data.

To address tasks of big data and communication in macroprudential oversight, it becomes evident that visual interfaces hold promise as a means for supporting policymakers. Indeed, visual interfaces are already today essential in supporting everyday decisions, ranging from visuals in human-computer interaction to the standard set of two-dimensional graphs of statistics used in external communication. This paper takes a step further by matching the tasks of a macroprudential supervisor with visualization techniques available today, to achieve maximum usefulness of available data. To support the use of big data and analytical tools for timely and accurate measurement of systemic risk, one essential ingredient to dealing with complex data and modeling problems is to improve end users' understanding of them. A particular benefit relates, as noted by Jean-Claude Trichet, to the support of disciplined and structured judgmental analysis based upon policymakers' experience and domain intelligence. Further, the mandates of macroprudential supervisors most often stress, or are even limited to, issuing risk warnings and policy recommendations, as well as overall communication. This highlights the importance of communicating broadly and effectively timely information about systemic risks.

This paper has discussed the fields of information visualization and visual analytics, as well as techniques provided within them, as potential means for risk communication. Particularly, a common thread throughout the paper has been to draw upon the visualization literature, in order to better support the tasks of macroprudential oversight. We have concluded that two essential features for supporting the analysis of big data and communication of risks are analytical visualizations and interactive interfaces.

For visualizing the macroprudential data cube through analytical and interactive visualization, this paper has provided the VisRisk platform with three modules: *plots*, *maps* and *networks*. We have illustrated the platform and its modules with five web-based interactive visualizations of systemic risk indicators and models, of which three make use of analytical visualizations. As VisRisk enables and is open to the visualization of any data from a macroprudential data cube, the work in this paper aims at providing a basis with which systemic risk indicators and models can be widely communicated. The illustrative applications highlight the usefulness of coupling analytical and interactive visualizations with systemic risk indicators and models, which VisRisk brings into web-based implementations to supplement the static view of today's notion of a document. The aim is to change this view, by advocating the use of interactive data-driven documents and analytical visualization techniques – both with an ultimate aim of improved means for disseminating information.

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Appendix A: Information visualization and visual analytics

This appendix provides supplementary information regarding topics in information visualization and visual analytics.

Appendix A.1: How visuals amplify cognition

Ware (2004) summarizes as follows the principles that our brain and visual system follows when attempting to interpret and comprehend visuals:

Proximity: Items close together are perceptually grouped together.

Similarity: Elements of similar form tend to be grouped together.

Continuity: Connected or continuous visual elements tend to be grouped.

Symmetry: Symmetrical elements are perceived as belonging together.

Closure: Closed contours tend to be seen as objects.

Relative size: Smaller components of a pattern tend to be perceived as objects.

Card et al. (1999) present visuals as a means to amplify cognition and list five ways how well-perceived visuals could amplify cognition. They can be exemplified as follows.

Examples of the *first* way to amplify cognition, the increase in available resources, are parallel perceptual or visual processing and offloading work from the cognitive system to the perceptual system (Larkin and Simon, 1987). *Second*, visuals facilitate the search procedure by the provision of a large amount of data in a small space (i.e., high data density) (Tufte, 1983) and by grouping information used together in general and information about one object in particular (Larkin and Simon, 1987). *Third*, abstraction and aggregation aid in the detection of patterns and operations for perceptual inference (Card et al., 1991). *Fourth*, perceptual monitoring is enhanced, for instance, through the use of pop-out effects created by appearance or motion (Card et al., 1999). Likewise, Card et al. (1999) exemplify the *fifth* way to amplify cognition, the use of a manipulable medium, by allowing the user to explore a wide range of parameter values to interactively explore properties of data.

Appendix A.2: The visual system and correctly perceived graphics

Visual representations, while providing means to amplify cognition, also constitute a large set of issues that may hinder, disturb or otherwise negatively affect how visualizations are read. A key starting point is to take into account the deficiencies and limitations of human perception. Preattentive processing, for instance, becomes a deficiency if visuals are not designed properly. Patterns a user is supposed to identify quickly – or give visual but not conscious attention to – should hence be made distinct from the rest by using features that can be preattentively processed. Likewise, visual attention functions as a filter in that only one pattern is brought into working memory (Baddeley and Logie, 1999). Hence, if provided with multiple patterns, we only see what we need or desire to see by tuning out other patterns. It is also important to note differences in visual features, as others are perceived more accurately, such as color vs. position, where perception of the latter dominates over the former. Ware (2005) also mentions the fact that humans process simple visual patterns serially at a rate of one every 40–50 msec. and a fixation lasts for about 100–300 msec., meaning that our visual system processes 2–6 objects within each fixation, before we move our eyes to visually attend to some other region. In addition, one important factor to account for is how perception of visuals is affected by properties of the human eye, such as acuities, contrast sensitivity, color vision, perception of shape or motion with colors, etc. Another aspect of crucial importance is obviously to pay regard to human perceptions of shapes in visuals, such as distances, sizes and forms. Cognitive deficiencies should also be accounted for when designing visuals, such as the limited amount of working memory. For instance, Haroz and Whitney (2012) show that the effectiveness of information visualization is severely affected by the capacity limits of attention, not the least for detecting unexpected information. Hence, an understanding of the functioning of the human visual system aids in producing effective displays of information, where data are presented such that the patterns are likely to be correctly perceived.

Appendix A.3: A framework of the planar and retinal variables

Bertin (1983) describes the *plane*, and its two dimensions (x, y), as the richest variables. They fulfill the criteria for all levels of organization by being selective, associative, ordered and quantitative. The retinal variables, on the other hand, are always positioned on the plane, and can make use of three types of implantation: a point, line, or area. First, *size* is ordered, selective but not associative, and the only quantitative retinal variable. Second, *value* is the ratio of black to white on a surface, according to the perceived ratio of the observer, and is also sometimes called brightness. The usage of value in this case is close to that in the HSV (hue, saturation and value) color space, which is a cylindrical-coordinate representation of points in an RGB (red, green and blue) color space. It is an ordered and selective retinal variable. Third, *texture* represents the scale of the constituent parts of a pattern, where variation in texture may occur through photographic reductions of a pattern of marks. That is, it may range from null texture with numerous but tiny elements that are not identifiable to large textures with only few marks. Texture as a retinal variable can be ordered and is both selective and associative. Fourth, variation may occur in *color*. The variation of two marks with the same value or brightness is thus more related to changes in hue of HSV. Color as a retinal variable is selective and associative, but not ordered. Fifth, the *orientation* variable enables variation in the angle between marks. In theory, this opens up an infinite set of alternatives of the available 360 degrees, whereas Bertin (1983) suggests the use of four steps of orientation. The orientation variable is associative and selective only in the cases of points and lines, but has no direct interpretation of order. Finally, the sixth variable of *shape*, while being a retinal variable on its own, also partly incorporates aspects of size and orientation. It is associative, but neither selective nor ordered.

The eight variables can be categorized according to the following levels of organization, or so-called perceptual properties:

1. **Associative** ($\equiv$): If elements can be isolated as belonging to the same category, but still do not affect visibility of other variables and can be ignored with no effort.
2. **Selective** ($\neq$): If elements can immediately and effortlessly be grouped into a category, and formed into families, differentiated by this variable, whereas the grouping cannot be ignored.
3. **Ordered** ($\mathbf{O}$): If elements can perceptually be ordinally ranked based upon one visually varying characteristic.
4. **Quantitative** ($\mathbf{Q}$): If the degree of variation between elements can perceptually be quantified based upon one visually varying characteristic.

When having an understanding of the four levels of organization, we can return to Bertin's (1983) eight visual variables. Bertin describes the plane, and its two dimensions (x, y), as the richest variables. They fulfill the criteria for all levels of organization by being associative ($\equiv$), selective ($\neq$), ordered ($\mathbf{O}$) and quantitative ($\mathbf{Q}$). The retinal variables, on the other hand, are always positioned on the plane, and can make use of three types of implantation: a point, line, or area. Their perceptual properties are as follows: size ($\neq, \mathbf{O}, \mathbf{Q}$), value ($\neq, \mathbf{O}$), texture ($\equiv, \neq, \mathbf{O}$), color ($\equiv, \neq$), orientation ($\equiv, \neq$), and shape ($\equiv$).

Tufte's (1983) two principles on graphical excellence and integrity covered in the main text, while being his main guidelines on graphic design, cover only a small fraction of his work. Beyond these two principles, but still relating to them, he highlights *data-ink maximization*, by advocating a focus on the data, and nothing else. Hence, a good graphical representation focuses on data-ink maximization with minimum non-data-ink. The data-ink ratio is calculated by 1 minus the proportion of the graph that can be erased without loss of data information. Tufte puts forward the following five guidelines related to data ink: (*i*) above all else, show data; (*ii*) maximize the data-ink ratio; (*iii*) erase non-data-ink; (*iv*) erase redundant data-ink; and *v*) revise and edit. Moreover, Tufte (1983) highlights *data density maximization*, which relates to the share of the area of the graphic dedicated to showing the data. For too low densities, graphics should either be reduced in size (shrink principle) or replaced with a table. In terms of concrete design, he proposes the small multiples, a design for showing varying data onto a series of the same small graph repeated in one visual.

Appendix A.4: Visualization techniques as per data and output

Zhang et al. (2012) categorize visualization techniques into four groups from the viewpoint of the underlying data. First, *numerical data* can be visualized by a vast number of approaches, such as standard visualization techniques like bar and pie charts and scatter plots. These focus most often on the visualization of low-dimensional numerical data. On the other hand, visualization techniques like parallel coordinates, heatmaps and scatter plot matrices provide means to display data with higher dimensionality. Second, visualization of *textual data* is a relatively new but rapidly growing field. Recent well-known techniques include theme river (Havre et al., 2000) and word cloud (Kaser and Lemire, 2007), for instance. Likewise, the availability of the third type of data, *geo-tagged data*, has caused a soar in the demand for geo-spatial visualizations. Geo-related univariate or multivariate information is oftentimes projected into conventional two-dimensional and three-dimensional spaces. Fourth, graph visualizations provide means for displaying patterns in *network data* with relationships (i.e., edges) between entities (i.e., nodes). They most often consist of a technique for positioning, such as force-directed drawing algorithms, as well as coloring or thickness of edges to display the size of a relationship. Graph or network visualizations have been increasingly applied in a wide range of emerging topics related to social and biological networks, not to mention financial networks.

From the viewpoint of visualization output, Keim and Kriegel (1996) provide a five-category grouping of techniques. First, *geometric techniques* provide means for visualization of geometric transformations and projections of data. Examples of the methods are scatterplot-matrices, parallel-coordinate plots and projection methods. Second, *icon-based techniques*, as already the name states, visualize data as features of icons. The methods include, for instance, Chernoff-faces and stick figures, of which the former visualize multidimensional data using the properties of a face icon and the latter use stick figures. Third, *pixel-oriented techniques* map each attribute value to a colored pixel and present attribute values belonging to each attribute in separate subwindows. For instance, query-independent techniques arrange data from top-down in a column-by-column fashion or left to right in a line-by-line fashion, while query-dependent techniques visualize data in the context of a specific user query. Four, *hierarchical techniques* provide means to illustrate hierarchical structures in data. Most often, hierarchical methods focus on dividing an n-dimensional attribute space by 'stacking' two-dimensional subspaces into each other. Finally, the fifth category, *graph-based techniques*, focus on the visualization of large graphs, or networks, to illustrate the properties of the network, as was above discussed. In addition, Keim and Kriegel also illustrate the existence of a wide range of hybrids that make use of multiple categories.

Appendix B: Analytical techniques

This appendix provides supplementary technical details regarding the analytical methods applied in the paper.

Appendix B.1: Self-Organizing Map

The SOM (Kohonen, 1982, 2001) is a method that performs a simultaneous data and dimension reduction. It differs from non-linear projection techniques like Multidimensional Scaling (MDS) by attempting to preserve the neighborhood relations in a data space Ω on a k-dimensional array of units (represented by reference vectors m_i) instead of attempting to preserve absolute distances in a continuous space. On the other hand, it differs from standard Vector Quantization (VQ) by also attempting neighborhood preservation of m_i. The VQ capability of the SOM performs this data reduction into mean profiles (i.e., units m_i). It models from the continuous space Ω, with a probability density function $p(x)$, to the grid of units, whose location depend on the neighborhood structure of the data Ω.

We employ the batch training algorithm, and thus process data simultaneously instead of in sequences. This reduces computational cost and enables reproducible results. Following an initialization based upon two principal components, the batch training algorithm operates a specified number of iterations t (where $t = 1, 2, \ldots, T$) in two steps. In the first step, each input data vector x_j is assigned to the BMUs m_b:

$$d_x(j, b) = \min_i d_x(j, i), \tag{1}$$

where $d_x(j, b)$ is the input space distance between data x_j and reference vector m_b (i.e., BMU) and $d_x(j, i)$ is the input space distance between data x_j and each reference vector m_i. Hence, data are projected to an equidimensional reference vector m_b, not a two-dimensional vector as in MDS. In the second step, each reference vector m_i (where $i = 1, 2, \ldots, M$) is adjusted using the batch update formula:

$$m_i(t+1) = \frac{\sum_{j=1}^{N} h_{ib(j)}(t) x_j}{\sum_{j=1}^{N} h_{ib(j)}(t)} \tag{2}$$

where index j indicates the input data vectors that belong to unit b, N is the number of the data vectors, and $h_{ib(j)}$ is some specified neighborhood function. In comparison to the update formula of the k-means algorithm, the batch update of the SOM can be seen as a spatially $\left(h_{ib(j)}\right)$ constrained version. The neighborhood function $h_{ib(j)} \in (0, 1]$ is defined as the following Gaussian function:

$$h_{ib(j)} = \exp\left(-\frac{d_r(b, i)^2}{2\sigma^2(t)}\right) \tag{3}$$

where $d_r(b, i)$ is the distance between the coordinates r_b and r_i of the reference vectors m_b and m_i on the two-dimensional grid. Moreover, the radius of the neighborhood $\sigma(t)$ is a monotonically decreasing function of time t. The radius of the neighborhood begins as half the diagonal of the grid size $((X^2 + Y^2)/2)$, and decreases towards a user-specified radius σ.

Appendix B.2: Self-Organizing Time Map

The SOTM (Sarlin, 2013b) uses the clustering and projection capabilities of the standard SOM for visualization and abstraction of temporal structural changes in data. Here, t (where $t = 1, 2, \ldots, T$) is a time-coordinate in data, not in training iterations as is common for the standard SOM. To observe the cross-sectional structures of the dataset for each time unit t, the SOTM performs a mapping from the input data space $\Omega(t)$, with a probability density function $p(x, t)$, onto a one-dimensional array $A(t)$ of output units $m_i(t)$ (where $i = 1, 2, \ldots, M$). Preservation of orientation and gradual adjustment to temporal changes is accomplished by initializing $A(t_1)$ with the first principal component of Principal Component Analysis (PCA) and initializing A$(t_{2,3,\ldots,T})$ with the reference vectors of $A(t-1)$. Hence, the model uses short-term memory to retain information about past patterns and preserve orientation. Adjustment to temporal changes is achieved by performing a batch update per time t. For $A(t_{1,2,\ldots,T})$, each data point $x_j(t) \in \Omega(t)$ (where $j = 1, 2, \ldots, N(t)$) is compared to reference vectors $m_i(t) \in A(t)$ and assigned to its BMU $m_b(t)$:

$$\|x_j(t) - m_b(t)\| = \min_i \|x_j(t) - m_i(t)\| . \tag{4}$$

Then each reference vector $m_i(t)$ is adjusted using the batch update formula:

$$m_i(t) = \frac{\sum_{j=1}^{N(t)} h_{ib(j)}(t) x_j(t)}{\sum_{j=1}^{N(t)} h_{ib(j)}(t)}, \tag{5}$$

where index j indicates the input data that belong to unit b and the neighborhood function $h_{ib(j)}(t) \in (0, 1]$ is defined as a Gaussian function

$$h_{ib(j)}(t) = \exp\left(-\frac{\|r_b(t) - r_i(t)\|^2}{2\sigma^2}\right), \tag{6}$$

where $\|r_b(t) - r_i(t)\|^2$ is the squared Euclidean distance between the coordinates of the reference vectors $m_b(t)$ and $m_i(t)$ on the one-dimensional array, and σ is the user-specified neighborhood parameter. In contrast to what is common for the standard batch SOM, the neighborhood σ is constant over time for a comparable timeline, not a decreasing function of time as is common when time represents iterations.