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The application of visual analytics to financial stability monitoring

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ABSTRACT

This paper provides an overview of visual analytics—the science of analytical reasoning enhanced by interactive visualizations tightly coupled with data analytics software—and discusses its potential benefits in monitoring systemic financial stability. The core strength of visual analytics is to combine visualization's high-bandwidth information channel to the human analyst with the flexibility and power of rapid-iteration analytics. This combination is especially valuable in the context of macroprudential supervision, which is increasingly dominated by large volumes of dynamic and heterogeneous data. Our contribution is to describe and categorize the analytical challenges faced by macroprudential supervisors, and to indicate where and how visual analytics can increase supervisors' comprehension of the data stream, helping to transform it into actionable knowledge to support informed decision- and policy-making. The paper concludes with suggestions for a research agenda.

1. Introduction

This paper provides an overview of visual analytics and discusses its potential benefits in monitoring systemic financial stability. Macroprudential supervisors face a daunting challenge—the financial system is complex, enormous, highly diverse, and constantly changing.[1] The recent crisis demonstrated that stakes are high. The global financial crisis highlighted the need for enhanced capability to detect, identify, analyze, and understand threats to financial stability. Inadequacies in supervisors' access to and ability to process information have hindered an effective and timely response. A joint Financial Stability Board (FSB) and International Monetary Fund (IMF) report (FSB-IMF, 2009) notes that, "... the recent crisis has reaffirmed an old lesson—good data and good analysis are the lifeblood of effective surveillance and policy responses at both the national and international levels." Since the crisis, macroprudential supervisors have been working to address data gaps and developing new approaches to financial stability analysis. Beyond the need to create new data sources and analytic approaches, however, the crisis also revealed a need for greater capacity to integrate and make sense of voluminous, dynamic, and heterogeneous financial data.[2] The system generates a seemingly infinite stream of information from diverse sources, arriving at ever-increasing frequencies and of variable reliability. Visual analytics has the potential to increase supervisors' comprehension of

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[1] Because we are mostly unconcerned in this paper with the legal details of the supervisory authorities under which formal policies are implemented, we use the following terms interchangeably to avoid cluttering the text with superfluous clarifying language: "financial stability supervisor (or monitor)," "macroprudential supervisor," and "systemic risk supervisor" refer to national or international authorities responsible for maintaining awareness of and responding to financial-sector stresses and crises with ramifications that extend beyond individual firms or markets.

[2] For further discussion, see Flood et al. (2010, 2013b). The present paper originated in a series of interdisciplinary discussions that brought together experts in financial systemic risk and visual analytics. The first of these discussions occurred in May 2012 at the Banff Visual Analytics Interdisciplinary Workshop on Canadian and Global Challenges in Financial Systemic Risk Analysis. A subsequent interdisciplinary panel discussion on Global Challenges in Financial Systemic Risk Analysis: Defining Visual Analytics Solutions, was part of the IEEE Visual Analytics Science and Technology Conference (VisWeek) in Seattle in October 2012. A third group of discussions took place as part of a series of talks hosted by the Open Financial Data Group (OFDG), an informal discussion group concerned with issues of financial data governance and management. The OFDG conversations took place between January 2013 and July 2013. A more expansive version of this paper, including additional visualization examples, appeared as Flood et al. (2015).

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1572-3089/

the data stream, helping transform the raw data into actionable knowledge to support decision- and policy-making.

There is a range of visualization technologies available to support financial stability monitoring; Sarlin (2015) provides a very useful general survey of this broad class of tools. Among these, the relatively new field of *visual analytics* represents one important approach for enhancing the information-processing capabilities of macroprudential supervisors. "Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces." (Thomas and Cook, 2005, p. 4). The emphasis here is on user interaction, because visual analytics gives human users, with their extensive visual perceptual and cognitive powers, a central role in a software-assisted analytical process. Keim et al. (2010) state that "Visual analytics combines automated [data] analysis techniques with interactive visualisations for an effective understanding, reasoning, and decision-making on the basis of very large and complex datasets." Ultimately, the goal is the ". . . creation of tools and techniques to enable people to:

- Synthesize information and derive insight from massive, dynamic, ambiguous, and often conflicting data.
- Detect the expected and discover the unexpected.
- Provide timely, defensible, and understandable assessments.
- Communicate these assessment [sic] effectively for action." (Keim et al., 2010, p. 7).

A crucial aspect is that the visualizations are designed specifically to support the interactive dynamics (Heer and Shneiderman, 2012) required for users' analytic involvement with the data in real time.

Visual analytics is part of a spectrum of visualization techniques available to financial stability supervisors, offering varying degrees of user interaction, display animation, and computational analytic capabilities. Visual analytics integrates the most interactive of those tools to support analytical reasoning. In the context of financial stability analysis, visual analytics is a complement, not a substitute, for traditional econometric approaches. Indeed, the analytics underlying a given visual analytics tool may incorporate econometric or other computational analytics in support of human cognitive processes. A familiar example of visual analytics is the dashboard interactive global positioning system (GPS) for trucks and cars, in contrast to an old-fashioned, static paper map. An important difference between visual analytics and other visualization techniques is that visual analytics requires or encourages users to explore data interactively, even when both the questions and the nature of the answers may be unknown in advance—in effect, looking for the next systemic financial risk around the corner. Other visualization techniques typically presume that users already know what they want to see, and are simply choosing how to view it. Visual analytics presumes that answers to complex questions will not come simply through application of computational approaches, but additionally require human intelligence and sensemaking. Applying visual analytics tools to macroprudential supervision is a multi- and interdisciplinary exercise, potentially integrating techniques from many fields, including statistics, mathematics, data mining and knowledge discovery, cognitive and perceptual sciences, knowledge representation and information management, and decision sciences.

We make three main points in this paper about the potential of visual analytics in systemic financial risk analysis. First, visualization in general and visual analytics in particular are natural aids for financial stability monitors. Supervisors have overlapping mandates, including identifying new sources of financial instability, maintaining situational awareness of developing stresses, implementing decisions and rules that bind the financial sector, and promoting transparency of information to market participants. Visual analytics can support all these objectives, which frequently involve iterative, user-directed search and analysis of more than a single data source. This requirement fits naturally with the user feedback loop of visual analytics (see Fig. 14). Examples include detecting and identifying new sources of financial instability and developing and maintaining situational awareness. We consider this institutional context in Section 2.

Second, cleaner, better structured data will improve visual analytics. At the same time, visual analytics will also help validate and refine the input data by more quickly revealing what is misleading, missing, contradictory, or not comparable in supervisory data. The development of shared ontologies and data standards can assist this feedback loop. Improving both the visual analytics tools and their input data will therefore typically be an iterative process. Section 3 of the paper considers examples of the state of the art for visualization and visual analytics in financial stability analysis, and outlines a broad research agenda to guide future efforts in the area.

Third, because visual analytics strongly emphasizes comparisons and relationships among empirical data, it is important to define clear, measurable, and meaningful abstractions that capture the relevant data semantics and are comparable when applied across the financial system. Systemic risk analysis is relatively immature in this area and may benefit from work in the cognitive systems engineering community, which has developed techniques for identifying and representing these meaningful abstractions (Woods and Roth, 1988; Rasmussen et al., 1994; Bennett and Flach, 2011). This approach has been applied in a variety of domains, such as air traffic control (Wong et al., 2007; Vuckovic et al., 2013), power grid monitoring (Memisevic et al., 2005; Sanderson et al., 2003), and cyber situational awareness (Varga et al., 2014). Section 4 of the paper provides an overview of visual analytics discussing its structure and strengths relative to traditional visualization.

2. Institutional context for visualization in financial stability analysis

The analysis of data and information to identify, understand, and respond to threats to the stability of the financial system makes extensive use of visual depictions of data and models. Because it covers the full financial system, financial stability monitoring faces a broad range of data and information sources, as well as potential threats and models of those threats. This diversity distinguishes macroprudential and microprudential supervision and underscores the need for effective tools to navigate the data deluge.

One way to organize a discussion of financial stability monitoring is to focus on common system-level determinants of financial instability, such as liquidity, volatility, concentrated exposures, macroeconomic imbalances, business cycles, etc. Financial stability maps, such as those in Fig. 8, frequently feature such thematic taxonomies. Another approach, highlighted in Fig. 4 and Zhang et al. (2012, pp. 176–177), is organized around the type and structure of the input data. Because a central element of visual analytics is cognitive support to users in interactive exploration of data, we opt to structure the discussion around the broad categories of user tasks, which we group as sensemaking, decision-making, rulemaking, and transparency. We use the other dimensions of systemic phenomena and input data types as a source of illustrative examples.

An extensive literature has analyzed both the craft of visual rendering of data of diverse kinds and the wide-ranging research into the psychology of perception and decision-making based on data visualizations. For example, Tufte (1990, 2001) and Wilkinson (2005) discuss the core principles of graphical design and data modeling for data visualization. Ware (2013) focuses on the psychology of perception as a key factor in the effectiveness of visualization. Lemieux et al. (2014b) and Schwabish (2014) provide a general

Table 1
Classification of visualization techniques.

	Noninteractive	Interactive
Static	No user input after initial rendering, and image does not change. "Fixed." *Example*: Newspaper infographic	Ongoing user input, but rendering does not change between input events. *Example*: Spreadsheet chart
Dynamic	No user input after initial rendering, but image may change. *Example*: Animated GIF	Ongoing user input, and rendering may change between input events. *Example*: Video game

overview of the application of visualization techniques in economics and finance. Sarlin (2013a,b, 2015) surveys visualization for financial stability analytics in particular. Table 1 suggests a simple classification of visualization techniques. "Dynamic" here is synonymous with "animated." Because static, noninteractive visualizations are so common, we assign a special label, calling them "fixed" renderings. The classification in Table 1 forms a rough continuum, based on the intensity of user involvement required. Visual analytics falls in the final category, giving a central role to the human analyst. We argue below that this is an important determinant of where visual analytics should be used in the organizational context of macroprudential monitoring. For example, visual analytics could meet the need for situational awareness in emergent scenarios, such as financial crises. On the other hand, fixed visualizations (which might themselves be the output of a visual analytics process), would typically best meet the need for ex post accountability for important policy decisions.

Interactivity provides an effective means of "playing" with or exploring the data by, for example, asking what-if questions naturally while working through a problem. Importantly, visual analytics allows users to redirect the computation of the underlying algorithms by directly manipulating the visual form. For example, a *nonanalytic* interactive visualization might allow a user to add or remove particular data series from a time-series plot. This form of interaction, while dynamic, does not recompute the underlying data. Visual analytics, in contrast, offers the additional ability to act on the algorithms that control the outputs rendered in the visual form. For example, we might instruct the visualization application to combine two securities into a portfolio and calculate or recalculate the risk characteristics of the new entity by simply dragging one security's rendering onto the other's within the time-series plot or in some semantic space to generate and render new results. By performing these transformations in real time, visual analytics extends, develops, and refines techniques for user interaction at the pace of the user's own cognition.

Visual analytics is only part of the toolkit that macroprudential supervisors will need to transform data into actionable knowledge. Visual analytics does not replace the need for statistical tools or, indeed, other purely computational approaches to data analysis. Rather it incorporates and extends such tools with an overlay of interactive visual display that marries human analytic processes with computational analysis. For example, the strength of visual analytics for evolving a statistical design is in facilitating rapid visual iterations of data analysis and/or model structure. Robust statistical models may be less distracted by shiny outliers and can provide formal hypothesis tests and significance bounds.

Data mining (Khandani et al., 2010), also is a promising alternative for high-dimensional or unstructured data. Dimensionality refers to the number of attributes measured for the objects under consideration. As sensors and measurement proliferate, and because new attributes can be derived from existing data, it is possible for dimensionality to proliferate as well. Unstructured data refers to data without the well-defined and consistently applied schemas or constraints on data types, storage formats, and allowable values that facilitate automated analysis. Data mining algorithms are typically highly efficient for exploring high-volume or high-dimensional data. The algorithms are typically also designed for generic application and can process unstructured data (Rajaraman et al., 2014). Interactive visual interfaces can support macroprudential oversight in combination with other analytics and reasoning techniques, such as traditional statistics, on-site examinations, network analysis, stress testing, data mining, Monte Carlo simulation, agent-based modeling, etc., by providing the cognitive scaffolding to support human reasoning in interaction with the results of other analytic approaches. Visualization alone, even when interactive, merely presents data in a more digestible form. On the other hand, analytics alone can provide verifiable and robust results, but with little room for further exploration and generation of new hypotheses. The coupling of visualization and data analytics through interactivity is greater than the sum of the parts.

Macroprudential supervisors convert data on institutional and financial market conditions into analyses, such as briefings, reports to Congress, research papers; and formal decisions, such as enforcement actions, Federal Reserve open-market operations, prompt corrective action interventions, etc. Broadly, macroprudential tasks tend toward one of two poles: (1) general monitoring of potentially stressful conditions in the financial sector, and (2) formal supervision, which implies the possibility of regulatory enforcement actions. Monitoring focuses on situational awareness, for which the tools should be as diverse and flexible as possible to help analysts understand evolving conditions. Supervision, in contrast, focuses on formal decisions with tangible consequences, where tools and techniques should be streamlined for clarity and after-the-fact accountability. As a simple organizing framework, we suggest a high-level breakdown of core functions:

- Sensemaking
- Decision-making
- Rulemaking
- Transparency

We compare this grouping with Sarlin (2015), who classifies supervisory tasks into the slightly more abstract categories of risk identification, risk assessment, and policy assessment. Sensemaking here corresponds roughly to risk identification and assessment in Sarlin's scheme, while our rulemaking corresponds roughly to his policy assessment. Decision-making, rulemaking, and transparency are typically defined by formal bureaucratic processes, which we find fitting, because they impose actionable boundaries on the sorts of visual technologies that are appropriate for the individual tasks.

Macroprudential monitoring inevitably involves a sensemaking exploration of "uncharted territory." The financial system evolves and innovates to exploit real or imagined new profit opportunities, often creating real or imagined new risk exposures in the process. Supervisors must maintain research capacity for this purpose. Sensemaking for unusual circumstances is the detailed front end of supervisors' information-management challenge, with data specialists, economists, and bank examiners focused on exploratory analysis to gain a nuanced understanding of specific events or issues. Data are fine-grained and often raw. Analytical tasks are tactical and often opportunistic. Trial-and-error analyses

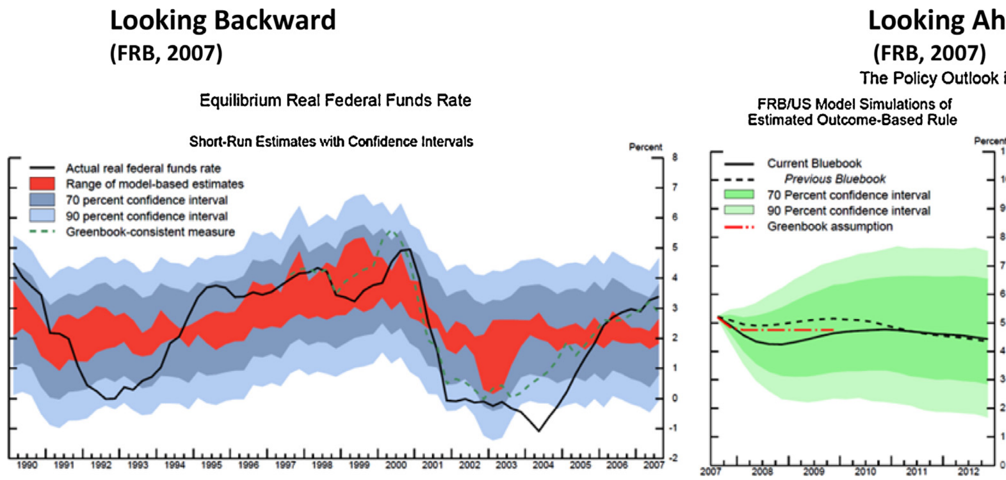

Fig. 1. Model uncertainty and decision support.

may be prevalent, and deadlines may be tight, precluding refined investigations. Sensemaking capacity is especially crucial for macroprudential monitors because of the possibility of financial crises. A financial crisis episode is the supervisory "perfect storm": the stakes are high, time frames for decision and action are likely to be compressed, and familiar statistical and economic relationships in the data are unreliable, inadequate, or misleading. The interactive techniques of visual analytics are likely to be especially fruitful at this level. In later sections, we focus on the sensemaking challenges for financial stability monitoring.

Decision-making is an operational role. Decisions occur within the bounds of existing authorities and rules. For example, the Federal Open Market Committee meets every five to six weeks to decide an implementation of monetary policy as open market operations (FRB, 2013a,b,c). Formal decision processes typically generate agendas and minutes for the public record. Decision-makers often receive formal or informal advance briefings; the "arbitrary and capricious" standard for accountability (Watts, 2009) implies a need for solid analysis and solid documentation. One benefit is the reduction in uncertainty from a conversion of complex, subjective, and ambiguous information into a clear and objective ruling. To support accountability and aid recordkeeping, fixed visualizations are generally preferred at this level because interactive visualizations are still difficult to capture and preserve as fixed evidence of inputs to decision-making. Such systems can be designed to alert or guide an analyst to avoid biases or problematic tendencies (Kahneman, 2011; Hutchins, 1995), and to capture the analytic provenance of their decisions (Gotz and Zhou, 2008; Xu et al., 2015). Such designs, however, are predicated on a careful analysis of decision-makers as they make decisions in real life situations, using such techniques as cognitive task analysis, verbal protocol analysis, and pair analysis (Trickett et al., 2007; Crandall et al., 2006; Schraagen et al., 2000; Arias-Hernández et al., 2011).

Rulemaking is a strategic role, in which formal authorities of supervisory action are defined or refined. The primary examples are legislation and regulation. The process of introducing or modifying regulations is highly formalized and open to public scrutiny, which is often extensive. In the United States, notices of proposed rulemaking are published in the *Federal Register* (OCC et al., 2006), followed by extended periods of public comment; iterations of proposed rules may be repeated as appropriate and may be preceded by an advance notice of proposed rulemaking. Because the law does not have formal structures for interpreting and applying nontextual rules, visualizations tend to be rare at this level, even as supporting analysis. When used, visualizations are most often fixed. There is a potential to apply text visualization to the analysis and understanding of textual documents (Chuang et al., 2012).

Macroprudential agencies pursue transparency through the publication of formal reports, technical analyses, and economic and financial statistics. Transparency can reduce asymmetric information and policy uncertainty, facilitating coordination and contracting among market participants.[3] Publications of formal reports and policy deliberations are important inputs into the accountability process for supervisory authorities. For example, Fig. 1 reproduces two depictions of the Federal Reserve's confidential briefing materials, called the Bluebook (FRB, 2007, 17 and 21) for the Federal Open Market Committee as the recent financial crisis was beginning in September 2007.[4] The left panel compares the realized historical rate (black line) with the dispersion of (red range) and confidence intervals around (blue ranges) the contemporaneous model estimates. The right panel shows the best-estimate forecast (black lines) and confidence intervals (blue and green ranges) for the Federal Funds rate in the future. Briefing materials like these provide decision-makers with a core set of common knowledge. It is important that these materials employ *fixed* visualizations, because this provides a basis for common knowledge and clarity—all committee members see the identical image, and staff can explain precisely how it was constructed—for both ex-ante decision support and after-the-fact accountability. The figures do a good job of presenting the uncertainty that surrounds many policy decisions. (In fact, as the crisis unfolded, the Federal Reserve dropped the funds rate to essentially zero in late 2008, where it has remained since. Hindsight is 20-20.)

Transparency publications often include visualizations, typically tailored to a particular constituency. Traditionally, macroprudential supervisors have mediated transparency in printed publications, such as the annual reports of the Office of Financial Research (OFR, 2013a,b), the Financial Stability Oversight Council (FSOC, 2013), the Federal Reserve (FRB, 2013c), and the semiannual financial stability reports of the Bank of England (B of E, 2013) and the IMF (IMF, 2013). These documents contain numerous visualizations, which are naturally fixed. On the other hand, more recent

[3] For a recent survey of transparency issues in a supervisory context, see Flood et al. (2013a). For a discussion of the costs of policy uncertainty (and benefits of reductions), see for example Amengual and Xiu (2013) and Pástor and Veronesi (2013).

[4] The confidential Bluebook is made public after five years to balance the pressures for transparency and confidentiality in policymaking.

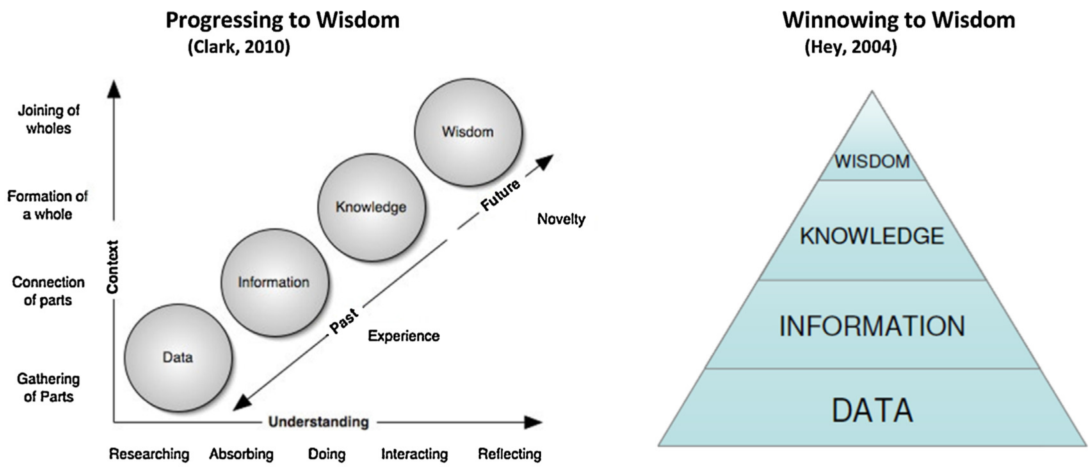

Fig. 2. Two perspectives on data-information-knowledge-wisdom (DIKW).

online transparency tools provide access to downloadable data and visualizations with varying degrees of interactivity; examples include the Federal Reserve Economic Data site (FRED, Fed-St. Louis, 2013), the IMF Data Mapper® (IMF, 2013), World Bank's DataBank (World Bank, 2013a), and the Global Legal Entity Identifier Watch project, which sought to integrate global LEI data to create a platform for non-expert exploration of global financial flows (Lemieux et al., 2014a).

Both the decision-making and rule-making roles have a preference for fixed visualizations because of the need to preserve evidence of decision-making for accountability. This requirement for fixed renderings can prevent decision-makers from exploring options and simulating decision outcomes, however. To overcome this limitation without sacrificing accountability, dynamic visual analytics systems must have the capacity to generate trustworthy evidence (Lemieux and Dang, 2013). One alternative, known as analytic provenance, uses a visual analytic process to trace the emergence of decisions. Provenance captures changes to an entity, to facilitate a comparison of its original and present state, for example to judge the authenticity (i.e., whether the entity is what it purports to be) and integrity (whether it has been altered from its original state).

Provenance can also help identify and preserve the antecedents and context of an object, such as a decision, so that it can be properly understood and evaluated. A number of visual analytics researchers are working on techniques to capture the provenance of human analytical reasoning, such as a decision process. For example, the SchemaLine and TimeSets techniques of Nguyen et al. (2014a,b) enable a user to construct explanatory narratives from automatically extracted information, while annotating the choices made in the evolving story. Other approaches include techniques for tracking the analytical processes, the order in which they occurred, and annotating changes in one's analytical considerations (Gotz and Zhou, 2008; Kadivar et al., 2009; Walker et al., 2013).

In practice, of course, authorities engage in a spectrum of activities that mix various monitoring and transparency tasks with formal interventions and new rulemakings. This transformation of data into knowledge and action suggests the familiar data-information-knowledge-wisdom (DIKW) hierarchy, depicted in Fig. 2; see Sarkar (2013) for details. The four levels of the hierarchy are complex concepts, and there is a vigorous debate (see Hey, 2004; Rowley, 2007; Frické, 2009) around both terminology and meaning of each level. We focus on one aspect of the hierarchy, applied narrowly to the series of transformations that convert raw input data into a final two-dimensional image rendered to pixels on a display device or printed page.

The key distinction is the extent to which information is lost while stepping through the hierarchy. Simply, in the left panel of Fig. 2, the balls retain the same size at each stage; in the right panel, each stage discards extraneous information to converge on the core truths. The sharp dichotomy in information density between the two panels of Fig. 3 exemplifies the issue. The right panel in Fig. 3, from the Federal Reserve's *Annual Report to Congress* (FRB, 2013a,b,c, p. 8), distils the input data down to a single key abstraction, civilian unemployment, normalized to adhere to a stable scale and plotted monthly over time; everything else is omitted as superfluous.

The left panel presents two versions of the information dissipation length (IDL) statistic of Quax et al. (2013, p. 3). IDL is an abstract, entropy-based measure of the degree of "tight coupling" in a system, with higher values suggestive of instability. Fig. 3 shows the IDL for interest rate swaps and exchange rates over time along with an enormous amount of contextual information from both markets. Clearly, Quax et al. (2013) believe the additional context will be useful for their readers; the authors of the unemployment graph do not. This choice is reasonable in both cases: IDL is a complicated calculation, newfangled and abstract. Unemployment is a simple aggregation, familiar from the nightly news and (for most readers) from personally experience. A key constraint driving these visualizations to opposite extremes is that they are both rendered for a static print medium. Given that there must be a single rendering, one has maximized clarity, the other has maximized context. An interactive medium could finesse the dichotomy by highlighting only the most important series while offering details on demand.

The distinction is important for financial stability monitoring, because there is no consensus yet on a canonical set of familiar abstractions that are the "correct" way to measure systemic fragility. Bisias et al. (2012, p. 256) emphasize that a "robust framework for monitoring and managing financial stability must incorporate both a diversity of perspectives and a continuous process for re-evaluating the evolving structure of the financial system and adapting systemic risk measures to these changes." There will always be new emergent risks and approaches to their identification. In other words, financial stability monitors do not have the luxury of optimizing fixed tasks in a relatively stable operating environment, like air traffic control (Wong et al., 2007) or professional sports (Pileggi et al., 2012). The environment in which financial systemic risk analysis is carried out is highly complex. Financial systemic risk analysis tasks are not performed by a single individual working alone on deterministic tasks. Instead, risk analysis involves the collaboration of many individuals across organizational and, increasingly, geopolitical boundaries, often

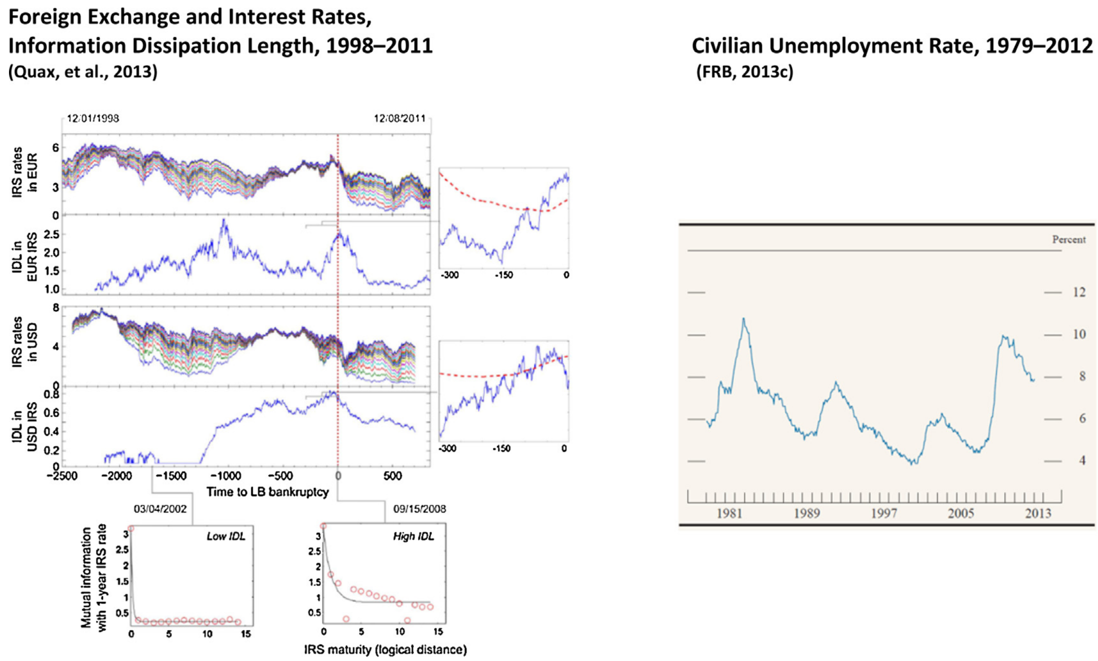

Fig. 3. Disparate information density in time-series plots.

under uncertain conditions. These constraints require that proposed enhancements to analytic capacity be flexible, fluid, and able to deal with unpredictable circumstances, changing tasks, and the integration, presentation and interpretation of large amounts of uncertain, incomplete and contradictory information that degrades over time.

Many of the tasks in financial stability analysis that would benefit most from visualization techniques are exploratory sensemaking tasks, often performed ad hoc, with a human in the loop. Visual analytics, which ideally blends the best of human and computational approaches, has the potential to address the information challenges in this domain by combining humans' judgment and pattern-recognition strengths with the machine's raw calculating power. Though computation can help address the information processing requirements, for example, for text mining of contract data or machine learning for aggregation of systemic risk indicators, it is insufficient on its own. Computational approaches require certain preconditions: that machines can compute the optimum clustering of data; that data are certain, clearly structured, and semantically well defined; and that data are valid, complete, relevant, correct, up-to-date, and do not change over time.

In practice, computation also requires that domain problems are well defined and clearly specified. In financial systemic risk analysis, these preconditions are rarely met. Clustering algorithms still require human assistance to determine the optimum clusters. Data structures and semantics are often ill defined and ambiguous, requiring a human to interpret meaning. Data are often incomplete, corrupt, incorrect, contradictory, out-of-date, deceptive, uncertain, and change over time, again requiring human intervention to interpret, clean, or preprocess them. These challenges are factors in the research agenda outlined in Section 4.

3. Examples of fixed and interactive visualization for financial stability

Given the complexity of the problem, the new data sets that are becoming available, and the growing range of systemic risk models (see Bisias et al., 2012), information visualization is growing in importance for systemic supervision.[5] However, many traditional renderings do not scale well to large or high-dimensional data sets. For example, as high-frequency trading expands, the U.S. consolidated tape is producing several orders of magnitude more observations at the trade level than are available from traditional daily closing prices (Jones, 2013). Larger data sets can be filtered or aggregated to make them accessible to legacy tools but this might discard potentially useful information. Inevitably, new visualization tools are emerging to help address the larger data sets (Keim et al., 2013; Fox and Hendler, 2011; Choo and Park, 2013).

Sarlin (2013a, ch. 3, 2015) surveys current visualization approaches to financial-stability analytics. He follows ECB (2010) in categorizing financial stability risks according to origin (systematic vs. idiosyncratic), effect (simultaneous vs. sequential), and trigger (exogenous vs. endogenous), reducing eight categories to three broad forms: (1) endogenous build-up and unraveling of widespread imbalances; (2) exogenous aggregate shocks; and (3) contagion and spillover (Sarlin, 2013a,b, pp. 39–40). We focus here on a few examples from that literature.

The use of new visualizations often goes hand-in-hand with proposals to adopt new financial systemic risk measures or analytic techniques, such as network analysis. Zhang et al. (2012, pp. 176–177), for example, identify four broad categories of input data—the lowest level of the DIKW hierarchy—each of which has special visualization considerations: (1) numeric; (2) geo-related; (3) network; and (4) text/web. The data type of the dominant dimensions for comparison primarily distinguishes the four types. Fig. 4 shows that all four types are relevant in financial stability analysis. The subsequent subsections provide some examples of fixed and interactive visualizations in several of these categories.

3.1. Examples of noninteractive visualizations

Most visualizations of systemic risk are numeric, as in Fig. 1, reflecting the basic fact that financial valuation is a measurement

[5] Instances are too numerous to list exhaustively. Examples include Sarlin (2013a, 2013b, 2015), Sarlin and Peltonen (2013), Zhang et al. (2012), Billio et al. (2012), Balakrishnan et al. (2010), and Markose (2013).

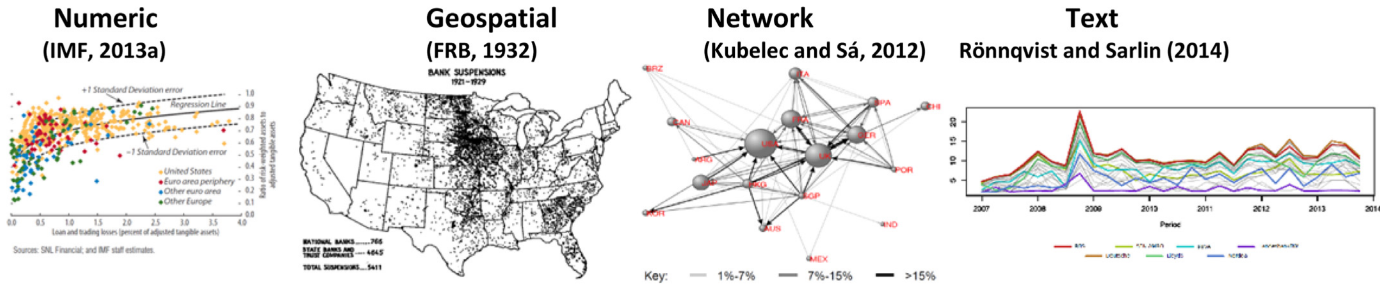

Fig. 4. Four types of financial stability data.

framework. Most financial stability visualizations are fixed as well, including the examples in this subsection. As we emphasize in our discussion of organizational challenges in Section 2, there are often good reasons to use fixed renderings, just as there are other important cases where interactivity can contribute significantly.

We focus in this subsection on three facets of financial stability. The examples touch on some of the enormous range of possibilities for visual renderings and highlight the importance of tailoring the measurement dimensions to both the available data and the concepts being depicted. Sarlin (2015) identifies three broad classes of systemic risk, namely the build-up of widespread imbalances, spillover/contagion, and exogenous aggregate shocks, exemplified as:

(a) Concentrated Exposures: Because concentrated hazards can trigger disruptive business failures, a natural measurement focus is on risk patterns at the level of individual financial firms. The geography of bank suspensions in the 1920s and Great Depression exemplifies an exogenous aggregate shock, for which the most appropriate (per Sarlin, 2015) policy tool is macro stress testing. The example uses geographic data.
(b) Systemic Interconnectedness: Because patterns in financial instability frequently emerge via the propagation of credit losses or withdrawal of liquidity support, a natural measurement focus is on the network of counterparty relationships. We focus on the practical need to filter or aggregate the network before rendering. This exemplifies a spillover/contagion hazard, suggesting (per Sarlin, 2015) a network modeling approach. The example uses network data.
(c) Accumulating Imbalances over Time: Because large-scale exposures typically build up gradually, it is natural to track selected signals over time. This exemplifies a widespread imbalance, suggesting (per Sarlin, 2015) an early warning model. The example uses numeric data.

A concentrated risk exposure is an unsustainably large contingent obligation or aggregation of obligations that, if triggered, would lead to the failure of a financial firm or system. No consensus definition exists, in part because the scope of exposure matters—firm versus subsystem versus system—and because there are so many often correlated sources of risk and ways to be exposed to them. Visualizations, because of their flexibility in the choice of measurement dimensions and rendering elements, are a natural tool to address this diversity.

Individual banking firms are natural atomistic components for systemic analysis. For example, Fig. 5 (FRB, 1932, pp. 31–32) compares banking crises in two episodes. The stable abstraction in this case is bank suspension, a binary variable readily comparable across institutions. Each point on the maps is the location of a suspended bank. The geographic pattern effectively conveys the important policy point: The ongoing (in 1932) banking crisis was far more urban and Eastern than the agriculture-related bank failure wave of the 1920s. The inclusion of state boundaries is important as an aid in locating business and financial centers and because banking laws differed significantly from state to state.

In contrast, network analysis measures interconnections across participants in the system. Interconnections matter, because stresses in the financial system can be transmitted quickly through these channels. For example, one firm's funding difficulties may cause it to withhold liquidity from others, or joint holdings of the same asset or asset class may create fire-sale feedback if one investor's sales temporarily force down the price for everyone. Fig. 6 (left panel) depicts a counterparty network, with legal entities as nodes and contractual transactions exposures as edges, in this case for interbank payment flows over Fedwire (Soramäki et al., 2007). The hairball at the top naïvely shows all participants and flows, while a simple filtering of the graph for the largest nodes generating 75 percent of total payments (at bottom) clearly reveals a core-periphery topology typical of dealer markets. The visual benefit of filtering the network suggests a useful dimension for user interaction.

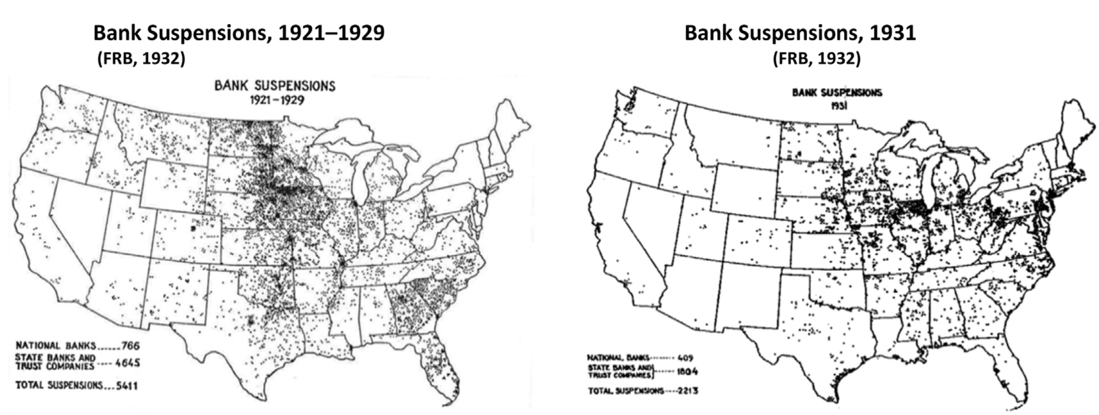

Fig. 5. Geographic distribution of U.S. bank suspensions, 1921–1929 and 1931.

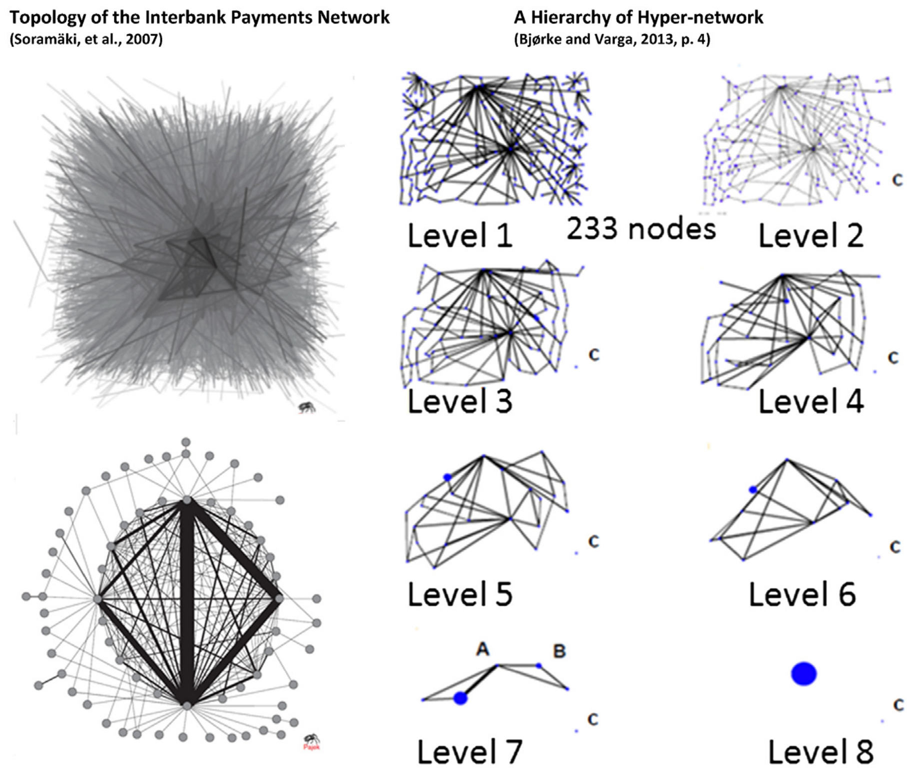

Fig. 6. Two approaches to filtering networks.

Alternatively, complex networks can be abstracted by aggregating nodes and links with similar properties into "hypernodes" and "hyperlinks" to generate hierarchies of hypernetworks; Fig. 6 (right panel). This aggregation helps reduce visual overload and enhance the understanding and analysis of complex networks' interdependencies, robustness, and vulnerabilities (Bjørke et al., 2010a,b; Bjørke and Varga, 2014). This approach can generate variable levels of abstraction, aiding the user in quickly grasping the underlying structure of the network. The user can adapt the level of detail and abstraction as needed. An anomaly, such as node C in the figure, might represent a potential trigger of future events. Unlike simple network filtering, the hypernode approach will not automatically remove such outliers.

Although generic network algorithms are useful, visualizations are more powerful when the nodes and edges have domain-specific interpretations. To adapt visualizations to financial data in a systemic context requires special attention to normalization of the input data, which typically come from diverse markets and institutions. A familiar example of data normalization is the maintenance of generally accepted accounting principles (GAAP), which provide standard semantics for financial reporting, augmented by the Extensible Business Reporting Language (XBRL), which provides standard formats for automated processing (see Engel et al., 2013). Similarly, standardized network data that capture important economic abstractions would be an important building block for higher-level understanding. The LEI, for example, will be invaluable in constructing both visual and nonvisual graphical analyses of financial networks (see Braswell and Mark, 2013; OFR, 2013a,b; Lemieux et al., 2014a; Chan and Milne, 2013). Similar universal identification is needed for the edges of financial networks, particularly counterparty networks. Standardized financial product identifiers may help meet this requirement. There is also a need to address inter- as well as intranetwork analysis (Bjørke et al., 2010a,b) so that we can understand the significance, effect, and correlation of the changes within one network and across other networks.

Many financial stability measures address patterns at the level of the system as a whole. Emergent phenomena with systemic implications include liquidity, volatility, concentrated or correlated exposures, macroeconomic imbalances, and business cycles. The emergent phenomenon par excellence is the price system. The interest rates that compose the sovereign yield curve are key prices that succinctly capture crucial systemic information about the demand for investment and the price of risk.

The relationship between long-term and short-term yields reveals much about expected inflation and net returns to financial intermediation. A simple time-series plot of the full curve over time, as in Fig. 7 (left panel), conveys a rich history of expansions and recessions, identified primarily by the peaks (expansionary episodes) and troughs (recessionary episodes) in the short-term rate (data from U.S. Treasury, 2016). The figure also embodies the broad, gradual decline in inflation rates over the period. The short-term interest rate, represented by the heavy red line, provides a succinct synopsis of the Fed's interest-rate policy over two decades. Those familiar with the economic history of the period will recognize other nuances; this historical context might be made explicit with markers for key events and episodes. As with accounting data described above, the exploration of cross-sectional relationships in interest-rate behavior is similarly well suited to visualization.

Fig. 7 (right panel) shows changes in interest rates in basis points on new bank loans between December 2010 and January 2013 (IMF, 2013, p. 10). The disparity in rate changes highlights the clear divergence between the core and periphery countries in Europe since the financial crisis. In a visual analytics context, the choice of housing and corporate loans rates as the measurement axes might result from user selections via interaction switches. An episode of accumulating imbalances naturally incorporates a temporal dimension. Operational issues affecting temporal data include frequency and

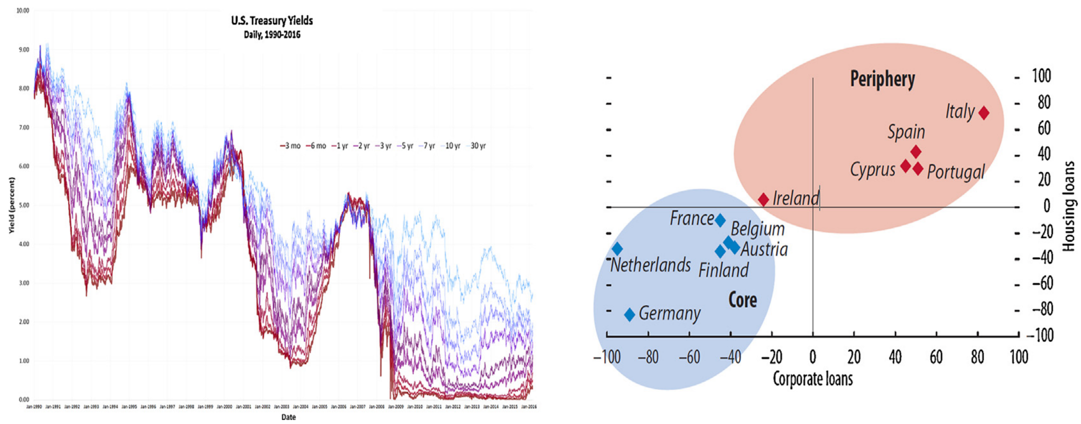

Fig. 7. Interest rate fluctuations in time series and cross section (U.S. Treasury, 2016; IMF, 2013).

timeliness, temporal resolution, and synchronization across data sources. Timestamps from separate sources may not align. Various arrangements have evolved to enable synchronization, such as end-of-day exchange “fixings,” and accounting statements prepared after the fact “as of” the fiscal year-end. These mechanisms are not universal, however. For example, the “Flash Crash” report by the Commodity Futures Trading Commission (CFTC) and SEC highlights problems with network latency in various trading message feeds that may have hampered the price discovery process (CFTC-SEC, 2010, pp. 76–79). More precise timestamps and visual tools for benchmarking message flows from diverse sources might be useful in this context.

3.2. *Examples of interactive visualizations and visual analytics*

Moving beyond these high-level, fixed renderings to interactive analytics—especially those with variable granularity or “details on demand”—will ultimately require the definition of meaningful hierarchies among concepts or abstractions measured on a comparable scale across the system or some subsystem. Consistent hierarchies enable this drill-down interaction of Shneiderman’s (1996, p. 2) mantra: “overview first, zoom and filter, then details-on-demand.”

Fig. 8 illustrates two recent attempts to represent systemic risk with numerous indicators simultaneously. Presenting multiple indicators jointly is sensible, because the financial system is multifaceted, so a higher dimensional data index is needed to capture everything. The left panel (OFR, 2015) presents a financial stability heat map with five aggregate measures, each comprising several submeasures of financial systemic risk.

Both visualizations are interactive, affording features such as mouseover help, selective highlighting, and user-defined date ranges. A more sophisticated application might provision more detailed interactions, such as a double-click gesture to retrieve the underlying input data. A full visual analytics solution might further allow the user to select in real time to recalibrate the algorithms for risk aggregation or dimensionality reduction, or to choose among the various unions and intersections of several different drill-down dimensions, such as geographic region, industrial sector, etc.

The self-organizing financial stability map in the right-hand panel of Fig. 8, like the left-hand panel of Fig. 3, is more abstract and information-dense. This rendering uses a self-organizing map, described by Sarlin (2015), to cluster the data into groups to reduce the dimensionality of the problem (see also Sarlin, 2013a,b; Sarlin and Peltonen, 2013). The user here can highlight a particular country as it traverses various groups over time, and hover over the edges in the graph to reveal group membership in a modal popup. As with IDL in Fig. 3, a certain amount of specialized training is needed to achieve facility with the self-organizing map.

Given the complexity of systemic analysis, it is often helpful to integrate various individual visualizations into dashboards that display multidimensional data in multiple coordinated views. Dashboards are mash-ups of diverse, coordinated perspectives on a collection of information, often optimized real-time monitoring (Few, 2006; MacNeil and Elmqvist, 2013). For engineered systems, unlike the financial system, functionality is allocated carefully to different components with clearly defined interrelationships and interdependencies, and each major subsystem has dedicated

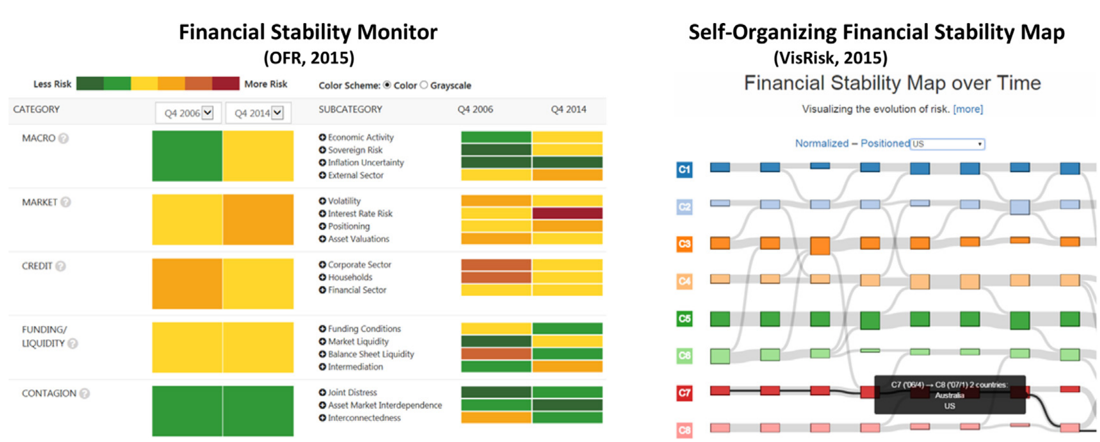

Fig. 8. Two financial stability maps.

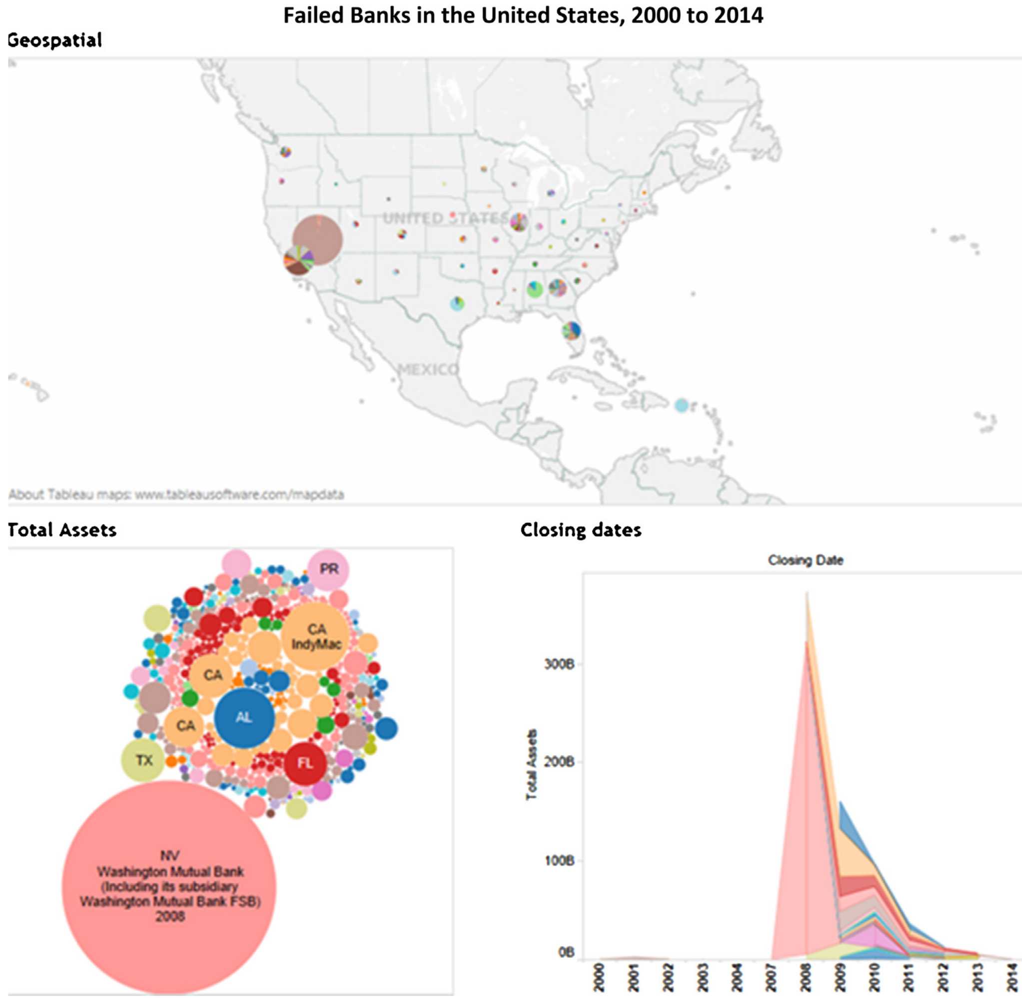

Fig. 9. Interactive system dashboard (FDIC data).

instrumentation—like the fuel and cooling gauges on an automobile dashboard—reporting its status for these well-defined physical and functional relationships.

Because formally engineered systems control the allocation of functionality more tightly than the financial system, financial dashboards require additional creativity to ensure that all of the important perspectives are captured effectively. For example, Fig. 9 presents a dashboard displaying three distinct perspectives—geographic, temporal, and economic significance—on the 519 U.S. banks that failed during 2000–2014. This dashboard transforms into a visual form raw data from the Federal Deposit Insurance Corporation (FDIC, 2014) failed bank list, augmented with facts from the press release associated with each failure. This visualization supports the sensemaking process of research analysts. Loan defaults and other credit losses are dominant sources of risk for most banks and financial institutions, and credit assessment is crucial in maintaining a bank's financial stability.

As Fig. 5 shows, bank failure is a binary variable, readily comparable across institutions, and structural patterns typically emerge during episodes of widespread failures. In contrast to Fig. 5, which depicts bank failures before the advent of interstate branching, Fig. 9 shows how headquarters location has become more arbitrary in the modern era. The map is dotted with pie charts that correspond to total assets of failed banks within each state, and colored slices in each pie distinguishes the individual failed banks. The biggest pie chart is in Nevada, which had 12 failed banks with combined total assets of more than $315 billion, including $307 billion in Washington Mutual (WaMu), the largest failed bank in U.S. history. The bottom right panel shows the timeline of events, revealing no bank failures during 2005–2006 and again underscoring the relative importance of the WaMu failure in 2008. The packed bubble chart at the lower left depicts the skewed cross-sectional distribution of failed bank sizes, colored and clustered to distinguish locations by state. As in Fig. 5, the user can see at a glance that the number of failed banks varies across the states. The significant difference is the opportunity for interaction to explore the data. For example, clicking on any part of the dashboard highlights the corresponding features in the other parts of the dashboard through the application of brushing and linking techniques. Interaction allows comparisons of interest to the user, a crucial component of data exploration and hypothesis generation.

Another coordinated mashup emerged as the winner in the Bank of England's 2015 public data visualization challenge (BoE, 2015a). The assignment was to develop novel visualizations using at least one of the six datasets provided for the competition. Sleeman (2015) augmented a competition-provided set of macroeconomic data (BoE, 2015b) with a second dataset of statistics from the Organisation for Economic Co-operation and Development (OECD, 2015). Fig. 10 shows two snapshots of the winning entry. The upper section of each snapshot uses the OECD data to compare every recession in the Group of Seven (G7) countries since 1970, highlighting the UK in white. The lower section compares every UK recession since 1860 using the BoE data.

Bank of England 2015 Data Visualization Challenge – the Winner
(Sleeman, 2015)

Fig. 10. Recessions and recoveries (OECD and Bank of England data).

In the left panel of Fig. 10, the rows in the lower section are sorted by year. The columns reveal at a glance several key measures of recession across G7 countries since 1970: duration, depth, inflation and productivity. User interaction—the columns are sortable by clicking on the relevant heading—allows exploration of G7 recession-recovery cycles. The lower section of the left panel shows the UK's growth in GDP, inflation and productivity since 1860. Vertical alignment of the time series facilitates comparison across the three indexes, highlighting the most recent UK recession (2009) in white.

The right panel of Fig. 10 reorders the characteristics of recessions in both the upper and lower sections by ranking according to inflation instead of time. This sort of interactivity provides several insights, such as that history repeats itself. For example, if one sorts the lower panel by GDP growth, the recessions of 1908, 1931, 1944 and 2009 bear strong resemblance to each other across the three indexes. Sorting instead by time reveals that the most severe UK recessions occurred in the aftermath of the two world wars in the 20th century and that the 2009 shock was among the most severe in history.

The crisis of 2007–2009 has also generated intense research interest in the possibility of network effects in financial markets, such as the possibility for fire-sale feedback loops to trigger a more broadly based deleveraging in dealer markets. Historically, analysts have typically not had access to data that directly measure the network of contractual connections in these markets. Instead, they have inferred the likely interconnections indirectly from observable facts such as correlations and Granger-causality statistics from stock returns. Brunetti et al. (2015) visually compare such "correlation" networks with the underlying "physical" networks, revealing that the two approaches indeed reveal different patterns in the data; inferred financial networks are not the same as directly measured networks. The danger is that inaccurate inference might lead to erroneous conclusions and strategies, with unpredictable results.

Illustrating this potential, Bech et al. (2015) infer a network of overnight exposures from interbank payments data. They analyze this network, making prominent use of visualization, and conclude that the introduction by the Federal Reserve of interest on excess reserves in October 2008 may have had a more pronounced impact on the network topology than the failure of Lehman Brothers a month earlier. Cook and Soramäki (2014) and Heijmans et al. (2014) similarly emphasize visualizations of interbank payment flows and network statistics to extract significant topological patterns. Cook and Soramäki (2014) analyze global interbank payments messages from the Society for Worldwide Interbank Financial Telecommunications (SWIFT). Heijmans et al. (2014) use animations—dynamic, noninteractive visualizations, per Table 1—to identify patterns in the Dutch interbank money market.

Since the crisis, macroprudential supervisors have gained access to a number of new datasets with counterparty identifiers that allow analysts to reconstruct a highly detailed network representation of positions and transactions in certain key markets.

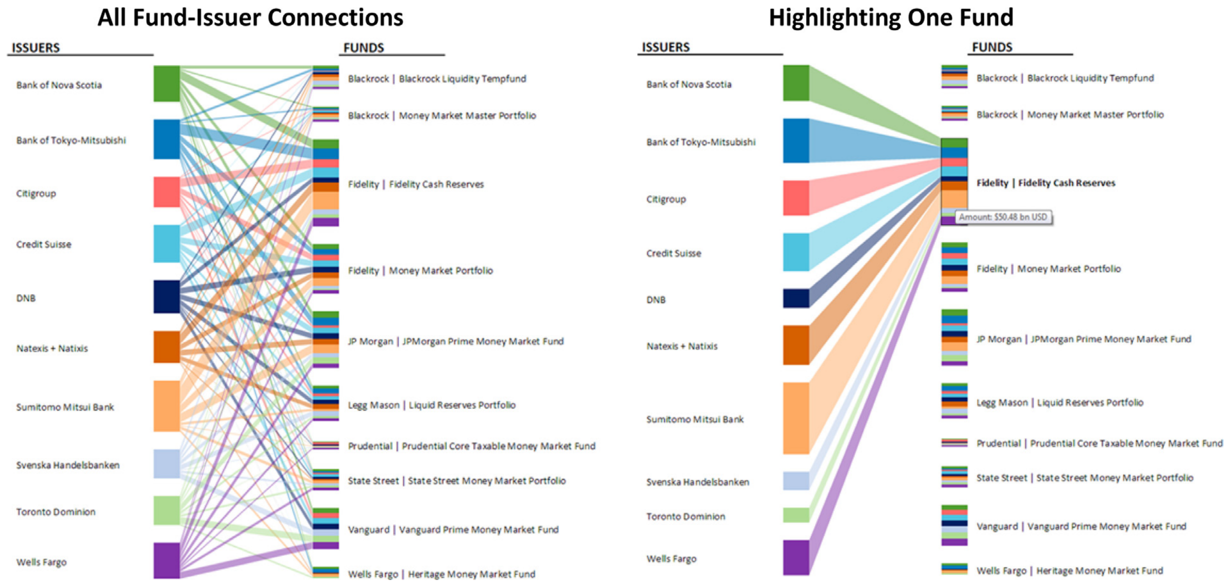

Fig. 11. Ten largest prime money funds as of July 2014 (OFR data, from SEC form N-MFP).

Supervisory access to this sort of granular detail for network modeling is largely unprecedented. Because they involve individual contracts, the data sets can be quite large, and so visualization techniques are especially apt as a means to summarize information and identify patterns. Interactive techniques and visual analytics can be especially powerful in this context.

Fig. 11 depicts month-end holdings of the 10 top issuers of money-market debt for the 10 largest prime money funds that submitted the SEC's new Form N-MFP.[6] The crisis demonstrated that spillovers in these markets are possible, such that the difficulties of one fund to meet redemption requests may raise concerns about the quality of the underlying assets (Duygan-Bump et al., 2013). This may trigger panicked redemptions by investors in other funds who are uncertain of their funds' holdings. The left panel of Fig. 11 shows the intricacy of the web of interconnections, with numerous common holdings, but of very different exposures from one fund to the next. The nexus is complicated, and it is easy to see how investor uncertainty might arise. The right panel interactively highlights a single fund, using a mouseover gesture, and isolates the fund's holdings. The important pattern surfaces immediately from the "haystack" of interconnections: this particular fund holds stakes in all 10 of the major issuers.

CrisisMetrics (Infolytica, 2015) is an interactive interface to explore of banks' cross-border exposures using quarterly banking statistics from the Bank for International Settlements (BIS). The tool provides supervisors and bank risk managers with a way to monitor spillover risks in the banking sector. CrisisMetrics offers two alternative network displays, namely a force-directed layout and a chord layout. The left panel of Fig. 12 shows a force-directed layout in the 4th quarter of 2003. This allows users to understand the network structure thus aspects such as strength, vulnerabilities and relationships. The chord display in the right panel of Fig. 12 presents the same data, but shows the immediate node neighborhoods in a circular manner. The user can zoom and pan to explore the data.

The hive plots in Fig. 13, taken from Haynes et al. (2015) show the over-the-counter CDS market, for which a different network visualization is appropriate. The CDS market has a core-periphery structure with a central and highly connected group of large dealers who trade heavily with each other while also servicing individual (non-dealers) client firms, such as hedge funds, usually in an exclusive relationship.[7]

A typical transaction in these markets creates a loop in the plot. A peripheral non-dealer takes a position by transacting with its dealer for a CDS on a particular reference entity. The position on the axis indicates the trader's accumulated position. To avoid accumulating too large an inventory from client trades, the dealer, in turn, will often lay off the position by transacting with another dealer; hence the dual "Dealers" axes in the hive plot. By "connecting the dots" across the three (or four) axes, using arcs between the non-dealer, the two dealers, and the reference entity, a beehive-shaped view of the network emerges; Krzywinski et al. (2012). Comparing the left and right panels of Fig. 13 gives a sense of the dynamism in position-taking over time. The right panel also shows the benefits of interactivity in this context, as a mouseover gesture highlights the positions of a single large non-dealer. Lastly, this example demonstrates the usefulness of visualizations for revealing the overarching patterns in large data sets while protecting the confidentiality of individual participants and their trades. The granular CDS data are confidential, but what matters most from a macroprudential perspective is the existence of crowded trades, rather than the identity of individual position holders.

4. The role of visual analytics

Visual analytics can provide effective means for extracting information and deriving insight from massive, dynamic, and frequently ambiguous (or even contradictory) data. Thomas and Cook (2005) emphasize the strength of visual analytics in exposing and discovering unexpected patterns in the data. Visual analytics can provide timely, defensible, and clear understanding and assessment of

[6] Form N-MFP is required for money market funds reporting under SEC rule 2a-7. The first mandatory reporting date was December 7, 2010, of holdings as of the end of November, 2010; see SEC (2010, 2011). After 60 days, the SEC publishes the filings on its EDGAR website. The OFR's version of this dataset presented here is not the official EDGAR presentation, but a modified version, which has been scrubbed to correct apparent misspellings, to eliminate duplications, and to reformat the data for database access.

[7] The OFR has access to a significant subset of CDS transactions held in the Trade Information Warehouse (TIW) of the Depository Trust & Clearing Corporation (DTCC). The sample consists of all trades in which the buyer, seller, or reference entity is a U.S.-domiciled firm.

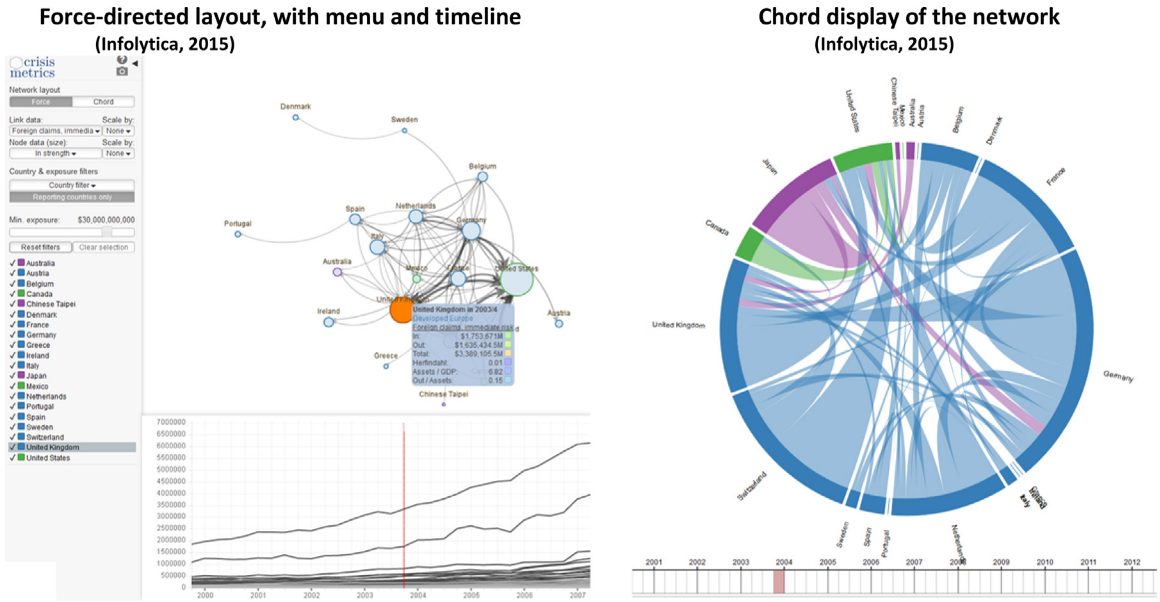

Fig. 12. CrisisMetrics—cross-border network of banking exposures (BIS data).

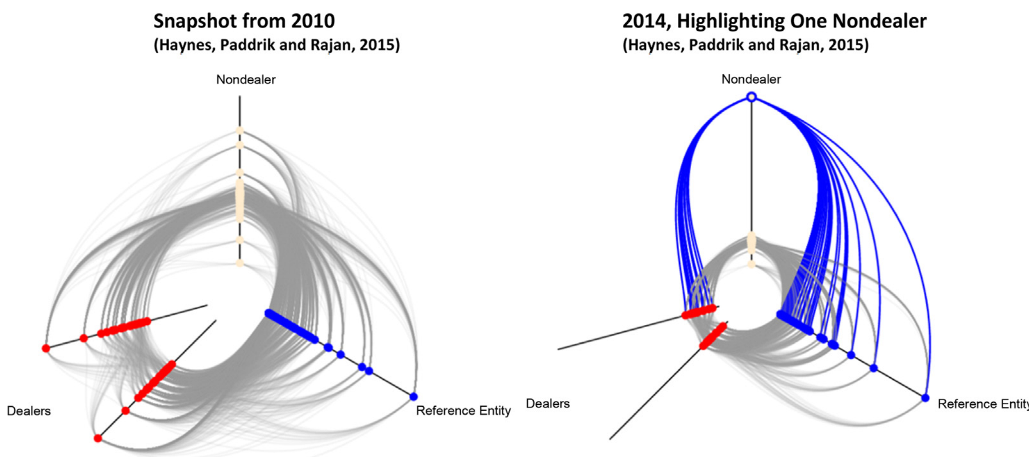

Fig. 13. Interactive visualization of the network of holdings in the CDS market (OFR data).

the situation and help communicate that assessment for effective decision-making. Visual analytics draws upon many different areas including, for example, analytical reasoning techniques, visual representation and interaction techniques, data representation and transformation, and techniques to support production, presentation, and dissemination of the results. The high-level goal is to combine the visual and cognitive intelligence of human analysts, such as pattern recognition or semantic interpretation, with machine intelligence, such as data transformation or rendering, to perform analytic tasks iteratively. In visual analytics, this feedback loop (see Fig. 14) operates through interactive visual interfaces.[8]

Visual analytics has notable advantages over traditional statistical methods of transforming large volumes of heterogeneous, non-visual data into actionable knowledge, because humans have evolved exceptional visual and spatial skills that include the ability to detect edges and discontinuities, exceptions, anomalies, and outliers, and patterns visually. This powerful visual interface effectively forms a high-bandwidth pipe to deliver information to the analyst. Visual and spatial attributes, such as color, shape, and motion, can be transformed into a graphical display to provide a rich visual depiction of the non-visual data. When a user can perceive features pre-attentively (before conscious attention), they are understandable at a glance and much more rapidly than words. On

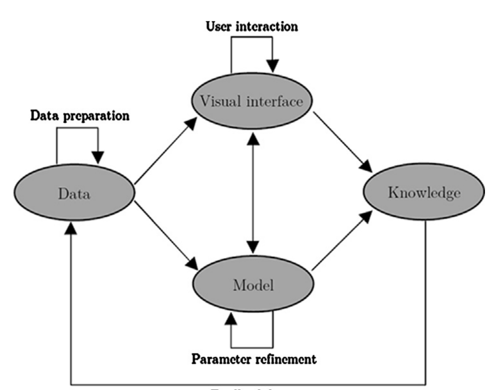

Fig. 14. Human-in-the-loop analysis (Sarlin, 2015).

[8] For an alternative rendering of the visual analytics process, which expands the user interaction into several nodes, see van Wijk (2005).

the other hand, traditional econometrics can deliver formal results, such as hypothesis tests, confidence bounds, or goodness of fit measures; these are often founded on well understood optimization methods. We emphasize that visual and statistical analytics are not contradictory or mutually exclusive approaches. It is possible, for example, to integrate traditional statistics as a core element of the analytical component of a visual analytics framework.

4.1. Visually representing underlying concepts and processes

The design of good visual representations for core financial stability concepts and their relationships is a key challenge. Good design requires the identification and refinement of stable abstractions—values, typically numeric, that reflect or illuminate the relevant concepts while remaining commensurate over time and across entities in the system. Good design also requires the selection of good visual renderings of the measured entities, concepts, and relationships (Wilkinson (2005) proposes a coherent implementation framework). For example, the World Bank's (2013b) "Data Visualizer" uses the abstraction of the standardized national income and product accounts (and other series) to compare across countries using three menu-selected macroeconomic variables for chosen countries and years. Their "bubble chart" uses the area of colored circles to render one attribute for each country; the bubbles' positions on an X/Y coordinate grid represent the other two attributes. Animation over time adds a fourth dimension.

Visual analytics aims to go beyond fixed renderings to integrate visual representations dynamically with algorithms, so the analyst can use computation to steer the algorithms in a deliberate manner. For example, in subspace clustering, a data mining technique used for reduction of data dimensionality, an analyst is able to steer the clustering algorithms to reveal low frequency but potentially interesting dimensions that would otherwise be overlooked by automatic data mining procedures (Tatu et al., 2012). Not only must visual analytics systems render the core concepts and processes well, these systems must also have carefully calibrated interaction techniques that support manipulating the underlying algorithms and the associated data spaces through fluid interaction with graphical elements.

Some key steps in the design of visual analytics systems are:

1. Determining what to represent.
2. Choosing visual forms to represent objects.
3. Designing underlying computational/analytical algorithms.
4. Choosing interactions to connect visual representations with underlying analytics.

The execution of these steps can significantly influence usability. The remainder of this subsection briefly describes some useful techniques for structuring the implementation of a visual analytics system.

An example of a common framework for decomposing complex systems for visual analytics implementations is the *abstraction-decomposition* space (Rasmussen et al., 1994; Vicente, 1999). To apply this framework, a visualization designer would deconstruct financial systemic risk analysis by identifying the different levels of abstraction along two dimensions.[9] The advantage of representing the financial system within such a formal framework is that it allows financial stability experts to describe domain-specific concepts and constraints in a way that is accessible to visualization designers and software engineers. In this approach, the users' exploration and analysis of the data are guided and defined by the framework.

The abstraction-decomposition space comprises two orthogonal dimensions: the *decomposition hierarchy* and the *abstraction hierarchy*:

1. The decomposition hierarchy consists of three levels of decomposition:
   a. The whole system
   b. Subsystems
   c. Components
2. The abstraction hierarchy consists of five levels:
   a. functional purpose—what the system is intended to achieve in the work domain;
   b. abstract function—important system concepts, such as liquidity or risk;
   c. generalized function—representation of subsystems and their components (for example, indicating the necessary outputs to calculate liquidity and risk);
   d. physical function—representation of components of the system and their states (for example markets, counterparties, intermediaries, etc.); and
   e. physical form—configuration and location of components and subsystems.

Achonu and Jamieson (2003) provide an example of an abstraction-decomposition hierarchy for a portfolio management system, depicted in the left panel of Fig. 15. They magnify and decompose only one branch of portfolio management, immediately making apparent that many different visual forms are needed to depict the performance and structure of financial portfolios. Fig. 15 also shows components ("Enablers" in the diagram) functionally related to "Processes" that perform the "Income transfer" function. In a financial stability context, one example for an abstraction-decomposition hierarchy might be the nested ownership of subsidiaries in financial holding companies. Each holding company would be a subsystem containing a tree with individual subsidiaries, branch offices, or business units as the leaf nodes. An obvious set of functionality to model in the abstraction hierarchy would be the legally permissible activities granted to each subsidiary under its corporate charter. However, straightforward lists of permissible activities will typically not correspond directly to financial stability factors, such as credit exposure, leverage, or liquidity.

Once a problem domain has been structured in this way, techniques of visualization, human-computer interaction design, and cognitive systems engineering can represent the relevant functional relationships visually by mapping key component attributes, facets, derived risk measures, etc., to particular rendering elements.[10] The goal is to present the "terrain" of the system, where elements in the visual display are carefully juxtaposed to highlight meaningful comparisons between processes, components, and derived metrics (Larkin and Simon, 1987). Such a presentation requires a sympathetic understanding of the subject matter domain. For example, Vuckovic et al. (2013) untradition-

[9] Because the financial system is complex, for the purposes of this paper we provide only a very cursory discussion of how the system might be decomposed to show where potential systemic risks might emerge. This overview is only to illustrate generally how the abstraction-decomposition space might highlight the potential benefits of visual representations for macroprudential analysts. No claim is made that the decomposition analysis here is rigorous—that is a topic for a future stream of research.

[10] For a detailed analysis of human–computer interface design, see Shneiderman et al. (2009). One particular design paradigm, ecological interface design (Burns and Hajdukiewicz, 2004), is well suited to ongoing financial market monitoring, where repeated tasks are commonplace (hourly price updates on key markets), but user attention must contend with manifold distractions, such as news alerts, office banter, etc., while the representation design paradigm (Bennett and Flach, 2011) provides human factors and ergonomics guidance on how to map semantically relevant process variables to visual renderings.

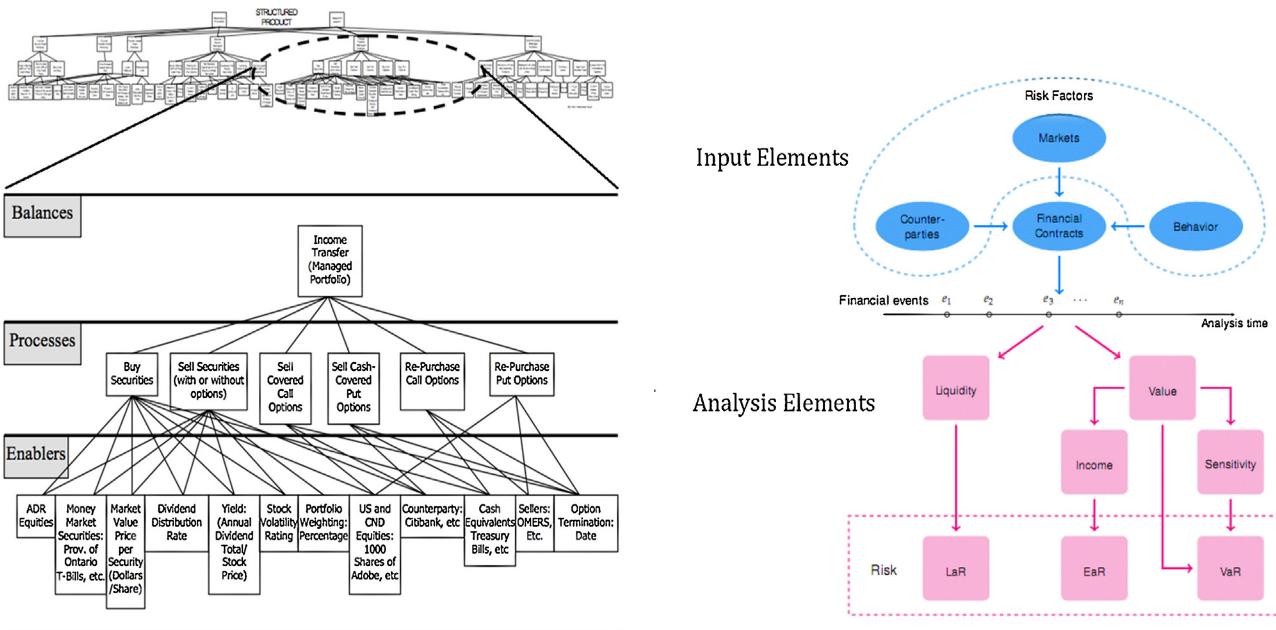

Fig. 15. Two examples of abstraction hierarchies in finance (Achonu and Jamieson, 2003; Mendelowitz et al., 2013).

ally represent a key functional relationship—potential air traffic conflicts—as relative position vectors that depict actual separations between aircraft pairs, instead of inferring possible conflicts from flight plans.

Another example of a structural modeling hierarchy in finance is the "unified model" of Brammertz et al. (2009), which decomposes financial contracts into bundles of promised cash flows that follow a relatively small number of standardized patterns. These cash flow patterns interact with an event stream over time to generate realizations of the risky exposures. Brammertz (2013) argues the primary source of complexity in the system arises from the financial contracts that connect financial entities. As depicted in the right panel of Fig. 15, financial contracts, buffeted by events along the timeline, yield a value and liquidity that can be expressed in terms of risk. The unified model provides an abstract description of the components and subsystems that make up the financial system, projecting contracts, market behaviors, income, revenues, and liquidity into abstract cash-flow patterns and relationships for a composable representation of financial risk.

Although an abstraction-decomposition hierarchy provides clear guidance on how to structure a problem domain to facilitate visual analytics, a moment's reflection reveals the daunting nature of this challenge. For example, none of the elements of either hierarchy is defined consistently across the financial system. Even assuming that a legal entity is the finest-grained component resolution needed, implementation of the global Legal Entity Identifier (LEI) is in its infancy (OFR, 2013a,b, pp. 82, 97–110). Central concepts, such as "liquidity" and "risk" have scores of concrete definitions, with little consensus on which to use in what context. Despite this, we use the organizing principles of the abstraction-decomposition hierarchy to help outline a research agenda (in the concluding section below) around data and modeling gaps for the financial system.

The implementation process for augmenting visualizations with interactivity brings its own challenges. Munzner (2014) captures the lessons of experience in the nested model depicted in Fig. 16. The basic design stages appear in the left panel. Note that the two outer stages, domain characterization and abstraction design, apply to visualization generally. Interaction comes into play significantly only at the third and fourth stages. A key point of the nesting, shown in the right panel, is that much of the validation needed at each stage to confirm threats have been adequately addressed cannot occur until nested implementations are complete and data are flowing through the system.

By encoding data and functional relationships into images that stand out in the human field of vision (Treisman, 1985), visualizations help shift cognition to the perceptual system, with visuals acting essentially as a form of externalized memory. Such externalized representations can enhance an analyst's problem-solving capabilities by enabling the processing of more data without overload. As previously mentioned, effective visualization can be used to help overcome cognitive biases that can prevent effective risk-based reasoning. Visual cues can help analysts understand where biases arise because graphical representations stand out forcefully in human perception. Visual analytics exploits these general strengths of visualization by using a visual interface to connect human experts as "components" in a larger analytical system.

There is terminological debate over the definitions of "visual analytics" versus "information visualization" (for example, Yi et al., 2007), centering on the nature of the analytical models available to the human user in the interaction loop. At one extreme lie fixed renderings, such as the examples in Fig. 1. As noted, noninteractive visualizations play a necessary role in the supervisory process, especially for the most important decisions and reports. Such fixed visual displays also represent a snapshot or endpoint from some analytical process. However, because common knowledge and accountability require that images be fixed, other considerations, such as information density and graphic design, become more salient—interactive data browsing, zooming, panning, filtering, summarization, details on demand, etc., are unavailable to the user. At the other extreme, sophisticated algorithms and analytics are available for the user to interact directly and dynamically with the data and underlying algorithms through the visual form (for example, in the bottom interaction pathway in the right-hand panel of Fig. 14) (Heer and Shneiderman, 2012). Wang et al. (2012) refer to this as "direct data manipulation;" their RiskVA prototype allows the user to create customizable workspaces to support individual analysis routines.

A spectrum of interactions is available between the two extremes. Interaction techniques include changing visual scale (zooming), filtering, grouping and summarizing, and fetching details on demand. Sarlin (2013, ch. 5) discusses many of the points

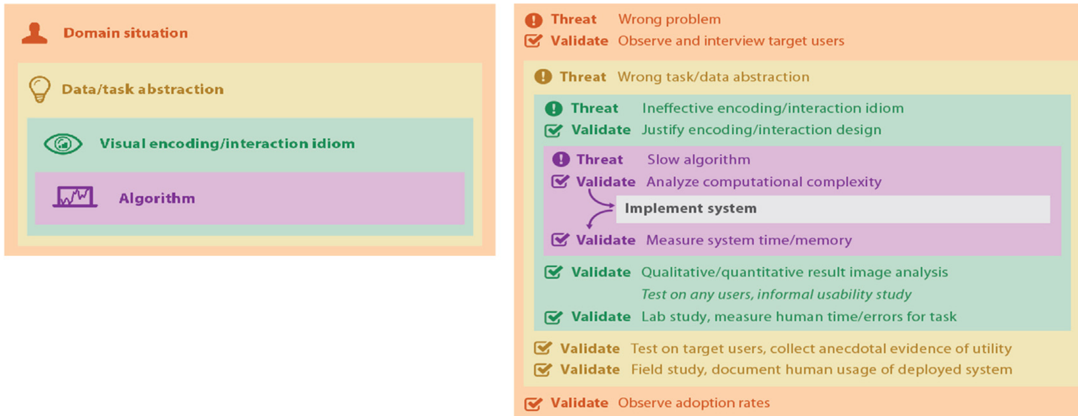

Fig. 16. Munzner's nested model for visualization design (Munzner, 2014).

between the extremes. These options include simple rendering refinements, data browsing, and exploratory data analysis, feature extraction, knowledge discovery in databases, and data mining. For macroprudential modeling, the functions should also include a range of domain-specific analytical and econometric techniques, such as those surveyed by Sarlin (2013, ch. 3) and Bisias et al. (2012).

5. Conclusion and directions for future research

Addressing the information processing challenges that have contributed to the global financial crisis remains a significant and unresolved challenge. Section 2 of this paper summarizes this challenge, focusing on the key supervisory tasks of: sensemaking, decision making, rulemaking, and transparency. Visualization can play an important role in exposing and summarizing intricate, nonlinear and multidimensional patterns in financial data. Interactivity is particularly useful for sensemaking and transparency tasks, where it is difficult to specify user needs in advance and requirements for common knowledge and ex-post accountability are less prominent.

Visual analytics offers special promise by combining the strength of analytical reasoning, the deep contextual knowledge of domain experts, and the unsurpassed pattern recognition capacity of the human visual system using interactive visual interfaces. Section 3 of the paper reviews some specific examples of fixed and interactive visualizations of financial stability data. We summarize in Section 4 the emerging field of visual analytics and offer some guidelines for implementation. Good visualizations work by presenting important facts, measured on relevant scales, and laid out so juxtaposition encourages comparison and reconciliation. Visual analytics augments the basic general strengths of visualization with analytic algorithms and interaction tools that allow the user to steer the depiction to enable effective understanding of the data and situation and thus to support informed decision making.

The general principles of visualization and visual analytics are well understood, but there are always research opportunities when these tools are brought to bear in a new application domain. The challenge looms especially large for financial stability monitoring, where the size, scope, and changeability of the system is compounded by the abstract nature of the tasks and formative understanding of useful analytical approaches. In this context, we offer some preliminary and incomplete suggestions for research:

- *Definition of core abstractions*—Visualization tends to work best when the data share one or more measurable dimensions that form a basis for comparison. Ideally, the dimensions (definitions, not the specific values) will be invariant across observations. To support comparisons across the financial system, it is necessary to have stable or "invariant" abstractions—semantically relevant concepts consistently measured across the ecosystem of economic models, institutions, and episodes. Ideally, these abstractions will have both standard machine-readable formats and well-defined semantics. The ultimate goal is a mapping from the data and vocabulary of financial stability to the more generic domain of visual analytics. Bridging the semantic gap between domain abstractions and visualizations requires a deep understanding of both financial stability analytics and a respect for implementation methodologies like the abstraction-decomposition hierarchy.
- *Definition of canonical algorithms*—Interactive visualization frequently calls for the calculation of derived attributes "on the fly" to supply characteristics for user-defined perspectives such as customized clusterings or filterings. For example, an analyst might filter out particular subsets of banks according to idiosyncratic values and then calculate the average liquidity coverage ratio or risk-weighted capital ratio for each subset. Similar to core data abstractions, there is a need for precise and semantically relevant algorithms, ideally with fast implementations, for embedding in visual analytics (Bisias et al., 2012, offer a start by providing skeleton source code to accompany the models they describe in their survey).
- *Publication of test data*—Visualization researchers need data sets with relevant scope, content, and ground truth to prototype and test their tools. "Live" data are preferred to synthetic substitutes, although licensing and confidentiality concerns may predominate. Whether live or synthetic, sharing data implicitly raises issues of standardization, formatting and licensing.
- *Development of evaluation techniques*—Visualization tools can support a wide range of applications, including broad categories such as sensemaking or decision support, and more targeted purposes, such as representing semantic relationships in knowledge bases, depicting degrees of risk and uncertainty in financial data, or identifying gaps and quality issues in raw source data. As tooling emerges to address these various concerns, evaluation techniques will be needed to assess effectiveness. For example, decision-support tools for financial stability analysis will interact with users' risk-based reasoning processes (see Oaksford et al., 2012), but little is understood about how to assess whether that interaction is effective.

In conclusion, we have discussed some of the possibilities as well as some of the pitfalls in applying visual analytics to the challenges of systemic financial stability monitoring. Much research remains to be done to further articulate the high- and low-level domain tasks, complete data and task abstractions, such as abstraction-decomposition hierarchies, develop visualizations and analyses for a visual analytics solution, and to enhance interaction techniques to aid exploration and analytic tasks. Validation and evaluation will also be needed. With further research and development, though not a panacea, visual analytics holds promise as an effective approach that could help financial systemic risk analysts meet the significant challenges associated with detecting, identifying, monitoring, and managing threats to global financial stability.

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