

Chapter 2

Macroprudential Oversight

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 November 2010

Paraphrasing Milton Friedman’s statement about Keynesians, Borio (2011) stated “*We are all macroprudentialists now*”. 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 central bank of central banks, 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, e.g., BIS (1986) and Borio (2011)], but the use of the concept remains somewhat ambiguous.

So, what is a macroprudential vis-à-vis a microprudential approach? With the help of a comparison to the microprudential approach, Borio (2011) summarizes the macroprudential orientation as follows. First, while the aim of the macroprudential approach is to limit system-wide stress and possible costs for the macroeconomy, a microprudential orientation attempts to limit an individual institution’s risk of failure with the aim of minimizing costs for depositors and investors. Second, the macroprudential approach explicitly accounts for the fact that risk is dependent on the collective behavior of financial institutions (i.e., endogenous), rather than being something outside their influence (i.e., exogenous) as is in the microprudential case.

This chapter is partly based upon previous research. Please see the following work for further information: Sarlin (2014a).

Third, the macroprudential approach has a system-wide perspective, where a top-down approach works out a desirable safety standard for the system as a whole, rather than the stand-alone soundness of individual institutions approached from the bottom-up. Thus, a macroprudential approach takes a holistic view on the financial system with the aim and mandate to ensure system-wide stability, rather than only being concerned with the failure of individual entities. Yet, the two approaches are difficult to compartmentalize because they most often co-exist.

The comprehensive macroprudential approach thus obviously also involves an understanding of a large number of other concepts. It is crucial for regulatory decision-makers to have a broad and deep understanding of financial systems, fragilities and instabilities, as well as risks and vulnerabilities, in the economy. Hence, to carry out macroprudential oversight aiming at ensuring system-wide stability, policy-makers need a thorough information basis and a large variety of risk identification and assessment models and tools for data to become actionable information. Macroprudential oversight, while also requiring a large share of domain intelligence and plain analysis of statistical data, has its core in analytical models and tools for analyzing, summarizing and interpreting the widely available masses of data.

This chapter focuses first in Sect. 2.1 on the definition of financial systems and financial stability—or rather its antithesis, financial instability—as well as fragilities in financial systems and the concept of systemic risk. Section 2.2 briefly summarizes some theoretical and empirical underpinnings of three identified forms of systemic risk. Then, Sect. 2.3, and the main focus of this chapter, attempts to give an overview of the state of the art of risk assessment and identification tools used by macroprudential policymakers, especially the use of visualization tools. Finally, Sect. 2.4 relates the fragilities, risks and tools to the macroprudential oversight process, to be followed by a summary of key implications of this chapter for the rest of the book in Sect. 2.5.

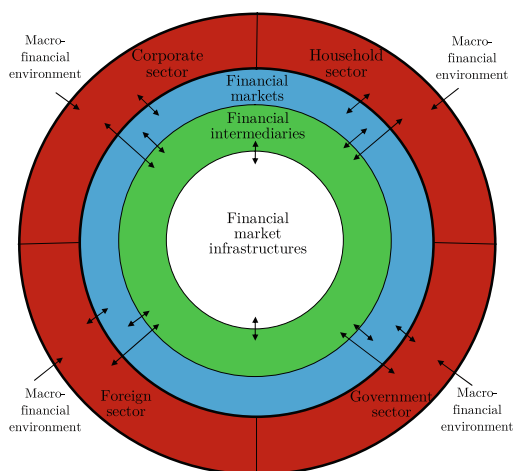
2.1 Financial Systems, Fragilities and Instabilities

Understanding the key concepts related to financial systems, and their (in)stability and fragility, is essential for a broader understanding of macroprudential oversight. This section presents some key principles of financial systems and defines the notions of stability and instability, as well as discusses why they are so fragile and what are the main risks to stability. Hence, this section provides a basis for the rest of the chapter, not the least by untangling systemic risks into three forms, to which we oftentimes refer in the sequel.

2.1.1 Key Components of Financial Systems

The basis for any discussion of financial fragilities, instabilities or risks ought to be an understanding of the notion of a financial system. Hence, the main questions are: *What is a financial system, which components does it comprise and how do they interact?*

Fig. 2.1 The financial system and its components. *Notes* The figure shows interrelations of the three components of the financial system: financial markets, intermediaries and market infrastructures. The figure is an adapted version of that in ECB (2012a) and follows the description in Fell and Schinasi (2005)



Broadly speaking, financial markets may be thought of as a mechanism for people to trade various financial securities, commodities and other fungible items at prices that reflect the markets. In a larger context, Schinasi (2004) summarizes the key functions of a financial system in fostering and supporting the real economy by matching investors with savers, allocating and pricing financial risks and resources and supporting various intertemporal economic processes like wealth accumulation, economic growth, and social prosperity. However, the functioning of financial systems is a multifaceted concept with multiple inter and intra relationships. Key components of financial systems, as well as their relationships, are illustrated in Fig. 2.1. As is pointed out in the figure, the financial system comprises three interrelated, yet separable, components [see, e.g., ECB (2005) and Fell and Schinasi (2005)]:

- (i) financial intermediaries (green layer);
- (ii) financial markets (blue layer); and
- (iii) financial market infrastructures (white layer).

Following the description in Fell and Schinasi (2005), entities of the household, corporate, foreign and government sectors (red layer) invest their savings and obtain funding for their activities through these three components. First, *financial intermediaries* comprise mainly financial institutions and have as their main task to pool risks and funds of one counterparty and allocate them to another. Financial institutions provide a wide range of services, in addition to those traditionally provided by banks. Depending on their profile, e.g., insurers, banks, pension funds, hedge funds and hybrids of financial and non-financial companies (e.g., General Electric) provide multiple different types of financial services. Second, *financial markets* mainly aim at matching those who need capital with those who have it (i.e., spenders with savers). The trading of financial securities (e.g., stocks and bonds), commodities (e.g., precious metals and agricultural goods) and fungible items in general occurs between people and firms, be they financial or not. For financial markets to support

the provision of credit, transfer of risk and risk management in general, it is crucial that they function smoothly and are resilient under various circumstances. Third, the *financial infrastructure* of the financial system is comprised of privately and publicly owned and operated institutions through which financial market operations are concretely carried out. The infrastructure may be provided by institutions like payment, clearing and settlement systems for financial transactions and other types of monetary, legal, accounting, regulatory, supervisory and surveillance infrastructures. Payment systems commonly transfer funds electronically from one institution to another, clearing systems commonly transfer credit risk in the derivatives market to a clearinghouse from each counterparty of a trade, and settlement systems complete transactions like securities trades. Thus, we herein follow Schinasi (2004) by defining the financial system as a term that encompasses “*both the monetary system with its official understandings, agreements, conventions, and institutions as well as the processes, institutions, and conventions of private financial activities*”.

While financial intermediaries connect to the financial architecture, the household, corporate, government and foreign sectors are connected both directly and indirectly to financial intermediaries, where financial markets may function as a middleman. Like private market participants, governments may borrow in markets and hedge risks. The working principles of the financial system, and the general performance of its key tasks, is based upon these components and their interrelations. Further, the external macro-financial environment will not only have a direct impact on private and public participants, but will also indirectly affect the functioning of financial markets and intermediaries, and in some cases even affect the design of infrastructures.

It is hence obvious to conclude that a resilient and well-functioning financial system is characterized by well-managed financial institutions and efficiently functioning financial markets, as well as by a strong and robust financial infrastructure. This might also be associated with less frequent and costly incidences of financial crisis. The fact that we have experienced frequent incidences of financial crisis does, however, indicate that financial institutions are not always well-managed, the functioning of financial markets may be inefficient, and the financial infrastructures may have cracks and weaknesses. Before discussing the reasons to this, we need a working definition of financial stability, particularly its antithesis.

2.1.2 Financial (in)stability

The term financial stability, not to paraphrase Justice Potter Stewart once again, belongs to the group of concepts that are broad and vague, yet implicitly understood. Still, we need to agree upon the definition of stable and unstable financial systems before delving into the causes of fragilities and risks. Coining financial stability with a commonly accepted and used definition has indeed been an elusive goal ever since it has shifted towards a common policy objective. In spite of numerous proposals, there is, as yet, no single, widely accepted definition for the concept.

Some define financial stability broadly, such as “*a condition where the financial system is able to withstand shocks*” (Padoa-Schioppa 2003), while others focus on situations when the financial system supports, rather than impedes, the functioning of the real economy [e.g., Schinasi (2004)]. However, guided by macroprudential thinking, with an aim to ensure system-wide stability, the definition of financial stability ought to be narrowed down along those lines. ECB (2009) provides a somewhat long, but descriptive definition of system-wide stability: “*a condition in which the financial system—comprising of financial intermediaries, markets and market infrastructures—is capable of withstanding shocks and the unravelling of financial imbalances, thereby mitigating the likelihood of disruptions in the financial intermediation process which are severe enough to significantly impair the allocation of savings to profitable investment opportunities*”.

Via its antithesis, Allen and Wood (2006) favor to define a financially stable system as simply one: “*which is not prone to episodes of financial instability*”. This leads to the question: What is financial instability? While being somewhat easier to define, also a broad variety of definitions of financial instability exist. We may want to call it “*a situation in which normal-sized shocks to the financial system are sufficient to produce financial distress*” (Borio and Drehmann 2009b) or “*any deviation from the optimal saving—investment plan of the economy that is due to imperfections in the financial sector*” (Haldane et al. 2004). From the sample definitions, it is easy to see the lack of unanimity with regards to these concepts.

Again, to meet the demands of a macroprudential approach, we narrow down from the broad concept of financial instability to systemic financial crises or strong systemic events. Such a crisis may be defined as an event that “*adversely affects a number of systemically important intermediaries or markets*” (ECB 2009). Rather than only being interested in the systemic events *per se*, an obvious central theme is to have an understanding of the underlying risk of experiencing a systemic financial crisis, i.e., systemic risks. In broad terms, systemic risk is defined as “*the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially*” (ECB 2009).

Now, when we have defined the concepts of a stable and unstable financial system, we can move forward in discussing what makes financial systems particularly fragile and what are the underlying risks to stability.

2.1.3 Fragility of Financial Systems

Any form of systemic risk, while having sources of its own kind, is most often preceded at an early stage by various market imperfections. Imperfections in markets may take the form of asymmetric and incomplete information, externalities and public-good characteristics, incomplete markets, etc., and are to some extent present in most economic sectors. However, the imperfections, when being related to a financial sector, may lead to significant fragility of not only individual entities,

but also the entire system (Carletti 2008; ECB 2009). Carletti (2008) illustrates the need for regulation of the banking sector with a large sample of examples of market imperfections, such as banks being exposed to deposit runs due to the maturity transformation by investing short-term deposits in long-term assets and informational asymmetries between depositors and borrowers, as well as debtholders and firm managers having so-called misaligned principal-agency problems, leading to agents not acting in the best interest of the principal. Another example is the parallel of financial stability to a public good and its absence to externalities like pollution, as each entity manages its own risks with no need to consider its impact on the system-wide risk as a whole. Bandt and Hartmann (2002) relate fragilities in financial systems to three causes:

- (i) the strong information intensity and intertemporal nature of financial contracts and transactions;
- (ii) the balance-sheet structures of financial intermediaries with a high reliance on debts or leverage, and maturity mismatches between assets and liabilities; and
- (iii) the high degree of interconnectedness between financial intermediaries and markets.

In the following, this subsection focuses on the above mentioned three main features behind the fragility of financial systems as identified by Bandt and Hartmann (2002).

First, the *information intensity and control intensity* relates to the fact that financial decisions concern intertemporal allocation of purchasing power [see, e.g., Stiglitz (1993)]. This relates to the issue of asymmetric information, in which lenders do not have full information about the intentions of the borrower, such as whether or not they are capable and/or willing to repay their debt. Likewise, the intertemporal nature leads to an inherent need for a lender to trust either the borrower to repay her debt or a third party to enforce the contract, not the least as the intertemporality leaves room for renegotiations of contracts. Thus, the decisions have their basis in whether the outcome of future asset values and future cash flows promised in contracts will meet expectations, such as is the case with deposit contracts. Another obstacle is changes in uncertainty affecting investment and disinvestment decisions [see, e.g., Shiller (1989)]. This leads, for instance, to substantial changes in asset prices not being explained by their fundamentals (e.g., companies' earnings and inflation rates are fundamentals to shares and exchange rates, respectively).

Second, the *maturity-mismatch structure of banks* is described by taking fixed-value deposits and enabling them to be withdrawn at a short notice, as well as by lending long term to the industry [see, e.g., Bryant (1980)]. When exceptionally high withdrawals occur and long term loans cannot be liquidated, the small fraction of held reserves may lead to insolvency. Hence, the strength of a bank depends on both the capability of lending to profitable investment projects and the confidence of depositors on the bank's loan book, as well as the confidence that other depositors will not run the bank. Yet, the better the deposit insurance scheme the less likely are confidence crises. While many fragilities relate to financial intermediaries in general, Goodhart et al. (1998) note that these types of confidence problems do most often

only apply to banks, except for cases when the non-bank intermediary is a part of the same entity as a bank.

Third, the complex *interconnectedness and network structure of banks* in particular and financial intermediaries in general implies that the failure of one bank may affect others [see, e.g., Humphrey (1986) and Folkerts-Landau (1991)]. Bandt and Hartmann (2002) relate the networks of real exposures among banks to consist partly of interbank lending and partly of those in wholesale and retail payment and settlement systems. While the aim of the interbank lending market is to provide a channel for short-term lending and borrowing to banks, a sudden low transaction volume in this market due to various reasons may lead to liquidity problems, such as during the financial crisis of 2007. Likewise, the exposures in payment and settlement systems may be large enough for a failure to meet payment obligations of one bank to impact the capability of other banks fulfilling their payment obligations. This could subsequently lead to failures spreading through amplified domino effects. However, the better the risk management measures, margin requirements and portfolio insurance, the more robust are payment and settlement systems (Bandt and Hartmann 2002).

These particularities support the role of governments and other supervisory authorities in addressing and monitoring systemic risks.

2.1.4 A Systemic Risk Cube

Above, we discussed systemic risk in broad terms, whereas the inherently complex issue can reasonably not be covered by such a simple definition. Hence, there is a need for a more precise and structured definition. To give some structure to the concept, the definition used herein is untangled with the help of the systemic risk cube (henceforth the risk cube) shown in Fig. 2.2. The risk cube presented here is an adapted version of that in ECB (2010). It represents the European Central Bank (ECB)'s conceptual framework for systemic risk and has its origin in the works by Bandt et al. (2009), ECB (2009), Trichet (2009) and ECB (2010). The sequel of this chapter is to a large extent guided by, and often paired with, the systemic risks identified through the risk cube.

Due to the great complexity of systemic risk, a virtue of the risk cube is that it not only helps untangling the forms of systemic risks, but also enables a subsequent mapping of them to the theoretical and empirical literature, as well as to analytical tools for identification and assessment of risks. The three dimensions of the risk cube are the *triggers*, *origins* and *impacts*. The nature of triggers unleashing the crisis could take the form of an *exogenous* shock, which stems from the outside of the financial system (e.g., a macro-economic shock and events like natural disasters or political turmoil), or could emerge *endogenously* from within the financial system or some other part of the economy (e.g., from financial intermediaries, markets and infrastructures). The origins of the events may be distinguished to limited *idiosyncratic* shocks and widespread *systematic* shocks. While idiosyncratic shocks

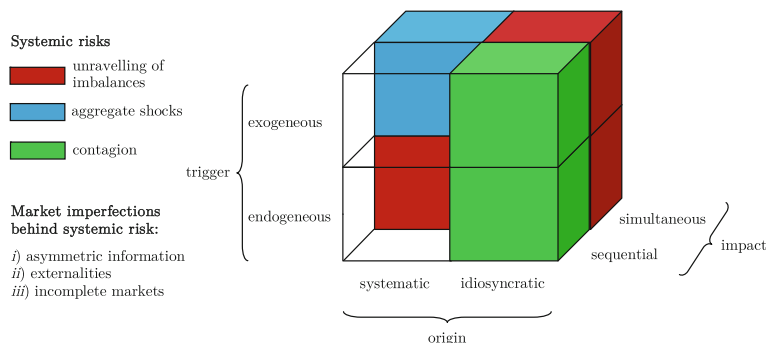


Fig. 2.2 Systemic risk cube with three forms of risks. *Notes* The figure represents the systemic risk cube with three dimensions and systemic risks, as well as possible market imperfections underlying systemic risk. It is an adapted version of that in ECB (2010)

are those that initially affect only the health of a single financial market, financial intermediary or asset, systematic shocks are those that, in the extreme, affect the financial system as a whole, such as the entire banking sector. Here, it is important to pay regard to the differentiation of the terms *systemic* and *systematic*. Bandt and Hartmann (2002) note that a systematic shock may cause a systemic event, but a systemic event does not need to have its origin in a wide systematic shock. Further, the impact of the events may be divided into those causing problems for a range of financial intermediaries and markets in a *sequential* and *simultaneous* fashion.

To reduce the complexity of the risk cube, combinations of its elements (the triggers, origins and impacts) may be limited to the materialization of three broad and interrelated forms of systemic risk (see Fig. 2.2):

- (i) endogenous build-up and unraveling of widespread imbalances (red boxes);
- (ii) exogenous aggregate shocks (blue boxes); and
- (iii) contagion and spillover (green boxes).

The first form of systemic risk refers to the risk that *widespread imbalances*, that have built up over time, *unravel abruptly*. The underlying problems are caused by an endogenous build-up of imbalances in one or several parts of a financial system, such as high concentrations of lending in certain parts of the economy or credit booms in general. While these imbalances, some may even say bubbles, may in the short term last with mainly profitable implications, a shock leading to a repricing of risk may be triggered by even a small event or change in expectations. This resembles Kindleberger's (1978) and Minsky's (1982) financial fragility view of a boom-bust credit or asset cycle. Hence, the subsequent abrupt unraveling of the imbalances may be endogenously or exogenously caused by idiosyncratic or systematic shocks, and may have adverse effects on a wide range of financial intermediaries and markets in a simultaneous fashion. Second, systemic risk may also refer to a widespread *exogenous aggregate shock* that has negative systematic effects on one or many financial intermediaries and markets at the same time. For instance, if banks go bad during recessions, they can be said to be vulnerable to economic downturns. The

third form of systemic risk is *contagion and spillover*, which usually refers to an idiosyncratic problem, be it endogenous or exogenous, that spreads in a sequential fashion in the cross section. For instance, a failure of one financial intermediary causing the failure of another financial intermediary, which initially seemed solvent, was not vulnerable to the same risks and was not subject to the same original shock as the former. It is worth noting that contagion refers to a situation when the initial failure is entirely responsible for subsequent ones, whereas the term spillover is commonly used when the causal relationship is not found or cannot be tested [see, e.g., ECB (2010)].

A categorization of systemic risks into the three forms provides means for a further discussion on the empirical and theoretical literature.

2.2 Theoretical and Empirical Underpinnings

This section draws upon the above defined terms and concepts. In light of the above discussion, the section reviews and discusses theoretical and empirical works on systemic risk. In both subsections, three parts match the identified forms of systemic risk. This chapter draws upon literature reviews in Bandt and Hartmann (2002), Bandt et al. (2009) and ECB (2009), in addition to a wide range of other sources to which in-text references are provided.

2.2.1 Theoretical Models

This subsection discusses the theoretical literature related to the three forms of systemic risk. While the literature is currently developing at a tremendous pace, many important older works continue to be relevant. We start by discussing the literature on lending booms and build-ups of imbalances that goes half a century back in time, then we focus on theoretical works on macroeconomic aggregate shocks to the economy, and finally on the literature on interbank contagion.

Endogenous Build-up of Widespread Imbalances

The notion of financial fragility and lending booms relates back to early work by Minsky (1977, 1982) and Kindleberger (1978), who pinpointed common historical reasons for financial crises to be the endogenous build-up and abrupt unraveling of widespread imbalances. The early authors explain the boom and bust cycle as follows. The imbalances oftentimes derive from the pro-cyclicality of financial behavior; in good times consumption and investment increases, which generates income, and further fuels consumption and investment. During this time of “euphoria” and “gregarious behavior”, the financial activities become more speculative, or even so-called

Ponzi finance, in which a lack of expected income flows causes a reliance on the rise of market value of assets or income to pay off interest or principal. In this “virtuous” circle, risks are often neglected with mainly profitable implications in the short term. Then, even a small trigger, shock, change in expectations, or other type of event, be it exogenous or endogenous, may lead to a repricing of risk, an end of the boom, unraveling of imbalances and possibly simultaneous adverse effects to intermediaries and markets. This event may even be called a Minsky moment—a term coined by the managing director of PIMCO, Paul McCulley, in 1998 when describing the Asian financial crisis. The early literature has its core in uncertainty rather than only risk, such as the discussion on the relation between Knightian uncertainty and investment returns and risk premiums in Guttentag and Herring (1984). The same authors also explain disaster myopia by subjective probabilities of disastrous events diminishing when time elapses after the previous realization of such an event. The here described characteristics of a financial stability cycle emerges, according to the early authors, endogenously in economies with particularly unregulated financial markets.

There are a number of reasons to the build-up of imbalances, of which four key notions are summarized, as is categorized in ECB (2009). *First*, financial markets are inherently featured by herd behavior, leading to entities sharing similar risks. Banerjee (1992) and Bikhchandani et al. (1992) describe these as rational herding waves, if relative returns of investments are highly uncertain. Likewise, the herding by Scharfstein and Stein (1990) involves investment or fund managers and loan officers that mimic each other when they are evaluated, which steers pay or reputation, in relation to the rest of the market. *Second*, the so-called curse of low interest rates may diminish incentives to screen borrowers when interest rates are low [see, e.g., Dell’ariccia and Marquez (2006)]. Low interest rates over a wide maturity spectrum have more often than not been quoted as an element of the imbalances prior to the current crisis. Another obvious channel is an increase in collateral values, such as real estate prices, when interest rates are low. For further discussions on the effect of low rates on crises, see Allen and Gale (2007). *Third*, positive shocks to collateral, while enhancing the borrowing capacity in an economy, may also contribute to leverage cycles (Kiyotaki and Moore 2002). When an industry, or another industry with similar collateral, benefits from an increase in collateral value, it also allows more borrowing and investment, and thus further amplifies leverage. Likewise, Geanakoplos (2010) asserts that variation in leverage impacts volatility in asset prices and thus contributes to financial booms and busts. He explains it by there being high-leverage buyers for whom an asset is more valuable than it is for others, for instance, due to them being more sophisticated investors, better in hedging exposures to the assets or less risk averse. This drives prices up, whereas losses in wealth will, due to leverage, move the assets into more pessimistic hands, which again amplifies the decrease in value. *Fourth*, risk-taking and moral hazard may also be amplified by better safety net provisions. One example is a decrease in depositors’ incentives to screen bank risks through deposit insurance [see, e.g., Boot and Greenbaum (1993)]. Similar effects can be derived from public bailouts or lenders of last resort, that is, an institution providing credit in the lack of other sources and with the aim of preventing failures of important institutions.

Exogenous Aggregate Shocks

It is no new notion that macroeconomic shocks or economic downturns have been a trigger of many historical financial crises [see, e.g., Gorton (1988)]. Yet, the theoretical literature directly addressing the topic is somewhat scarce. Even though direct interbank connections and contagion is missing, banking crises have still occurred simultaneously with aggregated shocks. Banks may be seen as vulnerable to aggregated shocks as credit risks occur on the asset side while liabilities are most often unaffected. A key point by Hellwig (1994) is that the effect of macroeconomic shocks would be decreased by letting liabilities be dependent on the macroeconomic state and depositors share the burden of asset losses. Still, banks expand credit, relating to the above discussed lending booms, while knowing that the risks may lead to problems as banks cannot pass on the risk to depositors. In individual bank models, any information on the macroeconomic state provides a signal about the quality of banks' loans to depositors. Accordingly, Allen and Gale (1998) show that macroeconomic shocks may lead to a banking crisis if depositors make their withdrawal decisions based upon leading indicators of business cycle fluctuations. Likewise, Chen (1999) illustrates in his model that adverse macroeconomic events also increase the probability of bank contagion. One may also assert the reverse when the business cycle is affected by restrictions in bank lending caused by financial fragility (Mishkin 1991).

Contagion, Spillover and Shock Propagation

A common feature of financial instabilities, in particular banking crises, is the notion of contagion. There is a rich and broad literature on the phenomenon. The theoretical literature may be distinguished into three types of contagion: (i) bank runs, and (ii) contagion through interbank lending and (iii) payment systems. This relates to two types of transmission channels. The first type of contagion can be defined to occur through the *information channel*, such as deposit withdrawals of creditors to whom the health and exposures of banks are imperfect, whereas the two latter types occur through *real channels*, such as domino effects through common exposures in inter-bank markets and payment systems.

The first type of contagion is related to *bank runs*. These events are mostly characterized by two features. First, the most prone banks and banking systems to runs to retail depositors are those not covered by deposit insurance schemes. Second, imperfectly informed investors judge the health of their own bank based upon the health of other banks. There is a wealth of literature on single banks' health based upon the balance-sheet structure and the intertemporal nature of financial contracts (as previously noted in Sect. 2.1.3), such as Bryant (1980), Diamond and Dybvig (1983) and Jagannathan (1988). The classical Diamond-Dybvig model illustrates how depositors' expectations of a bank run increase their incentives to withdraw their deposits, as late withdrawers lose all or some of their deposits. However, today's thorough deposit insurance schemes function as safety nets for this type of contagion, which might be one of the main reasons why recent waves of crisis have not, as yet,

experienced this transmission channel. Hence, it is important to distinguish between the notions of a bank run affecting one entity and a banking panic affecting multiple entities, i.e., the systemic nature of runs.

Bank run models have, accordingly, been extended to multiple banks. Chen (1999) presents an extension of the Diamond-Dybvig model, where the difference is that Chen includes two kinds of depositors: those who are informed and uninformed about the value of a bank's assets. As informed depositors are able to withdraw earlier when they comprehend that the bank cannot repay all depositors, the uninformed depositors may have an incentive to disregard their own information and respond to other sources of more noisy information (e.g., the failure of other banks). These misinterpretations may cause bank runs to become contagious. One might also reason that bank runs based upon noisier information incur higher societal costs as it might lead to defaults of healthier banks than those caused by expectations based upon correct information.

The second type of contagion focuses on the *interbank market*. This has also been a key focus of many contagion studies since the 1990s. While differences in liquidity shocks may be solved through interbank lending, the physical exposures among banks provide a channel for contagion. For instance, Rochet and Tirole (1996) show that peer monitoring, while resolving problems with moral hazard among bank shareholder managers and bank debt holders, also causes contagion risk. Along the same lines, Allen and Gale's (2000) model of interbank market exposures shows that even a small aggregate liquidity shock in a particular region can lead to systemic risk. A bankruptcy of one bank may cause other banks, which have deposits in it, to also go bankrupt. The key implication of many studies, yet not all, is that the more complete, or diversified, the markets in terms of lending relationships, the more resilient to contagion is the system.

More recent research has applied network theory to model connections between banks in the asset and liability side of the balance sheet. For instance, the findings of Babus (2006) corroborate those of Allen and Gale (2000) by considering optimal interbank network formations to reduce the risk of contagion. Leitner (2005), on the other hand, finds that the more interbank linkages a network exhibits, the better the risk sharing among banks, while the higher the potential for contagious multiple-bank failures. Conversely, emergency liquidity assistance by central banks may be motivated by surplus banks in the interbank market under-providing banks with a cash shortage, as suggested in Acharya et al. (2012). Further, already early literature has pointed out potential effects of information problems on interbank contagion. For instance, Flannery (1996) relates asymmetric information to interbank contagion through imperfect information on the quality of rivals' borrowers. A shock to the financial system may hence lead to a stop in interbank lending and hoarding of liquidity, something related to the recent crisis by Cassola et al. (2008).

The third type of contagion relates to *payment systems*. The interbank lending between financial intermediaries is determined by large-value payment systems. The lending through payment systems, while not being as explicit as interbank lending, is a more detailed view of interbank exposures that may influence the propagation of shocks. From the larger family of payment systems, the main source of systemic risk derives from pure net settlement systems as netting of payments and infrequent

settlements may continue for a longer time, such that they accumulate to significant exposures [see, e.g., Freixas and Parigi (1998)]. Kahn et al. (2003) relate vulnerabilities of gross settlement systems to gridlocks and payment delays. The problems in pay-ins may be driven by high opportunity costs in foregone interest rate and doubts about other banks' solvency.

2.2.2 Empirical Findings

Next, we survey empirical works with a focus on explaining the three forms of systemic risks. The main focus lies on comparing the scope of the theoretical studies to the evidence provided by empirical studies.

Endogenous Build-up of Widespread Imbalances

The build-up phase of widespread imbalances and the relation between a financial system's pro-cyclicality and fragility is, due to numerous reasons, not an entirely straightforward question. This is illustrated by a multifaceted literature. Gourinchas et al. (2001) point to the importance of lending by showing in a large cross-country study that the likelihood of a banking crisis is higher directly after a lending boom than during tranquil periods. Likewise, findings by Dell'ariccia et al. (2012) and Mian and Sufi (2009) suggest that lending standards related to the mortgage market in the US declined prior to the ongoing financial crisis, in particular in areas with larger mortgage credit booms, house price booms and mortgage securitization rates. However, a key monetary policy tool that obviously plays a vital role in pro-cyclicality is the interest rate. Jiménez et al. (2007) and Ioannidou et al. (2009) find that reductions in interest rates often first affect positively the net present value of loans, but then with low loan rates banks attempt to re-establish profitability by moving into riskier loans. These risks, while often having somewhat long build-up episodes, may materialize suddenly and strongly either to rises in interest rates or some other unexpected trigger. Another factor leading to pro-cyclical effects is financial regulation. Repullo et al. (2010) illustrate the pro-cyclicality through capital requirements that are increasing functions of various regulatory measures of default likelihood, which often affect the the supply of credit by decreasing in good times and rising in bad times.

Another line of research has focused on the determinants of banking crises through the analysis of univariate indicators (i.e., the so-called signaling approach) and multivariate regression. In general, periods prior to systemic banking crises have been shown to be explained by traditional vulnerabilities and risks that represent imbalances like lending booms. By an analysis of univariate indicators, Alessi and Detken (2011) show that best-performing indications of boom/bust cycles are given by liquidity in general and the global private credit gap in particular. Borio and Drehmann (2009a) show that banking crises tend to be preceded by strong deviations of credit

and asset prices from their trend. Likewise, in a multivariate regression setting, vulnerabilities and risks have, overall, been shown to precede country-level crises on a large sample of developed and developing countries in Demirgüç-Kunt and Detragiache (1998) and for the US, Colombia and Mexico in Gonzalez-Hermosillo (1999), as well as on a bank level in Eastern European transition economies in Männasoo and Mayes (2009). Borio and Lowe (2002) and Borio and Lowe (2004) show that already several years prior to the current financial crisis a lending boom was awaiting behind the corner if not already visible. Lo Duca and Peltonen (2013) show that modern financial crises have been preceded by a range of macro-financial vulnerabilities and risks, particularly credit growth, equity valuations and global measures like GDP growth, real credit growth and leverage. This only provides a snapshot of the broad literature, but clearly illustrates the unanimity of imbalances preceding modern financial crises.

Exogenous Aggregate Shocks

Aggregate shocks in terms of economic downturns have commonly been shown to precede systemic banking crises. Gorton (1988) shows that a large share of banking crises in the US in the latter part of the 19th and the early part of the 20th century occurred as reactions of depositors to cyclical downturns and could hence have been correctly called with a standard model for forecasting the business cycle. While partly being related to the literature on the build-up of imbalances, systemic crises may be explained with traditional macroeconomic fundamentals (e.g., current account imbalances, gross domestic product (GDP) growth, real interest rates and inflation). Macroeconomic fundamentals have been shown to be statistically significant explanatory variables on a sample of the United States (US), Colombia and Mexico (Gonzalez-Hermosillo 1999), the Eastern European transition economies (Männasoo and Mayes 2009) and European banks during the ongoing crisis (Betz et al. 2014). These studies have, however, long forecast horizons, which relates them to imbalances and vulnerabilities prior to the crises. Yet, a number of authors show that also the timing of banking crises is related to macroeconomic fluctuations, rather than other competing factors, such as contagion. Gorton (1988) illustrates evidence for the US, Gonzalez-Hermosillo et al. (1997) for the Mexican crisis of the mid-1990s and Demirgüç-Kunt and Detragiache (1998) for a sample of developed and developing countries. Further, whereas Alfaro and Drehmann (2009) show that a large number of banking crises were preceded by decreases in GDP growth, the share that do not experience weakened GDP points at other driving factors, e.g., macroeconomic feedback effects due to the fact that GDP generally drops during post-crisis episodes.

While extreme value theory is mostly used to understand the third category of systemic risk, the study of interbank contagion, it may also be used to compute so-called tail-betas for banks. Given an extreme crash in the market, the tail-betas illustrate how the probability of crashes in individual bank stocks would be influenced. The significance of aggregate shocks in stock markets in the US (Straetmans et al. 2008)

and Europe (de Jonghe 2010) relates this to the concept of systemic risk. In European context, de Jonghe (2010) finds that banks with a large share of non-interest generating activities are more vulnerable to these aggregate shocks. Further, a comparative analysis of the shocks in the two continents is put forward by Hartmann et al. (2005). They find the effects of macro shocks on banking systems to be relevant, but similar, in the euro area and the US. Interestingly, they also show that the introduction of the euro had close to no effect on banking system risk, and relate it to the possibility that the better risk sharing and ability to absorb shocks would be offset by increases of cross-border crisis transmission channels.

Contagion, Spillover and Shock Propagation

In the early contagion literature, the main attempts were related to measuring contagious effects of bank failures on stock prices of other entities. In addition to those studies, the empirical literature on measuring interbank contagion can be matched to the three types of theoretical works: *bank runs*, *interbank lending* and *payment systems*.

Early studies have attempted to capture contagion through variation in stock prices, e.g., by measuring effects of bank failures on stock prices of other entities using event studies. Aharony and Swary (1983) and Peavy and Hempel (1988) focused on (US) banks, and their resilience to a number of failures. However, many pieces of work along this line [see, e.g., Slovin et al. (1993) and Dockinga et al. (1997)] found mixed results on contagion effects depending on the considered banks. The concept of contagion in terms of adverse stock market reactions also has been asserted as being intertwined with flight-to-quality effects, where losses of someone are benefits of others [see, e.g., Caballero and Kurlat (2008)], and to similar exposures rather than pure interbank contagion [see, e.g., Smirlock and Kaufold (1987) and Wall and Peterson (1990)]. One explanation to the mixed results might be typically observed differences in patterns during tranquil and crisis periods, where crises include non-linear and extreme stock-price movements. Hence, the more recent literature has turned the focus from regular stock price reactions to substantial ones. One potential line of research is the use of extreme value theory to estimate the spillover risk among large and complex banks [see, e.g., Hartmann et al. (2005)]. The findings of Gropp et al. (2009) illustrate that cross-border contagion risk among key European countries was significant and increased between the early 1990s and early 2000s. Yet, the focus herein is on matching the empirical works to the three groups of theoretical studies.

The first group of models based upon theoretical research aiming at capturing contagion through *bank runs* focuses on analyzing deposit flows. When there is no deposit insurance, such as during the Great Depression in the US, Saunders and Wilson (1996) have identified episodes when “bad news” about one bank caused on some occasions withdrawals from other banks (i.e., herding behavior), and on other occasions depositions in other banks (i.e., flight-to-quality effects). The results of Calomiris and Mason (1997, 2003) show equally divisive results, as they observe

contagious behavior of uninformed investors on some occasions and not on other. Allen and Gale's (2000) assertion of interbank lending explaining contagious deposit withdrawals is corroborated in a case study on an Indian bank failure in 2001 by Iyer and Peydró (2011). They show that interbank exposures to a failing bank drive retail deposit withdrawals from the exposed banks. Likewise, Van Rijckeghem and Weder (2003) test in an international context the directions of bank flows during three major financial crises. After the Mexican crisis in the mid-1990s and the Asian crisis in the end of the 1990s, the authors show that spillovers from one country to another was caused by creditor banks' exposures, whereas not during the Russian crisis in 1998.

The second group of contagion models focuses on using counterfactual simulations on balance-sheet data to assess contagion risk through the channel of *interbank lending*. The network exposures are most commonly balance-sheet linkages and the simulations often test the effects of a failure of one or several banks on the rest of the network. The simulations are, however, somewhat sensitive to underlying assumptions like the share of recovered assets from failed banks. Accordingly, the literature has presented far from unanimous results, as simulated contagion risk is negligible in Austria, Belgium, Italy and US (Elsinger et al. 2006; Furfine 2003; Mistrulli 2011), whereas the risks are larger in Germany and the Netherlands (van Lelyveld and Liedorp 2006; Upper and Worms 2004).

The third group of contagion models focuses on using simulations in large-value *payment systems* to assess interbank contagion risk. Contagion in payment systems has been explored through similar simulations. Using payment data and Monte Carlo simulations, the early literature has identified significant contagion risks in net settlement systems [see, e.g., Humphrey (1986)]. However, given appropriate risk management in payment systems (e.g., legal certainty for multilateral netting, limits on exposures, collateralization and loss sharing), some later studies have shown that interbank contagion risk may be contained. Soramäki et al. (2007) explore the network topology of the interbank payments over the Fedwire Funds Service, the payment system operated by the 12 Federal Reserve Banks of the US. Whereas they show a low average path length and connectivity for the network, as well as a tightly connected core of banks and a close to scale free degree distribution, they still point out that it is not clear how the degree distribution and other topological measures relate to contagion. Wetherilt et al. (2010) make use of a dataset of individual trades in the United Kingdom (UK) Clearing House Automated Payment System (CHAPS) to construct a network of overnight market lending. They illustrate a diversification of lending relationships that decreases their dependence on the core during the crisis, in order to attempt reducing funding liquidity risk, but make no direct conclusions about overall resilience of money market liquidity. Further, using data from the pan-European large-value payment system (i.e., the Trans-European Automated Real-time Gross Settlement Express Transfer System (TARGET)), Galos and Soramäki (2005) illustrate low systemic consequences of one bank's failure on the solvency of other banks. This indicates that today's payment systems exhibit a low risk of having systemic consequences.

2.3 Tools for Safeguarding Financial Stability

The literature, while in many aspects being in its infancy, has provided a variety of tools for safeguarding financial stability. This section focuses particularly on tools for early identification and assessment of risks. Following ECB (2010), models can be distinguished into three broad analytical approaches that match the identified forms of systemic risks:

- (i) early-warning models,
- (ii) macro stress-testing models and
- (iii) contagion and spillover models.

While the first approach aids in *risk identification*, the second and third approaches provide means for *risk assessment*. From the viewpoint of the risk cube (see Fig. 2.2), each of these aim to detect at an early stage one of the three forms of systemic risk: (i) imbalances, (ii) aggregate shocks and (iii) contagion. First, early-warning models can be used to derive probabilities of impending systemic financial crises. Second, macro stress-testing models provide a means to assess the resilience of the financial system to a wide variety of aggregate shocks. Third, contagion and spillover models can be employed to assess how resilient the financial system is to cross-sectional transmission of financial instability. In addition to models for early identification and assessment, the literature has provided a large set of coincident indicators that measure the current state of instability in the financial system. While these serve as means to measure the contemporaneous level of systemic risk, and thus may be used to identify and signal heightened stress, they are not designed to have predictive capabilities. This is not the focus of this book, but it is worth noting that *ex post* measures may serve a function in communicating the occurrence of unusual events to resolve fear and uncertainty, e.g., after the so-called flash crash of May 6, 2010 in the US (Bisias et al. 2012). In the sequel of this section, we focus on the three analytical approaches to derive tools for early identification and assessment of risks. In line with the focus of this book, the final subsection summarizes advances in visualization approaches in both risk identification and risk assessment.

2.3.1 Early-Warning Indicators and Models

Early-warning exercises may be performed with a wide range of methods and indicators, which are also known in the literature as Early Warning Systems. The main aim of these tools is to predict vulnerable states prior to financial instabilities and crises. Hence, they oftentimes first define an index of financial instability or stress in an entity, e.g., country, bank or market. The contemporaneous level of systemic risk may, for instance, be derived from coincident stress indices, such as the Composite

Indicator of Systemic Stress (CISS) by Holló et al. (2012).¹ A threshold, or some combination with other rules, on the index value defines binary crisis/tranquil events for the entities. For the models to focus on imbalances, risks and vulnerabilities, a binary pre-crisis variable is then set to 1 during some specific horizon prior to the crisis events, and to 0 in all other periods. The other part of data used is a set of vulnerability and risk indicators. These are chosen and transformed according to their performance in explaining and predicting the binary pre-crisis variable. The outputs of such models mostly take the form of a probability of a crisis within a specific time horizon and are monitored with respect to threshold values (or cut-off values).

The early univariate signaling literature used country-specific percentile transformations of single indicators and turned them into signals by choosing an optimal threshold. The optimal threshold is commonly chosen based upon specified weights on the loss of type I and II errors (see Sect. 7.2 for an overview of evaluation frameworks and the one used in this book). Kaminsky and Reinhart (1996) and Kaminsky et al. (1998) introduced the signaling approach for predicting currency crises. Lately, it has been applied to boom/bust cycles (Alessi and Detken 2011), banking system crises (Borio and Drehmann 2009a), and to sovereign debt default (Knedlik and Schweinitz 2012). However, the key limitation of this approach is that it does not enable any interaction between or weighting of indicators, while an advantage is that it demonstrates a more direct measure of the importance and provides a ranking of each indicator.

Much of the early-warning literature deals, however, with models that rely on conventional statistical methods, such as logit/probit models. Logit or probit regressions use on the left-hand side the binary pre-crisis variable and on the right-hand side the early-warning indicators. The linear regression models make use of a cumulative probability function to force the value of the predicted variable within the interval $[0, 1]$. This estimation provides a direct aggregate measure of the intensity of the signal, i.e., the probability of an impending crisis. The two models are similar, except that the probit model uses the cumulative normal distribution and the logit the cumulative logistic function to transform variables into the $[0, 1]$ interval. Logit and probit models have frequently been applied to predicting financial crises. Eichengreen and Rose (1998), Frankel and Rose (1996) and Sachs et al. (1996) provide some early applications of probit/logit analysis to currency crisis prediction. Later, Berg and Pattillo (1999) apply a probit model to predicting currency crises; Schmidt (1984) and Fuertes and Kalotychou (2006) to predicting debt crises; Barrell et al. (2010) to predicting banking crises; and Lo Duca and Peltonen (2013) to predicting systemic crises. For an early, yet comprehensive, review, see Berg et al. (2005).

In comparison to the signals approach, binary-choice methods allow for a multivariate approach to estimating crisis probabilities, while providing means to rank

¹ There are many coincident stress indices. For instance, Illing and Liu (2006) focus on measuring financial stress in Canada and Hakkio and Keeton (2009) discuss more broadly what financial stress is, how it can be measured and why it matters. Cardarelli et al. (2011) and Balakrishnan et al. (2009) construct financial stability indices for a broad set of advanced and emerging economies, whereas the CISS aims at measuring stress in the euro area.

risks and assess most significant indicators, but still depend largely on a number of restrictive assumptions. While being non-linear in nature, the relationship between indicators and the events is still assumed to consistently follow some specific function (e.g., logistic or normal). Further, the lack of interactions between indicators may also limit performance as indicators of debt, currency, and systemic crises have been shown to be non-linearly related (Fioramanti 2008; Lo Duca and Peltonen 2013; Arciniegas Rueda and Arciniegas 2009). While interaction terms can be included in logit/probit specifications, manually specifying the complex relations between and interactions among various economic and financial factors is a demanding task. This should be accounted for when choosing a predictive method.

A new approach to early-warning modeling has been the introduction of methods commonly used in subfields of computer science, such as data mining, machine learning and pattern recognition. Since the turn of last century, the use of such intelligent, oftentimes also distribution-free and non-parametric, techniques in crisis monitoring have increased. Indeed, the flexible non-parametric techniques have slightly improved results in *ex post* crisis prediction [see Demyanyk and Hasan (2010) for a review]. The key methods in non-parametric early-warning models have so far been based upon biologically inspired computing in general and artificial neural networks (ANNs) in particular (Nag and Mitra 1999; Franck and Schmied 2003; Peltonen 2006; Fioramanti 2008). The first to publicly try predicting financial crises with the help of an ANN were Nag and Mitra (1999). Their findings on predicting the Malaysian, the Thai and the Indonesian currency crises suggested that their ANN approach performed better than the signaling approach. Similarly, Franck and Schmied (2003) also concluded that their application of an ANN for predicting the speculative attacks in Russia in 1998 and Brazil in 1999 outperformed a logit model. Peltonen (2006) used an ANN to predict the Asian currency crisis and showed that it outperforms a probit model. Fioramanti (2008) shows in his study that a non-parametric ANN-based early-warning model outperforms analyses using the signals approach and probit or logit models. Yet, when the focus is on the introduction of one specific method, it is important to note that mostly “successful” experiments are reported.

A task that remains to be unexplored is the choice of indicators in the models. A large number of studies use univariate predictive performance in terms of the signaling approach to assess the extent of discriminatory power of individual indicators [e.g., Kaminsky et al. (1998), Alessi and Detken (2011) and Lo Duca and Peltonen (2013)], of which Lo Duca and Peltonen (2013) use the best predictors as an input to a logit regression. Still, due to the possibly complex interactions, the choice of indicators should be performed in a multivariate setting.

2.3.2 Macro Stress-Testing Models

The key family of tools for assessing risks of exogenous aggregate shocks is that of macro stress-testing models. Hence, while the above discussed tools aim at

risk identification, the tools for risk assessment are literally of different nature. Stress-testing models allow policymakers to assess the consequences of assumed extreme, but plausible, shocks for different entities. As stress-testing is no new concept, there is a broad literature not only on micro stress-testing, but also on the macro level. While being macro stress-tests, they commonly follow many principles used in micro stress-testing and risk management to assess the loss potential of specific portfolios given extreme market conditions [see, e.g., McNeil et al. (2005)]. Kida (2008) pinpoints the differences between micro and macro stress-testing to three key factors. First, macro models commonly include multiple banks with different portfolios, where differences affect how resilient one bank is to shocks and how shocks to one bank affects the system. Second, macro models oftentimes include multiple time points by enabling shocks to propagate for several periods. Third, a macro stress-test focuses on how risk is propagated between banks or between sectors. The recent handbook edited by Quagliariello (2009) provides a comprehensive overview of the macro versions of such models.

The key question of macro stress-testing, or stress-testing in general, is finding the balance between plausibility and severity of the stress scenarios such that they are plausible enough to be taken seriously and severe enough to be meaningful [see, e.g., Alfaro and Drehmann (2009) and Quagliariello (2009)]. Then, the assessment of shocks most often includes also the propagation of the shock among entities. Kida (2008) pinpoints the feedback (or risk transmission and propagation) mechanisms into four key types: (i) interbank contagion (e.g., when exposures to risk spread through the interbank loans market), (ii) correlation between credit and market risks (e.g., when increases in interest rates raise the probability of default of borrowers of a bank, and causes thus also increases in interest rates), (iii) correlation between asset prices and the portfolio adjustment mechanisms of a bank (e.g., when increases in asset prices damage banks' balance sheets, leading to large-scale sales of assets, and thus further decreasing asset prices), (iv) propagation of shocks between the financial system and the real economy (e.g., when banking system shocks affect economic activity, and thus further weaken banks' credit environment). Contrary to the early-warning model literature, stress-testing does not attempt to derive the likelihood and severity of shocks, but rather takes that as given. This information could, obviously, come from an early-warning indicator or model. In a macro setting, a policymaker is more interested in the resilience of the financial system more broadly, or the banking system in particular. Policymakers may hence test various adverse scenarios and design policy actions related to individual institutions or the general architecture if the resilience of the system is judged not to be strong enough.

A macro stress-testing approach to assessing a banking system uses multiple inputs and consists of a number of different steps. First, most often a basis for the test is a scenario of an adverse aggregate macroeconomic or macro-financial shock. This shock may be defined on hypothetical grounds or estimated from data, such as a tail density forecast of a macroeconometric model. The second step uses a set of exposures and other mechanisms to link banks to the impact of the adverse scenario. The links may be banks' loan books or other credit risk exposures of a bank or a country-level banking system. Thus, the effects of the scenario are shown as changes

in the probabilities of default and losses given default, and also lead to indications of whether and how many banks fail [see, e.g., Castrén et al. (2009)]. Likewise, Castrén et al. (2010) estimate a so-called global vector autoregressive model and link it to firms' default probabilities for a model that may be used for analyzing a financial sector's probability of default given a range of macro shocks. Alfaro and Drehmann (2009) use country-specific univariate autoregressive models to forecast GDP growth, but focus more on showing that stress scenarios derived from historical data are not severe enough in comparison to actual events. Hirtle et al. (2009) describe the stress-testing model of the Supervisory Capital Assessment Program, which tests a range of macroeconomic scenarios, e.g., variation in GDP growth, housing prices and unemployment. For comprehensive reviews of the stress-testing literature, see Sorge (2004) and Drehmann (2009).

2.3.3 Contagion and Spillover Models

The main aim of contagion models is to assess the transmission of financial instabilities in the cross section. Hence, they attempt to answer the question: *With what likelihood, and to what extent, could the failure of one or multiple financial intermediaries cause the failure of other intermediaries?* Further, they may also focus on the failure of one or several financial markets and their likelihood to cause failures of other markets. Thus, contagion and spillover models attempt to grasp, show and quantify the transmission channels of instability across financial intermediaries and markets, as well as market infrastructures [(for comprehensive reviews, see Bandt et al. (2009) and Upper (2007)]. Herein, we discuss the use of three data sources to answer these questions: (i) market-based data, (ii) interbank balance-sheet data, and (iii) interbank payments data.

First, one can use *market-based estimates* to measure the extreme dependence of negative asset returns, the so-called tail dependence. The first approach measures the extent of losses, after controlling for common factors, caused by a large loss of market value or a large increase in default probability. These approaches commonly identify tail-risk drivers in a tail-dependence network and enable assessing which entities are particularly vulnerable to large losses in the market. For instance, IMF (2009) presents a co-risk model for assessing interdependence among banks under extreme events and a distress dependence matrix for assessing pairs of banks' distress probabilities, both using market data. Likewise, Hautsch et al. (2011) propose the systemic risk beta as a measure for financial companies' contribution to systemic risk given network interdependence between firms' tail risk exposures measured using equity prices. While being widely available and capturing other contagion channels than those in direct linkages between banks (Acharya et al. 2010), market price data assume that asset prices correctly reflect all publicly available information on bank exposures. Yet, it has repeatedly been shown that securities markets are not always efficient in reflecting information about stocks and are thus vulnerable to mispricing distortions [see, e.g., Malkiel (2003)]. In addition, market prices are most often

contemporaneous, rather than leading indicators, and it might be difficult to separate the factors driving market prices in order to observe bilateral interdependence (Borio and Drehmann 2009b).

The second approach, on the other hand, uses counterfactual simulations on *balance-sheet data*, or some proxy of them. These studies simply simulate to what extent and whether the failure of one financial intermediary would lead to losses of other intermediaries. For instance, Castrén and Kavonius (2009) provide a tool for assessing contagion and the transmission of risk in the euro area financial system. They construct a sector-level network of bilateral balance sheet exposures of the euro area financial accounts data, as well as include sensitivity of the balance sheets to changes in leverage and asset volatility, to illustrate the propagation of local shocks in the network. Likewise, Chan-Lau (2010) evaluates, under extreme adverse scenarios, interconnectedness risk in banking systems among mature and emerging market economies, and between individual financial institutions in Chile, using balance sheet-based network analysis. Along these lines, Battiston et al. (2012) developed a network measure of centrality, the DebtRank, as one approach to capture the impact of distress in a financial institution to the cross section across the entire network. Moreover, the IMF (2009) presents a default-intensity model that uses both direct and indirect linkages in the financial sector, as well as combines them with failure probabilities of banks, to achieve a measure of the probability of failure of a large fraction of financial institutions. Yet, balance-sheet data, while measuring direct linkages between banks, are mostly not publicly disclosed. In many cases, even supervisors and other market oversight authorities have access to only partial information.

The literature on the third group of models focusing on *payments data* is somewhat scarce. A concern once again is that interbank payment data, likewise interbank lending data, are locked behind the doors of confidentiality. Yet, while not always making use of real data, there exist some tools based upon payments data. In particular, the three compilations edited by Leinonen (2005, 2007, 2009) provide a broad overview of policy-oriented research on tools for payment systems simulation. Recently, along the lines of DebtRank for balance-sheet data, Soramäki and Cook (2010) developed a network metric for payments data, the SinkRank, for identifying systemically important banks and most affected banks in the case of distress.

2.3.4 Tools With Visual Capabilities

Data visualization can serve multiple purposes in macroprudential oversight. First, visual representations can generally be classified to be used to enhance communication with two audiences: (i) internal and (ii) external. The purpose of use in *internal* communication relates to enhancing the understanding of policymakers on various levels. One task is obviously to support the analysts themselves, and within other groups of active participants in the process of deriving analytical models. Further, one may also want to communicate to the outside of the involved counterparties,

which involves making use of visuals when presenting to the management, entire divisions and even on the level of the institution or organization as such. The key task, at the lower level, is to provide means for interaction with visuals in order to amplify cognition, that is, to better understand and model the task at hand (for further discussion see Sect. 4.1), whereas the higher level focuses more on reporting and presentation of information by the means of oftentimes static visuals. While the case of low-level analysts can easily be imagined, an example at a higher level could be the dissemination of identified risks by the risk identification division for assessment at the risk assessment division. *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. Whereas this mainly relates to communication of readily processed and finalized data products, such as on the high level of internal communication, it obviously is a more challenging task due to the large heterogeneity in the audience. A direct example of such communication is quarterly or biannual Financial Stability Reports, a recent phenomenon that has quickly spread to a large number of central banks.

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 (see Sect. 4.1.3). Ekholm (2012)—the Deputy Governor of Sveriges Riksbank, the first central bank to publish a stability report in 1997—notes that there is a strive for not only openness and transparency, but also clear external communication, in particular during times of crisis when *“a ‘negative’ but reliable announcement can [...] be better for confidence than a ‘positive’ but uncertain announcement”*.

Herein, we discuss a brief overview of used visualization tools for the above categories of models: (i) early-warning models, (ii) macro stress-testing models, and (iii) contagion and spillover models.

First, the standard predictive *early-warning models* may be complemented by the use of tools amplifying cognition. Due to the complexity of financial systems, a large number of indicators are often required to accurately assess the sources of financial instability. 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. 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. Work by International Monetary Fund (IMF) staff on the Global Financial Stability Map (GFSM) (Dattels et al. 2010) has sought to disentangle the sources of risks by a mapping of six composite indices with a standard radar-chart visualization. Even here, however, the GFSM falls short

in disentangling individual sources, for which separate visualizations are needed. 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 is illustrated in Fig. 2.3, where Country A and Country B have an area of significantly (i.e., infinitely) different size but the same aggregate risks (i.e., mean value). In addition, the use of adjustment based on market and domain intelligence, especially during crisis episodes, 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. 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”*.²

Data and dimension reduction methods 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). This type of analysis has the benefit of not only signaling a crisis in a timely manner, but also signaling the type and degree of various sorts of financial imbalances. 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. Resta (2009) also has applied the SOM to a large set of indicators, but with a focus on rather general economic and financial performance of countries and with limited evaluations of classification performance.

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. The visualizations seldom go beyond a framework or schematic structure for the designed transmission mechanisms in the model and plots of loss distributions in various formats. Obviously, standard visualizations 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

² The authors state that the definitions of starting and ending dates of the assessed crisis episodes are somewhat arbitrary. Similarly, the assessed crisis episodes are arbitrary, as some episodes in between the assessed ones are disregarded, such as Russia's default in 1999 and the collapse of Long-Term Capital Management. 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.

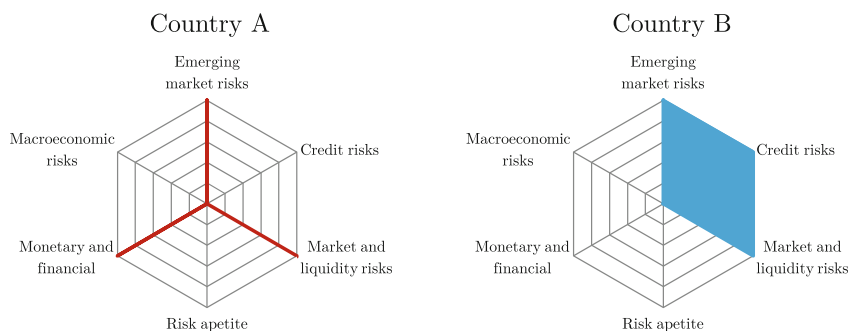


Fig. 2.3 Radar charts of two countries. *Notes* The figure provides an example of a radar chart, such as the one in Dattels et al. (2010)

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 *versus* undirected and weighted *versus* 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 as 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)]. Still, it is worth noting that recent advances in software for visualizing financial networks, such as Financial Network Analytics (www.fna.fi), hold promise in bringing aesthetics and the ease of use to visualizations in the financial domain. An additional essential feature, not the least to deal with hairballs, is the use of interaction techniques with visualizations.

2.4 A Framework for Macroprudential Oversight

To connect the concepts defined in this chapter, we discuss them in how they relate to safeguarding financial stability. One might thus also say that this section attempts to provide a holistic view of the macroprudential oversight process. The ECB's conceptual framework not only includes a systematic way of structuring risks through the risk cube, but also includes a process of the steps that a macroprudential super-

visory body would follow.³ The process in Fig. 2.4 is an adapted version of that in ECB (2010), where red components represent risks and vulnerabilities, the green components represent the need for risk identification and assessment, and the blue components represent the need for risk communication. Thus, the **black frames** mark the use of tools for safeguarding financial stability, where the **solid** lines represent the current approach and the **dashed** lines proposes an integration of means for risk communication into the tools. A discussion of policy assessments and implementations represented by gray components is beyond the scope of this book.

The macroprudential oversight process begins with underlying market imperfections that at a later stage propagate as possible risks. In the *first step* of the supervisory process (risk identification), 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 components of the financial system: financial intermediaries, financial markets and the financial infrastructure. The necessary tools to identify possible risks, vulnerabilities and triggers come from the set of early-warning models and indicators, as well as the use of market intelligence, and expert judgment and experience. This provides means for 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 (risk assessment), the rankings and probabilities may be used to assess the identified risks. The used tools come 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 general financial system, as well as its components. The 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 losses in macroeconomic 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* (policy assessment) involves the assessment 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 an implementation 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. While policy tools and their effectiveness is slightly outside macroprudential oversight and the general scope of this book, it is worth noting that actions tailored to the needs of a system-wide orientation are a key part of macroprudential

³ A macroprudential supervisory body is an institution tasked with macroprudential oversight of the financial system and the mandate of safeguarding financial stability. Examples are the European Systemic Risk Board in Europe, the Financial Policy Committee in the UK, and the Financial Stability Oversight Council in the US.

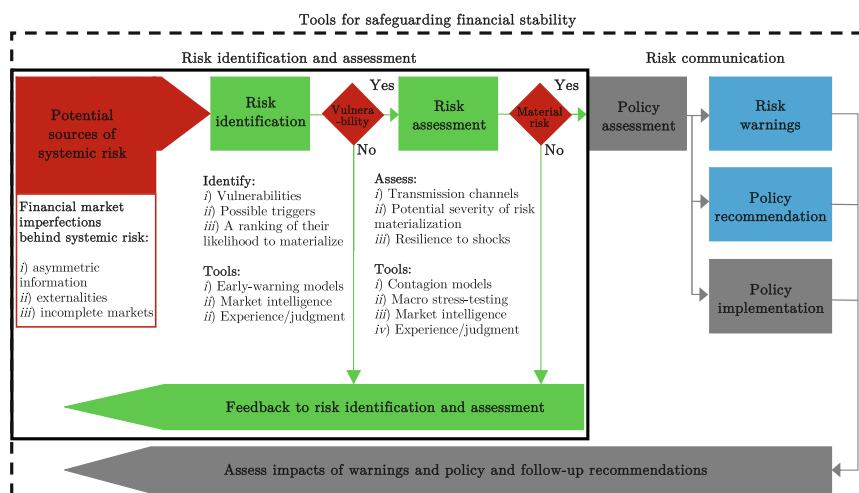


Fig. 2.4 The macroprudential oversight process. *Notes* The figure represents the role of analytical models and tools for identification and assessment of systemic risk in the macroprudential oversight process. The *red components* represent risks and vulnerabilities, the *green components* represent the need for risk identification and assessment, and the *blue components* represent the need for visual means facilitating risk communication. Thus, the *black frames* mark the need for tools for safeguarding financial stability, where the *solid lines* represent the current approach and the *dashed lines* represent means for risk communication integrated in the tools. The *gray components* are beyond the scope of this book. The figure is an adapted version of that in ECB (2010)

regulation and supervision. As interest rate policy may be a too blunt and powerful tool with material damage to 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.

Performing risk identification and assessment is generally seen as the key task of tools for safeguarding financial stability (solid **black** frame in Fig. 2.4). This points to a lack of integration between the tools for safeguarding financial stability and the communication that occurs after the policy assessment step, in particular the tasks of issuing risk warnings, giving policy recommendations and publishing Financial Stability Reports, as represented by the blue components in Fig. 2.4. To answer the question, *what is the overall purpose of communication through a Financial Stability Report?*, a survey among central bankers by Oosterloo and Haan (2004) pinpoints three main reasons for publishing these 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.

Thus, following the discussion in the previous section, a major concern is how the results of these risk identification and assessment tools are communicated to a wide range of stakeholders in easily understandable formats, with the ultimate aim of achieving transparency and accountability. The broader perspective proposed by the dashed **black** frame in Fig. 2.4 argues for relating the third step to risk communication, which would be supported by visual representations of the tools used in the prior steps. Although not being illustrated in the figure, internal and external risk communication would obviously have separate feedback loops: the former to risk identification and assessment (green components), and the latter to potential sources of systemic risk, vulnerabilities, and material risks (red components). This would translate to a threefold focus of tools: risk identification, risk assessment and risk communication.

2.5 Concluding Discussion

This chapter has provided an overview of macroprudential oversight. Not only have we discussed how financial systems work and what makes them fragile, but also the specific systemic risks and tools for safeguarding financial stability. Finally, the chapter ends by summarizing all the above ingredients within a larger framework of the macroprudential oversight process.

Macroprudential oversight as such is not a new concept. Yet, supervisory bodies with the mandate of safeguarding system-wide financial stability have only recently been created, all in the aftermath of the financial instabilities of 2007–2008. The European Systemic Risk Board in Europe, the Financial Policy Committee in the UK, and the Financial Stability Oversight Council in the US were all either established or announced in 2010. While we have discussed the complexity of factors affecting financial systems, how fragilities may build up and what form systemic risks may take, as well as empirical and theoretical underpinnings, an obvious focus of this chapter is on tools and models for macroprudential oversight. Given the mandate of multiple macroprudential supervisory bodies, the central task ought to be timely and accurate measurement of systemic risks. In this chapter, we have discussed the following three categories of systemic risks (*and tools*):

- (i) endogenous build-up of widespread imbalances (*early-warning models*);
- (ii) exogenous aggregate shocks (*macro stress-testing models*); and
- (iii) contagion and spillover (*contagion and spillover models*).

This sets an inherent need for a broad basis of tools for the identification and assessment of potential risks, vulnerabilities and imbalances. One key conclusion of the review of tools and models is the lack of visual means for identifying and assessing risks and vulnerabilities, particularly macro stress-test and early-warning models. In the case of contagion models, visualizations based upon network models and graph theory have been applied and are still gaining further interest within the policymaking community. Yet, the task of representing high-dimensional early-warning indicators

on a low-dimensional display has not been addressed in a sufficient manner. Visual aids to the representation of macro stress-test models may also hold promise due to their complex nature, but to provide a sufficient abstraction of the problem seems like an inherently different, yet highly interesting, task to address. However, this is generally beyond of the scope of this book.

Another line of research is to purely focus on the forecasting capabilities of models. The early-warning literature has indicated that ANNs are suitable for the complex task. They are effective data-driven non-linear function approximators, but are alas no *panacea* for binary-choice classification. To fully benefit from capabilities of ANNs, they need to be provided with their computational demands (i.e., large samples and computing power) and specific training schemes for generalization. In addition, the literature showed that the choice of the optimal set of indicators is either performed according to economic significance or univariate predictive performance, whereas the choice has not been performed in a multivariate framework.

Yet, in all above tasks, it is worth remembering that the quality of a model is highly dependent on the quality of the underlying data. The early-warning models are generally dependent upon country-level macroeconomic, banking system and market-based indicators of risks, vulnerabilities and imbalances. This takes us to the topic of data in macroprudential oversight.

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