Utilization of business intelligence tools and advanced analytics in systemic risk supervision

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Master Thesis

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Student name: ______VEDRAN BROZOVIĆ________

Student signature: VBrozović ________________________________

I would like to dedicate this thesis to my mother,
to whom I promised she shall witness my graduation.

I see a bit of you in my reflection.
Thank you for everything.

ABSTRACT

Systemic risk has become a widely observed and thoroughly researched topic in the years following the 2008 global financial crisis. A number of international and European financial stability bodies have been established in its aftermath with objectives of safeguarding financial stability and monitoring systemic risk. However, both practitioners and academics still struggle to produce a uniform definition of systemic risk itself. Indeed, even though this topic has been widely researched thus far, there are still many open challenges when it comes to identifying, assessing and monitoring systemic risk. For instance, many indicators of systemic risk are shown not to be effective in predicting the upcoming financial crises. In order to address such gaps, both researchers and practitioners increasingly use new information and digital technologies to tackle existing discrepancies and generate more accurate analyses. The prerequisites for this are big data, proper IT infrastructure and highly skilled personnel. The utilization of business intelligence tools and advanced analytics enable the creation of new systemic risk measures, more effective systemic risk monitoring and the automation of data collection and risk processing. This paper discusses the prerequisites for the implementation of BI and AA solutions, its limitations and potential benefits for systemic risk supervision. An example from the Croatian banking and non-banking financial sector serves to display a project-based example of systemic risk supervision using interactive dashboards and innovative visualization techniques. Additionally, the possible applications of advanced analytics are discussed, including machine learning and artificial intelligence for systemic risk supervision.

Keywords: systemic risk; financial stability; business intelligence; advanced analytics, SupTech

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1. INTRODUCTION

1.1. The aim of the paper

The topic of this thesis will be to examine the possibilities, case studies and researchers' preferences regarding the utilization of business intelligence tools and advanced analytics in economics and business, with specific focus on systemic risk. Systemic risk represents every endogenic and exogenous effect to the financial sector, which could as a result cause a disruption to systemically significant financial institutions and markets. The purpose of the paper is to analyze the theoretical concepts and the technological solutions specific to systemic risk supervision and management. This pertains to not only business intelligence tools, but also to the much broader topic of advanced analytics. Additionally, visualizations of simple macroeconomic and financial indicators are presented, as well as applications of artificial intelligence (AI), big data, and machine learning (ML) algorithms in constructing real-time econometric models. A case study on Croatian banking and non-banking financial sector will be used to demonstrate the possible methodological, technical and visual solutions for systemic risk supervision. This project-based example of business intelligence tools and advanced analytics utilization in systemic risk supervision will be demonstrated on data from the Croatian financial sector, with case studies from selected European central banks serving as a guideline.

1.2. Methodology

In order to achieve the prescribed objectives of the thesis the following methods were employed: literature review and critical and qualitative content analysis of relevant scientific and professional papers will provide a theoretical overview of the topic. Furthermore, a relevant data sample is chosen and thereafter through various graphical and statistical methods analysed. The ensuing research results are explained in detail, and further corroborated through the existing literature review.

Secondary data from relevant public financial institutions will be used to create a model, which will serve as a case study. Case study model will be prepared with data from publicly available sources. Namely, the Croatian National Bank and Croatian Financial Services Supervisory Agency. Additionally, financial indicator data from the European Central Bank and other supranational and international institutional pertinent to systemic risk supervision will be considered. The case study model will serve as a prototype solution for systemic risk supervision with a special focus on the technical solutions. This small-scale model will be developed according to the best practices in selected central banks and international regulatory institutions using solely publicly available data. The project-based database will be created in MS SQL Server, while the dashboard will be developed using business intelligence software MS Power BI.

1.3. Structure of the paper

Whilst the paper centres around the topic of systemic risk, to fully grasp the following thesis, the topics of business intelligence, advanced analytics, and artificial intelligence will be covered and explained thoroughly as well. Only after these topics are appropriately introduced will the reader dive into the main question discussed in the thesis: the utilization of various business intelligence and advanced analytics tools in the area of systemic risk supervision.

Firstly, a theoretical overview of systemic risk is given. The chapter starts by providing an overview of historical development of the concept of systemic risk. The definition and taxonomy of systemic risk are discussed in detail, with special reference to the mechanisms of systemic risk transmission. The third chapter provides a more detailed explanation of systemic risk supervision. International, European and Croatian regulatory and supervisory agencies are introduced and their functions comprehensively examined. An overview of existing and new systemic risk indicators is provided and the concept of systemically important financial institutions is presented separately.

Thereafter, an introduction to business intelligence tools and advance analytics is provided in the fourth chapter. The distinction between business intelligence and advanced analytics is highlighted, after which potential future applications of both BI and AA are discussed. The fifth chapter finally combines the two topics and examines the core question of the thesis – utilization of business intelligence tools and advanced analytics in systemic risk supervision. The topics of existing implementations, requirements, limitations and potential use cases are covered. The sixth chapter presents the case study on Croatian financial banking and non-banking financial sector, displaying the possible utilizations of interactive dashboards in systemic risk supervision. Finally, the seventh chapter summarizes the findings of the thesis.

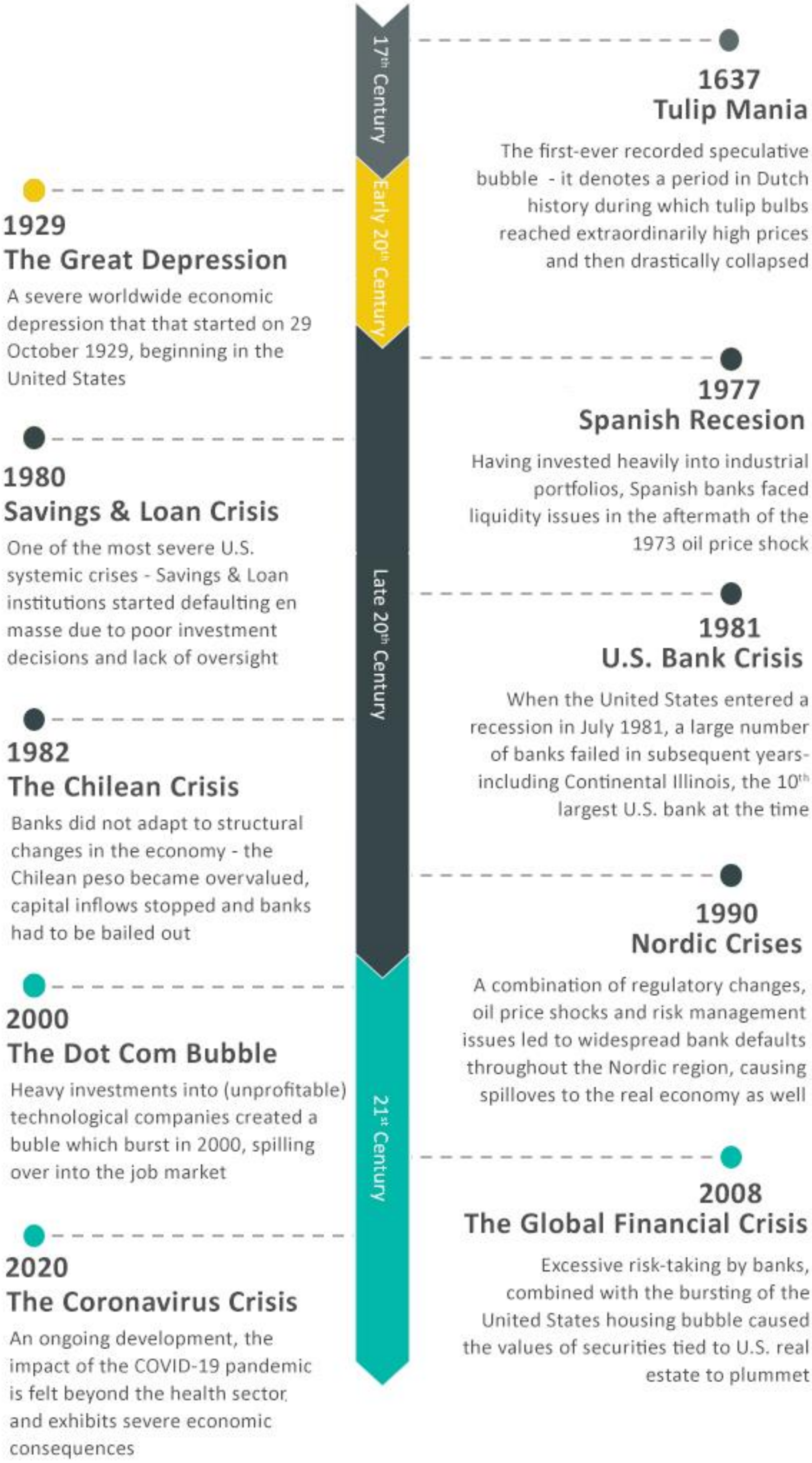
2. THEORETICAL OVERVIEW OF SYSTEMIC RISK

2.1. Historical development of systemic risk

The history of systemic risk is not at all easy to condense, let alone simplify. Although the concept of *systemic risk* in financial markets only became widely known after the Great Recession in 2008 – as we shall see later on in this chapter – its roots may be traced throughout history, dating as far back as the 17th century. Indeed, as Kreis, Leisen, and Ponce (2019) point out in their book, the first real recorded instance of a systemic risk crisis occurred in 1637 – a turbulent time in Dutch financial history called "The Tulip Mania". In 17th century Vienna, tulips were a rare, exotic, and highly valued species imported from the Ottoman Empire. Many merchants at the time took a keen interest in the flower, but it was not until the visiting Dutch merchants brought it back home – as Goodnight and Green (2010) evocatively explain – that the first-ever recorded asset bubble started to form. Sellers in the Netherlands began to buy this year's bulbs in anticipation of next year's higher prices. "The futures market flourished on the Amsterdam stock exchange" – the authors go on – "and new investors were encouraged to get in and go deeper by stockjobbers who let loans and wrote contracts". By mid-1637, no more than two years since the Tulip Mania began, bulb prices dropped significantly and the speculative bubble dramatically burst. Dutch florists suffered extensive losses in that period, but no significant spill-over effects were ever recorded to have hit the wider Dutch economy (McClure and Thomas, 2017; Dash, 1999). Nevertheless, stories of the Tulip Mania have now been circulating for nearly 400 years and provide the first-ever recorded instance of a systemic crisis (or in this case, a shock) that had the potential to impair a country's financial stability (Goodnight and Green, 2010; Kreis, Leisen, and Ponce, 2019).

From the 17th century onwards, systemic risk crises have been occurring throughout the world – the most significant of which are presented in **Figure *1***. Despite its global presence, however, systemic risk has slowly made its way to the forefront of regulatory and public attention. This increase in importance can primarily be attributed to various advances within the banking sector, triggered by changing regulatory requirements, technological innovation, and globalization (Kreis, Leisen, and Ponce, 2019). The authors further state that the way we perceive and understand systemic risk has also changed: during the 20th century, for example, systemic risk was mostly a national concern, without much thought being put into potential international spill-overs and other adverse effects.

Figure 1 The most prominent systemic risk crisis in history



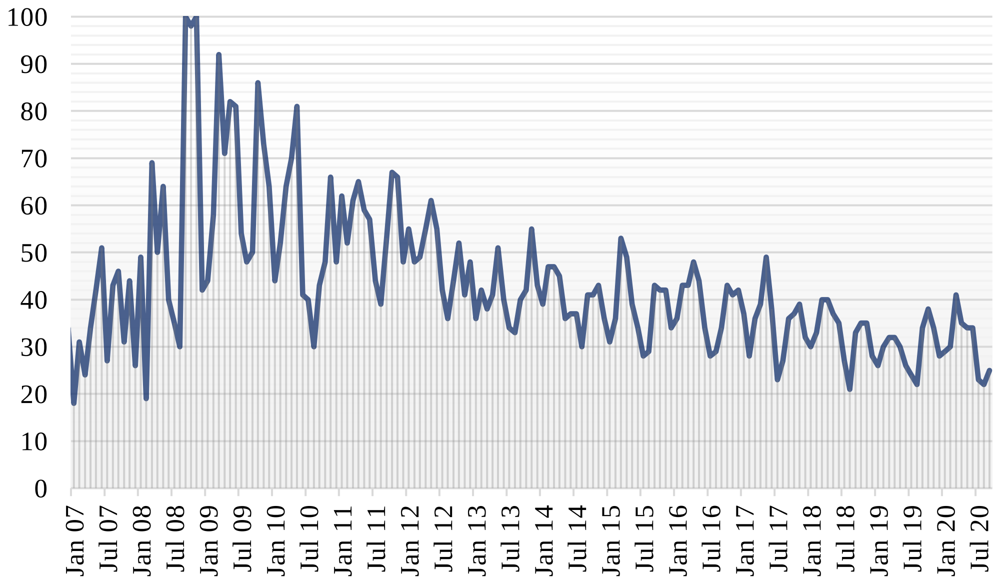
Source: author's work based on Kreis, Leisen, and Ponce (2019); and Adrian and Natalucci (2020)

Figure *1* The most prominent systemic risk crisis in history above provides a brief overview of the most notable systemic crises that have occurred throughout history. By observing the timeline alone, one can see that the vast majority of such crises have occurred in the 20th century, with the two latest ones taking a more serious, international dimension. Kreis, Leisen, and Ponce (2019) characterize the 21st century systemic crises as being global in scope, triggering financial instability across multiple countries. In order to understand how that came to be, we shall first take a closer look at some of the most prominent crises throughout the late 20th century. The first notable systemic crisis hit Spain in 1977 – widespread liberalization policies implemented earlier that decade prompted banks to expand rapidly without any meaningful supervision from relevant authorities (Betrán and Pons, 2014). What's more, Spanish banks held significant industrial portfolios at the time that were tightly connected with the real economy. Things started taking a turn for the worse with the oil price shock of 1973 which significantly altered the Spanish industrial environment: labor and energy costs gradually increased, with inflation soon following suit (Kreis, Leisen, and Ponce, 2019). The effect on Spanish banks was twofold: (i) many corporate clients defaulted on their loans; and (ii) banks holding large industrial portfolios saw their balance sheets further deteriorate (Betrán and Pons, 2014; Cuervo, 1988). In the aftermath of the crisis, 24 banks had to be bailed out; 20 were nationalized; 4 were liquidated; and another 4 were forced into mergers (Kreis, Leisen, and Ponce, 2019). Although the Spanish recession provides a clear example of systemic risk mechanisms in action (i.e. a sudden event which causes a chain reaction within the economy, thereby severely affecting a country's overall financial stability), perhaps the best example can be found in the Savings & Loans Crisis that hit the United States during the 1980s. In 1980, the U.S. government initiated a process of financial liberalization in the Savings & Loan sector by passing the Depository Institutions Deregulation and Monetary Control Act (Kreis, Leisen, and Ponce, 2019). Pyle (1995) explains the effects of the Act in further detail: "In the 1980 Act, federal savings and loans were authorized to invest up to 20% of their assets in consumer loans, commercial paper, and corporate debt securities (…) The authority of S&Ls to make acquisition, development, and construction loans was expanded, geographical restrictions on real estate lending were removed, and permissible loan-to-value ratios were increased". These new powers, however, substantially increased the potential for risk-taking and made monitoring such institutions much harder than before (Pyle, 1995). The outcome turned out to be catastrophic for the United States: between 1986 and 1995, a total of 1,043 Savings & Loan associations closed or were resolved by the Federal Savings and Loan Insurance Corporation.

The total cost of the crisis, moreover, is estimated at around $160 billion (Kreis, Leisen, and Ponce, 2019).

The two major systemic crises described above prompted regulators to fundamentally rethink the concept of systemic risk. Instead of modelling and explaining it via interbank linkages and allocation imbalances, regulators started observing it as an independent element – one capable of significantly damaging a nation's financial stability (Kreis, Leisen, and Ponce, 2019). Indeed, the concept of systemic risk in financial markets only became widely known after the Great Recession in 2008. The sharp declines in financial markets and the underlying contagion effect, which highlighted the interconnectedness of financial institutions, caused the term "systemic risk" to quickly gain popularity during the economic downturn. **Error! Reference source not found.** illustrates the popularity of the term through the selected timeframe, clearly indicating the peak of the interest during the Great Recession from 2007 to 2009[1]. Furthermore, the concept itself has been very relevant ever since then, with the effects of the nouvelle coronavirus Covid-19 on the economy and financial stability in 2020 still unveil.

Figure 2 Google Trends: Systemic Risk



Source: author's work based on Google Trend data (https://trends.google.com)

Keyword: "Systemic risk", geography: worldwide, date: 2020-09-09

The contemporary idea of systemic risk – that of a macroeconomic and independent force – only began to take shape at the onset of the 2008 Great Recession. Economics and finance

[1] Figure is based on global web searches using Google engine indexed at 100 for the maximum value in selected period

professionals at the time had little research available to understand what was happening on an economy-wide scale and policy response faltered as a response (Engle, 2018). Instead of explaining it through interbank linkages – as Kreis, Leisen, and Ponce (2019) thoroughly discuss – a new framework was needed, one that could explain both domestic and international spillovers that contaminated global financial markets. Freixas, Laeven and Peydró (2015) provide a deeper look into the key issues faced by regulators at the onset of the crisis. Firstly, regulators had to design a consistent set of regulatory rules so as to lower the macroeconomic costs of the crisis, whilst making sure other, similar crises do not occur in the future. Crisis prevention is a key takeaway from the recession, the authors claim, whereby regulators increasingly started developing preventive measures to curb the buildup of systemic risk during boom periods. Engle (2018) greatly shares this sentiment and takes a more detailed look at the systemic risk innovations that were developed as a response to the crisis: (i) regulators developed an array of macroprudential models and frameworks to better understand the global nature of systemic risk; and (ii) the SRISK measure became standard practice in measuring the (under)capitalization of financial firms. Although the measures set in place greatly broadened our overall understanding of systemic risk – propped up by a vast array of new academic literature on the subject – the COVID-19 pandemic might force regulators to yet again rethink the existing frameworks and crisis relief policies. Most governments responded immediately at the onset of the pandemic to manage the looming financial and economic shocks by providing fiscal, monetary, and macro-financial stimuli (Rizwan, Ahmad and Ashraf, 2020). However, extended lockdown periods, loan payment deferments, and political instability – as claimed by the authors – have increased the systemic vulnerability of the banking sector, while IMF experts believe that "Vulnerabilities in credit markets, emerging countries and banks could even cause a new financial crisis" (Adrian and Natalucci, 2020). It still remains to be seen whether this systemic instability will be mitigated by existing frameworks or will it, perhaps, sprout new innovation in the regulatory field.

2.2. Definition of systemic risk

Even though the concept of systemic risk is well known in the academic and professional community, there is still little consensus on its very definition (Kaufman & Scott, 2003; Hansen, 2012). This chapter will examine different definitions of systemic risk in order to provide a clearer understanding of the topic as well as to properly define the scope of this research.

2.2.1. Systemic risk in a broader sense

In a broad sense, systemic risk is a phenomenon not limited to the field of economics or the concept of financial stability. De Bandt & Hartmann (2000) compare the concept of systemic risk to epidemic diseases and use the example of the Great Plague, which affected the entire globe and significantly decreased world population, to illustrate systemic risk in public health. Moreover, the current COVID-19 global pandemic highlights the interrelationship between economic and health crises once again. Systemic risk, therefore, requires cooperation between experts and responsible institutions in the field of pandemics with financial stability regulators (Rizwan, Ahmad and Ashraf, 2020).

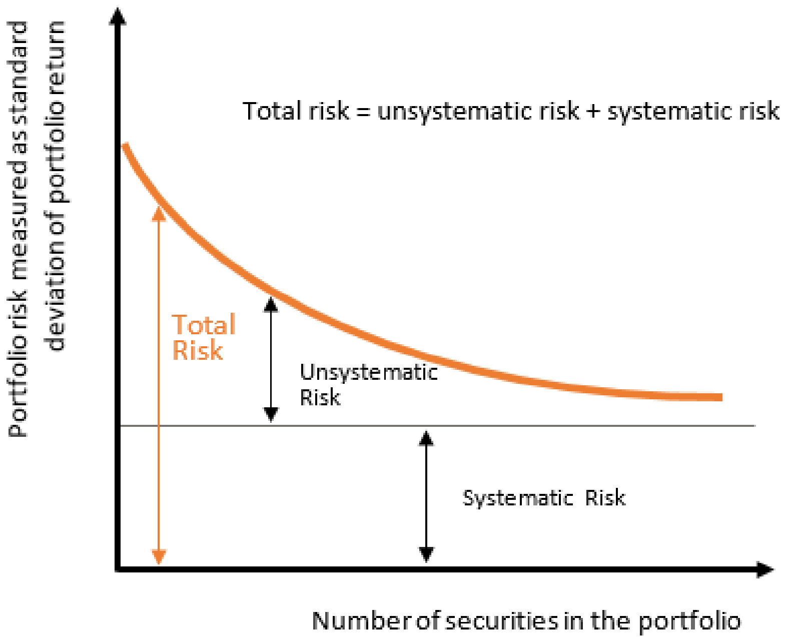
This multidisplinary approach is by no means limited exclusively to public health. For example, OECD (2020) mentions both natural disasters and technological disasters when referring to systemic risk. Furthermore, Jean-Claude Trichet (2009) used sustainability and environment as an example to explain the concept of systemic risk: “In the context of natural environment: [systemic risk] is the threat that the actions of millions of individuals, all acting in pursuit of their own interests, can cause a breakdown of the world’s ecosystem, a global catastrophe which will ultimately damage everyone.” (Trichet, 2009).

2.2.2. Systemic risk and systematic risk

Before analyzing specific academic and legislative dimensions of systemic risk, it is useful to first determine what systemic risk is not. The term systemic risk is not to be confused with the concept of systematic risk. This subchapter will provide a brief explanation of systematic risk that, although not at the center interest of this paper, is nevertheless crucial to comprehend systemic risk and will serve as a prerequisite for deeper understanding of the concept.

Systematic risk pertains to the level of financial risk that is impossible to avoid through further diversification (Hansen, 2012) and is a well-researched topic in the field of corporate finance, investment management and more specifically portfolio management. As can be seen on **Figure *3*** Systematic Risk, all combinations of different portfolios have a total risk comprising of systematic and unsystematic risk. Unsystematic risk refers to the part of the total asset’s risk specific to the entity and represents the variance unrelated to the market portfolio (Reilly & Brown, 2011, p.20). Unsystematic risk is determined by both business and financial risks, such as credit risk, currency risk, liquidity risk and solvency risk. Unsystematic risk is, therefore, a part of the security’s or portfolio’s total risk that could be reduced through further diversification, and is therefore not in the focus of portfolio management research. Conversely, systematic risk pertains to the portion of an individual asset's total variance that is attributable to the variability of the total market portfolio (Reilly & Brown, 2011, p.20). Hence, systematic risk is constant because it refers to the total market risk, i.e. the risk attributed to the portfolio comprising of all available securities.

Figure 3 Systematic Risk and Unsystematic Risk



Source: author's work based on Corporate Finance Institute (2020)

Therefore, systematic risk is also known as undiversifiable risk or aggregate risk. Brigham & Ehrhardt (2010, p. 943) explain systematic risk as the level of risk that remains when investors hold a perfectly diversified, efficient portfolio – and this risk is measured simply as the standard deviation of portfolio's returns. To conclude, systematic risk is clearly defined as the part of the security's total risk caused by factors outside of control of specific organization (CFI, 2020).

The concept of systematic risk, hence, is essential for the field of corporate finance and portfolio management because it is necessary for proper understanding of the Capital Asset Pricing Model (CAPM). It is not, however, as important of a subject when trying to understand, explain and prevent events in the financial markets that could in turn have negative effects on the market as a whole. The latter falls into the research interest of systemic risk - the primary focus of this paper.

2.2.3. The importance of defining systemic risk

As already discussed in the previous subchapter, unlike the definition of systematic risk the concept of systemic risk is ambiguous and unclear. In this subchapter, various definitions of systemic risk ranging from different sources – from central banks to academics and finance professionals – will be presented. Comparison between these different approaches will provide a deep insight into the topic and will serve as a guiding star when discussing possible measurement methodologies and available tools to monitor and supervise systemic risk in the following chapters.

Before diving into the discrepancies between numerous proposed definitions of systemic risk, it is valuable to briefly outline what researchers do agree upon and the significance of their discovery. Congruence on the definition of systemic risk is of paramount importance, as too broad a definition might lead to difficulties in measurement, management and supervision. A narrow definition, on the other hand, may lead to the omission of important determinants of financial stability (or rather instability), due to the subsequent limited scope of what systemic risk encompasses, thereby significantly impeding the regulator's ability to take action (Smaga, 2014).

Academics and practitioners alike concur on the difficulty of precisely quantifying, measuring and defining what systemic risk entails, which only further bespeaks its complexity in the field of financial stability (Covi et. al., 2019). Hansen (2012) illustrates this by arguing that systemic risk is evident only once it happens, lending credence to the lack of a uniform and concise definition. The author continues with two distinct issues with the idea that systemic risk is exclusively identifiable in hindsight. Firstly, it allows for a high amount of regulatory discretion and limits the transparency in policymaking decisions. Lack of transparency in definition, measurement and methodology leaves room for potential political pressure. Secondly, misalignments in the definition and measures for systemic risk also make it that more challenging to criticize the regulators as there is little to no external visibility on systemic risk monitoring and supervision (Hansen, 2012).

The concept of systemic risk itself implies that supervisory agencies should proactively aim to mitigate risks and minimize losses through macroprudential policy. However, given the ambiguity of systemic risk definition – the resulting economic downturn in all its severity can be attributed to supervisory agency regardless of what their action or inaction was. Here lies the true importance of explicit and uniform definition of systemic – to enable not only to engage in risk supervision but also to assess the policy effectiveness. Moreover, Galati & Moessner (2011) highlight the lack of consensus when it comes to both the concept of systemic risk as well as the definition of financial stability. Authors underline that the lack of commonly shared definitions leads to differing quantification and measurement approaches to systemic risk, which only fuels discordance more. This subsequently induces subpar macroprudential policy decisions.

2.2.4. Overview of definitions of systemic risk

After the importance of defining systemic risk has been discussed in the previous chapter, this subchapter will provide a systematical overview of existing definitions. The differences between these definitions and their adoption by the academics, practitioners and regulators will be examined. Exploring a set of systemic risk definitions builds a solid knowledge base necessary for gaining a deeper understanding of systemic risk and consequently the investigation of various analytical tools which could be used for supervision.

Kaufman and Scott (2003) thoroughly examined the discrepancies in the prevailing definitions of systemic risk and chose to explain the concept as "the risk or probability of breakdowns in an entire [financial] system, as opposed to breakdowns in individual parts or components […]". ***Table 1*** The evolution of the definition of Systemic Risk shows three different conceptual approaches on the topic of systemic risk. These three definitions build on top of each other and are all relevant for proper understanding of the concept of systemic risk. The initial view on systemic risk was only through the lens of a macroeconomic exogenous shock affecting the economic and financial system simultaneously and in its entirety. Three main authors, with subtle but important distinctions, shared this approach. Bartholomew & Whalen (1995) referred to systemic risk as an event that has an immediate effect on the entire system, rather than specific institution(s). Mishkin (1995) added the idea of a probability or likelihood of an event, however unexpected. While Mishkin also introduced the concept of channelization of funds and emphasized the crucial role of financial markets stability, Allen & Gale (1998) focused on bank runs as the causal effect of systemic risk. Kaufman (1995) and Kaufman & Scott (2003) shift the focus towards microeconomics in defining systemic risk by concentrating on the interconnectedness between various economic entities and the spillover effect or mechanisms by which the initial exogenous or endogenous shock is transmitted. Although all three conceptualizations of systemic risk are important for its understanding, regulators (FED, 2001; BIS, 1994) more broadly adhere to the latter two.

Table 1 The evolution of the definition of Systemic Risk

	Definition	Focus	Year	Authors and (Adopters)	Definition contribution	Source
1	"Big" shock or macroshock that produces nearly simultaneous, large, adverse effects on most or all of the domestic economy or system.	Macroeconomics; Exogeneous shock; Economic system in its entirety	1995	Bartholomew and Whalen	"Refers to an event having effects on the entire banking, financial, or economic system, rather than just one or a few institutions".	Bartholomew, Philip, and Gary Whalen. 1995. Fundamentals of Systemic Risk. In Research in Financial Services: Banking, Financial Markets, and Systemic Risk, vol. 7, edited by George G. Kaufman, 3–17.
			1995	Frederic Mishkin	"The likelihood of sudden, usually unexpected, event that disrupts information in financial markets, making them unable to effectively channel funds to those parties with the most productive investment opportunities".	Mishkin, Frederic. 1995. Comment on Systemic Risk. In Research in Financial Services: Banking, Financial Markets, and Systemic Risk, vol. 7, edited by George Kaufman, 31–45.
			1998	Franklin Allen and Douglas Gale	One process through which macroshocks can ignite bank runs.	Allen, Franklin, and Douglas Gale. 1998. Optimal Financial Crises. Journal of Finance (August): 1245–84.
2	Probability that cumulative losses will accrue from an event that sets in motion a series of successive losses along a chain of institutions or markets comprising a system.	Microeconomics; Interconnectedness of economic entities; shock transmission; spillover effect	1995	George Kaufman (Federal Reserve System, Bank for International Settlements)	**Direct risk transmission & spillover effect Correlation with causation** "The risk of a chain reaction of falling interconnected dominos"	Kaufman, G. 1995. Comment on Systemic Risk. In Research in Financial Services: Banking, Financial Markets, and Systemic Risk, vol. 7, edited by George G. Kaufman, 47–52.
3	The rise of uncertainty brought by the loss of one unit due to external shock increases risks for similar institutions.	Microeconomics; "Common shock" or "Reassessment shock" effect; Correlation without direct causation	2003		**Indirect connections spillover Correlation without direct causation** Between market participants without direct causal relationship	Kaufman, G. G. & Scott K. E. (2003) "What Is Systemic Risk, and Do Bank Regulators Retard or Contribute to It?"

Source: author's work based on Kaufman & Scott (2003)

2.3. Taxonomy and transmission mechanisms

2.3.1. Classification of systemic risk

Classification of systemic risk is another important prerequisite for suitable supervision. Numerous ways of categorizing systemic risk have been explored in empirical literature. A good starting point might be to explore different kinds of financial crisis that have occurred through history. Reinhart & Rogoff (2009) researched eight centuries of financial crisis and have decided to break the into four distinct categories: sovereign defaults, banking crisis, exchange rate crisis and inflation crisis. While sovereign defaults occur when governments fail to meet their debt obligations in form of payments either for external or domestic debt, banking crisis occur when there is spillover effect from banks due to insolvency issues, often caused by questionable, risky investments Anand et al., 2016). When trying to focus the discussion on the topic of systemic risk, one can produce a categorization of types with regards to geographical reach (De Bandt & Hartmann, 2000), initial trigger for the crisis, method of shock transmission, root cause of the chock (Allen & Carletti, 2013) and intensity of the systemic event, among other. **Table *2*** Classifications of Systemic Risk provides a systematic overview of different taxonomies of systemic risk.

Table 2 Classifications of Systemic Risk

<table>
<tr><th>Classification basis</th><th colspan="2">Categories (Subcategories)</th><th>Note</th></tr>
<tr><td rowspan="3">Geographical reach</td><td colspan="2">Regional</td><td rowspan="3">Whether the effects of the crisis will be transmitted from the source to the wider geographical area.</td></tr>
<tr><td colspan="2">National</td></tr>
<tr><td colspan="2">International</td></tr>
<tr><td rowspan="3">Initial trigger for the crisis
Source of the shock</td><td rowspan="2">Exogeneous</td><td>(Idiosyncratic)</td><td rowspan="3">Whether the cause of the crisis will be from within the financial system or will it be fueled by external factors.

If external source - whether the shock was initiated from specific entity -with limited sope - and then transmitted to the wider economy or was the shock experienced by the financial system in its entirety.</td></tr>
<tr><td>(Widespread)</td></tr>
<tr><td colspan="2">Endogeneous</td></tr>
<tr><td rowspan="2">Method of shock transmission</td><td colspan="2">Sequential</td><td rowspan="2">Whether the effects of the crisis will be vsible across the financial system immediately or will they be transmitted from one part to another through a period of time.</td></tr>
<tr><td colspan="2">Simoultaneous</td></tr>
<tr><td rowspan="4">Root cause
(ECB classification)</td><td colspan="2">Contagion</td><td rowspan="4">ECB (2009) classification of three main <u>forms</u> of systemic risk - not necessarily mutually exclusive.

Discussed in more detail in the chapter.</td></tr>
<tr><td colspan="2">Macroeconomc shock</td></tr>
<tr><td colspan="2">Unravelling of imbalances</td></tr>
<tr><td colspan="2">Hybrid (combination)</td></tr>
<tr><td rowspan="4">Root cause
(Allen & Carletti classification)</td><td colspan="2">Panics - banking crises due to multiple equilibria</td><td rowspan="4">Allen & Carletti (2013) classification of the four main <u>areas</u> of systemic risk.

Discussed in more detail in the chapter.</td></tr>
<tr><td colspan="2">Banking crisis due to asset price falls</td></tr>
<tr><td colspan="2">Contagion</td></tr>
<tr><td colspan="2">Foreign exchange mismaches in the banking system</td></tr>
<tr><td rowspan="2">Intensity of systemic event</td><td colspan="2">Strong</td><td rowspan="2">Systemic events that evenaully causes the affeted institition(s) to crash are considered as strong events, while weak events do not actually result in failure of the affected institution(s).</td></tr>
<tr><td colspan="2">Weak</td></tr>
</table>

Source: author’s work based on Allen & Carletti (2013), De Bandt & Hartmann (2000) and ECB (2009)

Bandt & Hartmann (2000) differentiate systemic risk by few factors. One of them is geographical reach, which indicates whether the transmission of the initial shock will affect the system on regional, national or international level. Authors also elaborate on different sources of initial shock, or trigger for the crisis. The trigger could be endogenous - coming from within the financial system itself, or exogenous – caused by external factors. In the latter case, Bandt

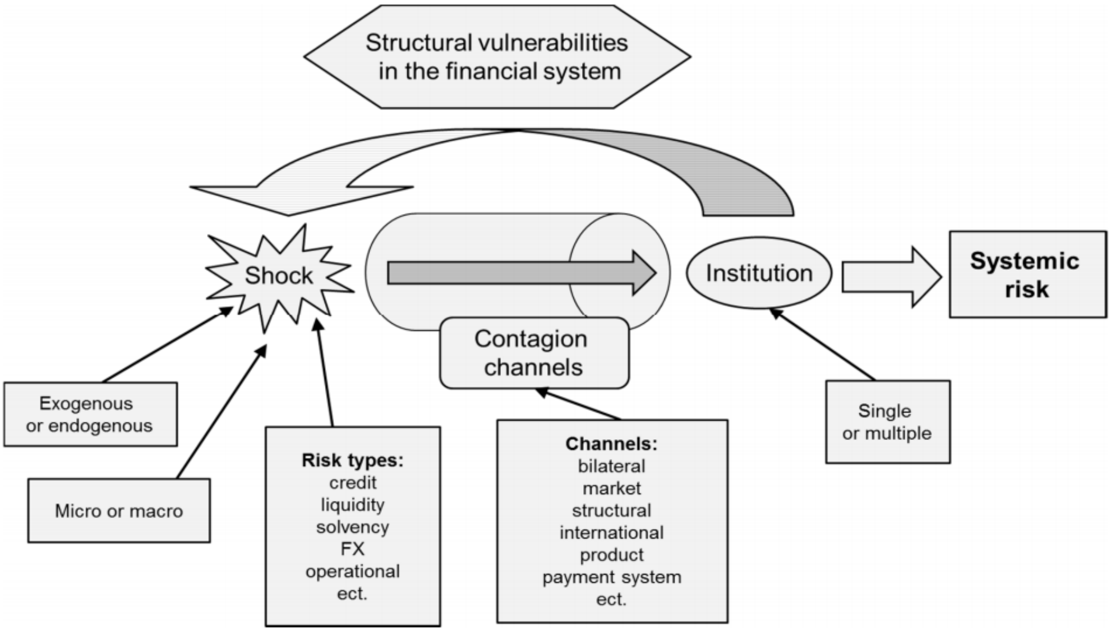
& Hartmann (2000) stress the important distinction between idiosyncratic shocks – affecting only one financial institution or price of a single financial asset – and widespread shocks – affecting the economic system as a whole. Furthermore, one can distinguish crisis as those in which the shock simultaneously affects the entire system and those in which the system is affected by sequential shock transmission.

2.3.2. Mechanisms of systemic risk transmission

To elucidate on the transmission mechanism of systemic risk, firstly, the most important factor for systemic risks – its root cause – is analysed. The conceptual model of systemic risk is incomplete without the full picture of cause and effect: from the form in which the initial shock occurs together with the mechanism in which systemic event is transmitted and then finally affects the entire system. ECB (2009) uses three different main *forms* of systemic risk: contagion, macroeconomic shock and unravelling of imbalances. It is important to note that, according to the authors, these forms are not mutually exclusive. Moreover, most crisis fall into the fourth, hybrid category, which represents a combination of two or more forms. Out of these three forms, contagion is the most commonly known one. Contagion is most often connected to banking and by far the most known example of this type is the 2008 financial crisis. Although contagion risk is partially offset by the introduction of deposit insurance schemes (ECB, 2009), it still represents a major factor of uncertainty due to the size of leading financial institutions as well as the high level of interconnectedness in the banking and overall financial sector (Allen & Carletti, 2013). Contagion is characterized by liquidity issues which then cause *fire sales* of assets and subsequently result in cyclical multiplication of the initial shock. Probably the easiest form to grasp are macroeconomic shocks. Macroeconomic shocks cause systemic risk in a predictable manner, explainable by standard business cycle forecasting models making use of macroeconomic variables such as GDP growth, interest rates and inflation (ECB, 2009). The macroeconomic shocks can present a risk in direct or indirect ways, one of which is panics and banking crisis, as Allen & Carletti (2013) suggest. Finally, unravelling of built-up imbalances has been the least researched systemic risk form. Unwinding of imbalances refers to the increasing vulnerability of the financial system, usually as a result of too much risk-taking activities in the financial market due to factors such as conditions of low interest rates and herding effect in investment decision making (ECB, 2009). Allen & Carletti (2013) highlight falling asset prices as one of the key facilitators of systemic risk. Authors differentiate five distinct reasons for the sudden decline in asset prices: natural outgrowth of the business cycle, bursting of the real estate bubbles, inefficient liquidity provision and limits to arbitrage, sovereign default, and finally sharp increases in interest rates.

Smaga (2014) summarizes and adds to the understanding of mechanism behind the systemic risk. **Figure** *4* Conceptual model of systemic risk illustrates how initial shock triggers the process of accumulation of imbalances and consequently their materialization through contagion channels. This *blueprint for systemic risk* enables better understanding of how different elements affecting systemic risk interrelate and affect each other, ultimately representing a potential risk to financial stability.

Figure 4 Conceptual model of systemic risk



Source: Smaga (2014)

The initial trigger or shock can be exogenous or endogenous, experienced because of microeconomic or macroeconomic instability of a single institution or a range of organizations (Smaga, 2014). The initial shock is then transmitted via contagion channels, be it bilateral direct connections between organizations, asset price effects through markets as a result of negative information signals, vulnerability as a result of similarity in asset and liability structure, exposure to common financial products such as securitized derivatives or links through the payment system (Smaga, 2014). Systemic risk pertains both to the probability of initial shock or a systemic event, as well as the channels through which this shock is spread to the entire system due to the interconnectedness of financial institutions as well as the structural vulnerabilities of the system enabling the effect to cause disruption to financial stability and economic system.

3. SYSTEMIC RISK SUPERVISION

3.1. Regulatory institutions

To gain more clarity on the most prudent way to tackle systemic risk - and through that extent a country's financial stability policies and measures - in addition to the internal financial institutions, markets, structures and relevant legislature, one must comprehensively tap into and analyse the external environment. By utilising this method, one might levy invaluable insight into other expedient benchmarks. Consulting the external environment, through an analysis of good international practices related to systemic risk supervision, can help maximize the soundness of one's macroprudential policy and additionally garner synergies that aid in the mitigation, more effective control, and supervision of systemic risk. Moreover, implementing the recommendations of various international standard setting bodies will result in a more resilient financial macro-environment. With such a goal in mind, this paper endeavours to cover all relevant international and EU financial stability standard-setting bodies whose objectives revolve around improving the robustness of domestic financial systems and promoting international financial stability. Firstly, the most important international standard setting bodies (FSB, BCBS, IAIS, IOSCO, IMF and WB) will be discussed alongside their role in systemic risk supervision. Secondly, European micro- and macro-prudential authorities (ESRB, ESMA, EIOPA and EBA) are explored, and the supervisory mechanisms they employ further analysed.

3.1.1. International organizations

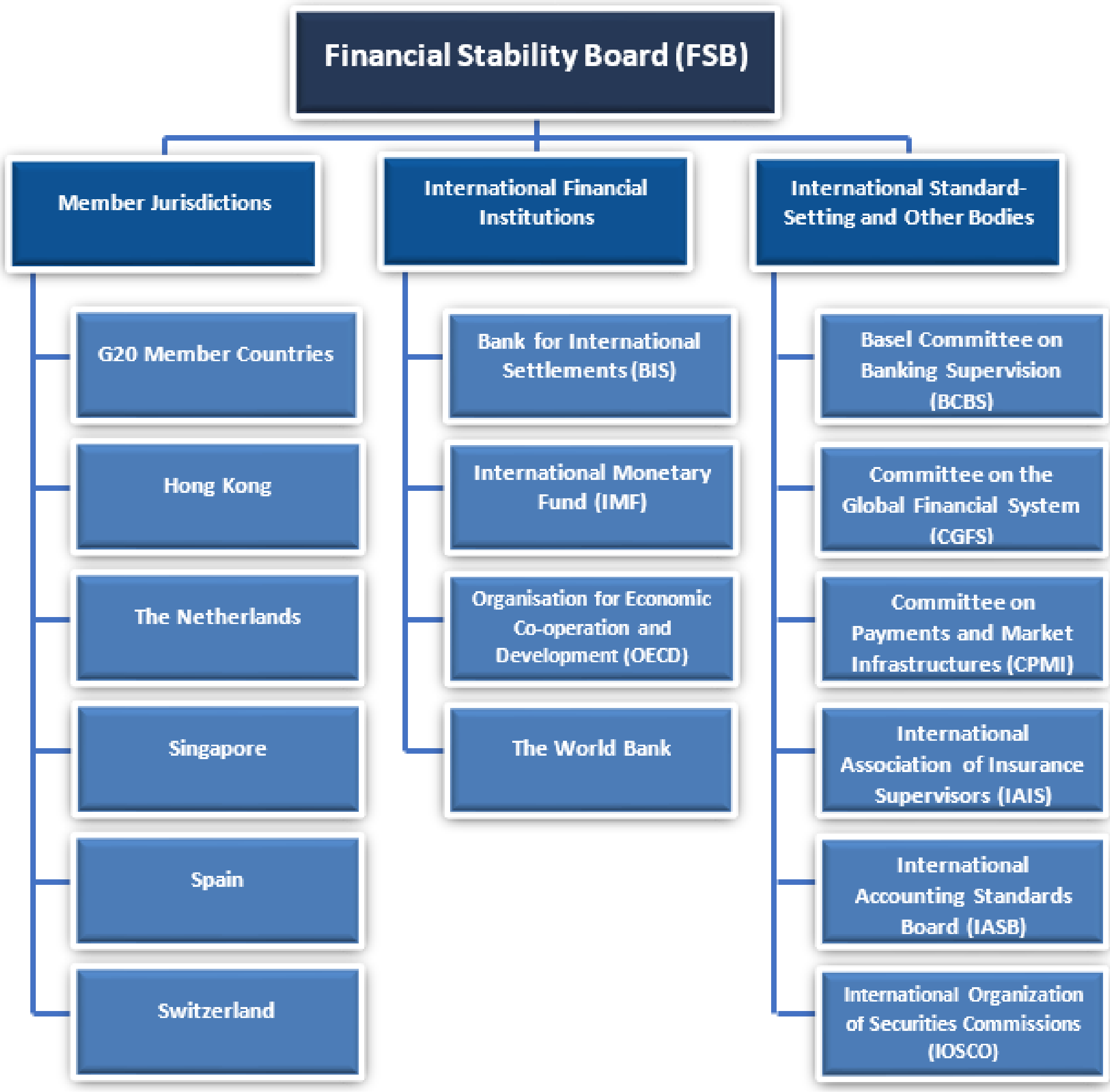
Financial Stability Board (FSB) was established in the wake of the 2008 financial crisis as a successor to the Financial Stability Forum (FSF) by the G20. The Financial Stability Board (FSB) serves to monitor and make recommendations with respect to the prudent functioning of the global financial system, and the financial stability thereof. To this end, the FSB assumes a key role in promoting structural financial regulation and supervision reforms. It promotes a level playing field by fostering harmonious implementation of their policy reform recommendations across sectors and jurisdictions.

Amidst a wide-array of roles, the FSB is primarily tasked with promoting the exchange of information and coordination among member authorities responsible for financial stability, monitoring market developments and advising best practices for respective member regulatory policy, undertaking strategic reviews of international standard setting bodies, and coordinating their respective policy developments etc (FSB, 2020a). It is important to mention that the FSB's recommendations are not legally binding on its members and, therefore, reliant on member organisations moral suasiveness and peer pressure.

A systemic risk identification framework is inherently embedded into FSB's structure (FSB, 2020a). In general, this framework focuses mostly on the systemic risk which arises from systemically important financial institutions (SIFI). To mitigate possible backlash from systemic risk related failure, the FSB advises strengthening the existing supervision framework intensity toward riskier financial institutions, a resolution framework for the prevention of possible financial institutional collapse, and bolstering the robustness of the financial market infrastructure by setting international standards for payment systems, securities settlement systems, OTC derivatives contracts, and central counterparties. For the identification and monitoring of systemic risk, the board argues that various aggregate indicators of systemic imbalances and market conditions should be monitored through integrated monitoring systems such as dashboards and heatmaps, while the identification should be done through various risk and common exposure metrics, keeping in mind the importance of country- and context-specific factors. The FSB includes all major G20 economies under its jurisdiction, four international financial institutions such as the World Bank and International Monetary Fund (IMF), and six international standard setting bodies (FSB, 2020b). **Figure *5*** Financial Stability Board (FSB) organization and members illustrates the organization of FSB and highlights all of the member institutions.

Basel Committee on Banking Supervision (BCBS) is coordinated by the FSB to develop global regulatory standards for banks and is the primary global standard-setter for prudential banking regulation. It encompasses 45 members from 28 jurisdictions. The members include country central banks and authorities with powers to influence banking regulation. While the majority of recommendations and methodologies inherently align with the ones from FSB, BCBS focused its attention and effort toward the broader economic landscape by analysing global systemically important banks (GSIB). Succinctly, by utilizing indicators such as bank size and substitutability, GSIBs are identified and "bucketed" according to the impact that bank's failure can have on the global economy and global financial system (BCBS, 2018). Perhaps the most well-known contribution of the BCBS can be seen in the Basel Accords – a global, voluntary regulatory framework that was developed to address financial regulation deficiencies by mandating several key principles such as certain capital adequacy levels, market liquidity requirements and certain leverage ratios for a bank to be Basel compliant, thereby helping regulate systemic risk exposure (BCBS, 2020).

Figure 5 Financial Stability Board (FSB) organization and members



Source: author's work according to FSB (2020b)

Despite these two standard setting institutions being most prevalent and important in assessing systemic risk exposure, several other institutions must also be outlined. Although the **International Association of Insurance Supervisors (IAIS)** focuses mainly on the insurance industry, their holistic framework to assess and mitigate many types of risks – including systemic risk, liquidity risk, cyber risk, and climate risk – has led to a framework whereby such risks are considered as "key factors" whose impact can lead to a chain-like wide reaching systemic impact on the financial market. Additionally, asset liquidation, critical functions and exposure channels have been identified as the main transmission channels of systemic risk (IAIS, 2016).

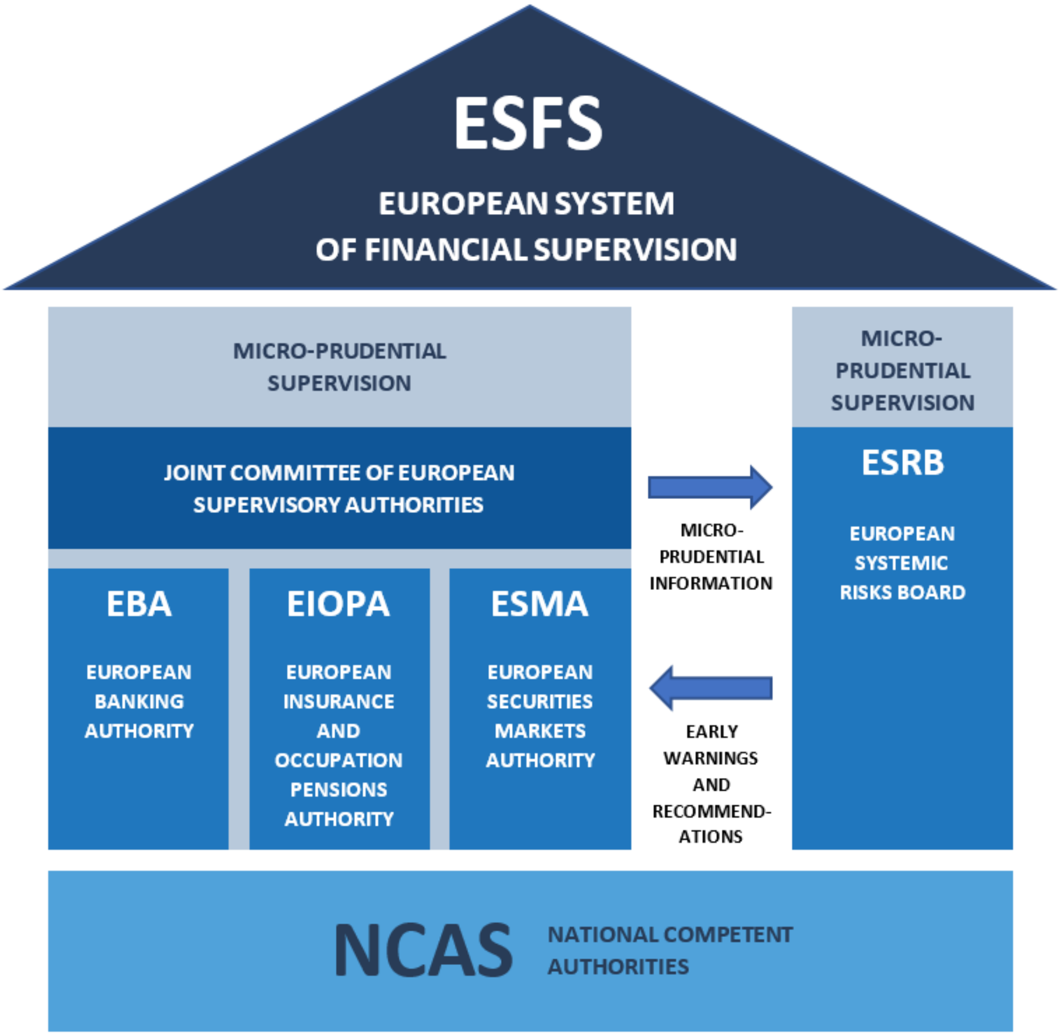
The intergovernmental economic **Organisation for Economic Co-operation and Development (OECD)** is another member of the FSB which, among others, studies systemic risk. In their Emerging Systemic Risks in the 21st Century: An Agenda for Action (2003) book, the organisation draws the over-arching conclusion that systemic risks by nature of their existence require a systemic response to be combated. OECD presents a set of general recommendations which include: adopting new and innovative policy approaches to risk management, implementing similar monitoring requirements for the public and private sectors alike, strengthening international co-operation in all facets of risk management to facilitate the required systemic responses and making better use of emerging technologies to aid in the research and monitoring efforts – a perfect opportunity for the usage of business intelligence. Next, the International **Organization of Securities Commissions (IOSCO)** should be mentioned as it is recognized as the global standard-setter for more than 95% of global security markets in more than 115 jurisdictions. The main objectives of the organisation revolve around maintaining fair, efficient and transparent markets whilst seeking to address systemic risks. Accordingly, IOSCO studied systemic risks and their transmission mechanisms and came to recognise three channels of financial distress transmission, namely the counterparty channel, the market channel, and the substitutability channel (IOSCO, 2014). These findings further corroborate BCBS's and FSB's previous research and highlight another area of necessitated high supervision.

Finally, two of the largest international financial institutions and organisations fostering global monetary cooperation and financial stability should be mentioned – the **World Bank** and the **International Monetary Fund (IMF)**. Both institutions contribute a wealth of knowledge on a myriad of topics ranging from the functioning of financial market to global economic challenges, as such, systemic risk is also naturally ingrained in this research and discussed. The World Bank (2010) identified several channels or contagions of systemic risk transmission which grow as a result of the interconnectedness between institutions, markets and infrastructure and their innate disturbances. By studying and monitoring these deficiencies, shortcomings in the banking resolution framework can be revealed. IMF (2020a) also highlights the systemic risk transmission channels as contagious and emphasize the Minsky cycle – a period in which the economy does well, optimism changes, and agents tend to invest more in the riskier asset – as the most important determinant of systemic fallout and economic instability. Once again, as the institution which coordinates all the ones outlined above, the FSB is the one which determines whether to accept the recommendation from member international standard setting bodies and whether to publish it or not.

3.1.2. European Union institutions

On the level of the European Union, before and during the 2008 financial crisis, financial stability was ensured through central bank policies and the supervision of individual financial institutions, i.e. micro-prudential supervision. In the aftermath of the crisis it was clear that ensuring lasting financial stability of the financial sector can only be achieved through the harmonisation of the overarching legislature as well as more robust institutional structures, financial infrastructure and related procedures. For this reason, the European System of Financial Supervisors (ESFS) was created, encompassing national supervisors (such as central banks), three European Supervisory Authorities (ESAs) – the European Banking Authority (EBA), the European Securities and Markets Authority (ESMA) and the European Insurance and Occupational Pensions Authority (EIOPA), and the fully specialized European Systemic Risk Board (ESRB). **Figure *6*** European System of Financial Supervision (ESFS) depicts ESFS's organization and hierarchy, as well as the communication channels and cooperation between subentities.

Figure 6 European System of Financial Supervision (ESFS)



Source: author's work

The ESFS objectives focus on preserving financial stability, providing protection for European consumers and promoting confidence by adequate micro- and macro-prudential reform and rule implementation, thus facilitating common supervisory culture and a single European financial market (ESFS, 2020). The most discerning difference between ESAs and the ESRB is that the former deals with micro-prudential regulation and supervision, whereas the latter focuses on macro-prudential issues. All three ESAs are organised in a same manner, and play a role in facilitating the proper functioning on the internal market, ensuring the soundness and effectiveness of the financial markets through integrity, transparency of undertaking, and assurance of international supervisory coordination (ESFS, 2020).

The European Systemic Risk Board (ESRB) is responsible for the macroprudential oversight of the EU financial system and the prevention and mitigation of systemic risk (ESRB, 2020d). The decision-making body of ESRB is its General Board, meeting at least four times a year and responsible for issuing recommendations and warnings (ESRB, 2020d).

Figure *7* European Systemic Risk Board (ESRB) - General Board below depicts the organizational structure of the ESRB's General Board. The circle outline indicates voting rights, with 38 representatives possessing voting right and 61 without.

Figure 7 European Systemic Risk Board (ESRB) - General Board

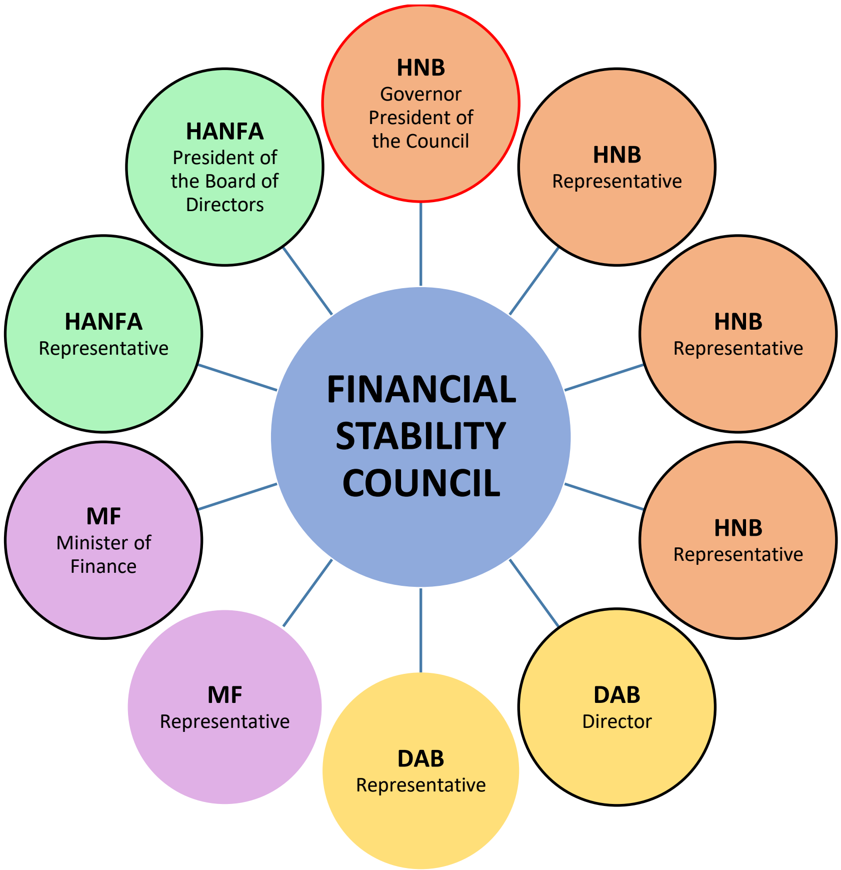
Source: author's work based on ESRB (2020c)

As the more specialized and macro-prudently oriented institution, the ESRB's goal revolves around the prevention and systemic financial stability risks mitigation. Same as with other standard setting bodies, the ESRB detects risks to the financial system as a whole, and issues warnings and recommendations when needed. To comprehensively monitor and understand macroprudential risks, the board collects and analyses relevant information, identifies and prioritizes systemic risks, issues warnings and recommendations, carries out tasks specified in EU legislation and coordinates its actions with other international financial and standard setting institutions such as the International Monetary Fund (IMF) and the Financial Stability Board (FSB) (ESRB, 2020b).

3.1.3. Institutions in Croatia

As is the case in most countries, the central bank is the main regulatory institution responsible for systemic risk. The single most important body for systemic risk management and macroprudential policymaking is The Croatian Financial Stability Council. The Financial Stability Council was founded by the financial stability council act passed by the Croatian Parliament on December 20th, 2013 (Zakon o Vijeću za financijsku stabilnost, NN159/13). The law governs issues in the field of financial stability, the formulation and implementation of macroprudential policy and its objectives, the establishment, operation, and jurisdiction of the aforementioned council, as well as various other issues in respect to the implementation of macroprudential policies. The council itself is an inter-institutional body that regulates and shapes the macroprudential policy of the Republic of Croatia. It is composed of representatives from the Croatian National Bank (HNB), the Croatian Financial Services Supervisory Agency (HANFA), the Ministry of Finance (MF), and the State Agency for Deposit Insurance and Bank Resolution (DAB). **Figure *8*** Croatian Financial Stability Council below depicts the financial stability council members.

Figure 8 Croatian Financial Stability Council Representatives



Source: author's work according to HNB (2020a)

As seen in the figure above, there are 10 members of the financial stability council. The Croatian National Bank (HNB) has the most representatives (4) followed by HANFA, MF and DAB all of whom have 2 representatives on the council. The circle outline indicates voting rights, with 8 representatives possessing voting right and 2 without. In the event of a tie, the President of the Council casts the deciding vote (HNB, 2020a).

The main tasks and powers of the council, as defined by the act, include:

1) Shaping of the macroprudential policy of the Republic of Croatia
2) Identification, assessment and consideration of systemic risks
3) Ensuring cooperation and exchange of information between competent and supervisory authorities, especially in the event of crises
4) Undertaking activities that help meet the requirements from the warnings and recommendations of the ESRB, and the preparation of appropriate justifications in case of non-compliance with these requirements
5) Harmonization of methodologies pertinent to the identification of systemically important financial institutions or structures

6) Issuing recommendations and warnings in relation to systemic risks and financial stability
7) Participation in designing and implementing relief measures for the recovery and rehabilitation of credit institutions and non-bank financial institutions
8) Participation in the design of the deposit insurance system
9) Participation in the design of investor protection systems
10) Other tasks outlined in the Financial Stability Council Act

The most important task of the council relates to the issuance of warnings and recommendations to competent bodies, other state administration bodies and legal persons with public authority operating in the Republic of Croatia (Croatian National Bank – Financial Stability Department, 2020). The warnings mostly serve as tools which draw attention to systemic risks that might endanger the country's financial stability, whereas recommendations are utilized mostly to highlight the necessity for the introduction of new or the amendment of existing financial stability preservation measures and instruments. Competent bodies and legal persons to whom the council has issued a recommendation are mandated to act in accordance with the recommendation and required to regularly inform the council of the activities undertaken to enforce and implement the recommendation.

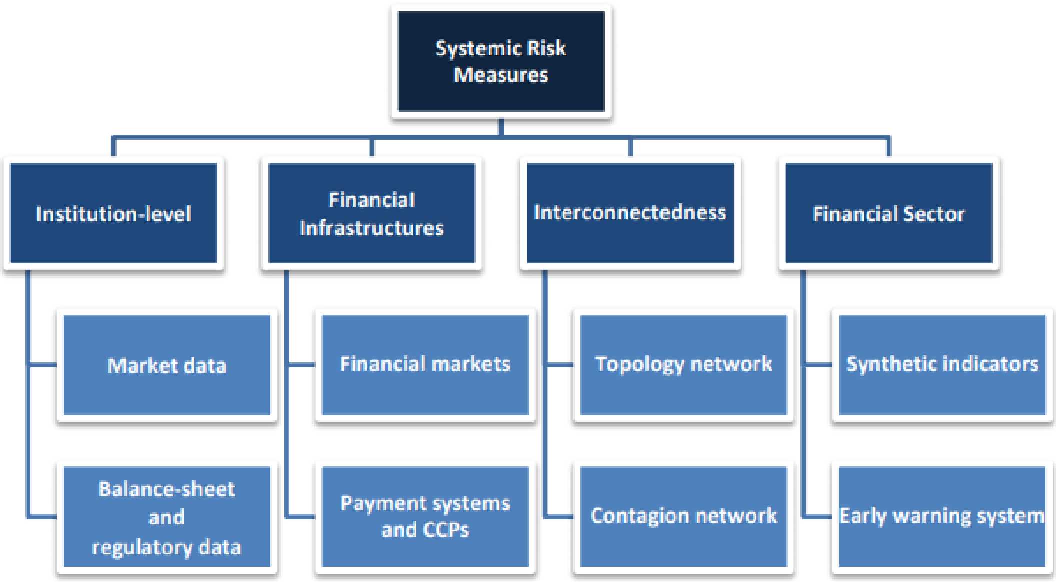
3.2. Measuring systemic risk

The importance of systemic risk definition and measurement, as already discussed, lies in the underlying assumption that with proper supervision and monitoring, actionable decisions can be made. Regulators aim to minimize the risk of systemic events within the financial system occurring in the first place, to ensure that the system as a whole does not have vulnerabilities to such events, an finally to limit the initial shock transmission through contagion channels (Smaga, 2014). Hansen (2012) notes that the two prerequisites are necessary for suitable systemic risk measurement: (i) the formalization of the concept of systemic risk; and (ii) the acquisition of data necessary to support the measurement. The concept of systemic risk has already been explored in the chapter on systemic risk definition, while this chapter will explore different methods of measuring systemic risk and metrics used to achieve that goal. Although the complete overview of systemic risk measures is beyond the scope of this paper, the taxonomy of systemic risk indicators as well as description of selected commonly used measures will be presented.

3.2.1. Taxonomy of systemic risk indicators

Since the financial crisis of 2008, systemic risk received great attention from regulators, central banks, and researchers who proposed a staggering number of different metrics. De Bandt et al. (2013) classified the measures used in systemic risk supervision into four distinct categories: indicators based on financial institutions, measures focusing on financial infrastructures, indicators on interconnectedness and contagion networks and financial sector indicators. **Figure *9*** Systemic Risk Measures below illustrates these four main categories of risk measures[2].

Figure 9 Systemic Risk Measures



Source: De Bandt et al. (2013)

Institution-level indicators focus on *systemic importance* and *systemic fragility* of financial institutions and will be discussed in more detail in a separate subchapter. Measures of systemic risk that fall into the financial infrastructure bucket pertain to the cross-sectional dimension of systemic risk and test the resilience of financial markets to shocks (De Bandt et al. 2013). Indicators on interconnectedness, on the other hand, measure the network effects of an interconnected financial system using a descriptive approach and analysis of contagion mechanisms. Finally, systemic risk measures within the category of financial sector include synthetic indicators and early warning systems.

[2] Table with a full list of measures of systemic risk by De Bandt et al. (2013) available in the Appendix 1 Overview of Measures of Systemic Risk

Blancher et al. (2013) provide an alternative classification of systemic risk measures, focusing on different phases of systemic risk and models which are appropriate for each of the phases. **Table *3*** Categorization of Systemic Risk Models and Measures**Error! Reference source not found.** below shows the classification of systemic risk models and measures by Blancher et al. (2013).

Table 3 Categorization of Systemic Risk Models and Measures

Measurement classification basis	Categories	Explanation	Measurement focus
Systemic risk phase	Buildup phase	Increase in the level of systemic risk over time due to overheating, increased risk-taking etc.	Monitoring wheather the likelihood for the crisis is increasing
	Shock materialization	Economic and financial system already fragile and susceptible to shocks	Assesment of potential losses in the financial system and real sector
	Amplification and propagation	Initial shock could affect other financial institutions, markts and sectors, including other countries	Measurement of inerconnectedness in the financial system, crossborder exposures and monitoring potential fire sales
Level of aggregation	Individual financial institutions and markets	Focus on the systemically important financial institutions (SIFI)	Monitoring equity price deviations from fundamental analysis
	Risk transmission channels	Interactions between financial institutions and method of risk transmission	Marginal contribution of individual financial institution to the level of systemic risk
	The whole financial system and the economy	Capturing the risk that the entire financial system is impaired	Crisis prediction and stress-test models, general equilibrium models
Types of risk	Credit risk	Probability of defaults, potential losses	Stress-testing, loss-gived default (LGD)
	Liquidity risk	Financial insttution's liquidity and market's liquidity	Liquidity ratios, collateralization channels
	Market risk	Aggregate measures of market volatility	Stress-testing for interest rates and exchange rates changes, asset prices shocks

Source: author’s work based on Blancher et al. (2013)

Blancher et al. (2013) differentiate between the *buildup phase*, *shock materialization* phase and the final phase of *amplification and propagation*. The underlying idea is that during the systemic risk buildup phase it is important to focus on the indicators of systemic event likelihood and aim to decrease the probability of such a shock. In the case that a systemic event is already very likely to occur it is better to focus on measures of potential losses and policies that will minimize the effects on the financial system and the economy. Finally, if the initial shock has already occurred, it is crucial to focus on the measures of interconnectedness of the financial system and monitor cross-border activities to reduce the amplitude of contagion and spillover effect.

3.2.2. Systemically important financial institutions

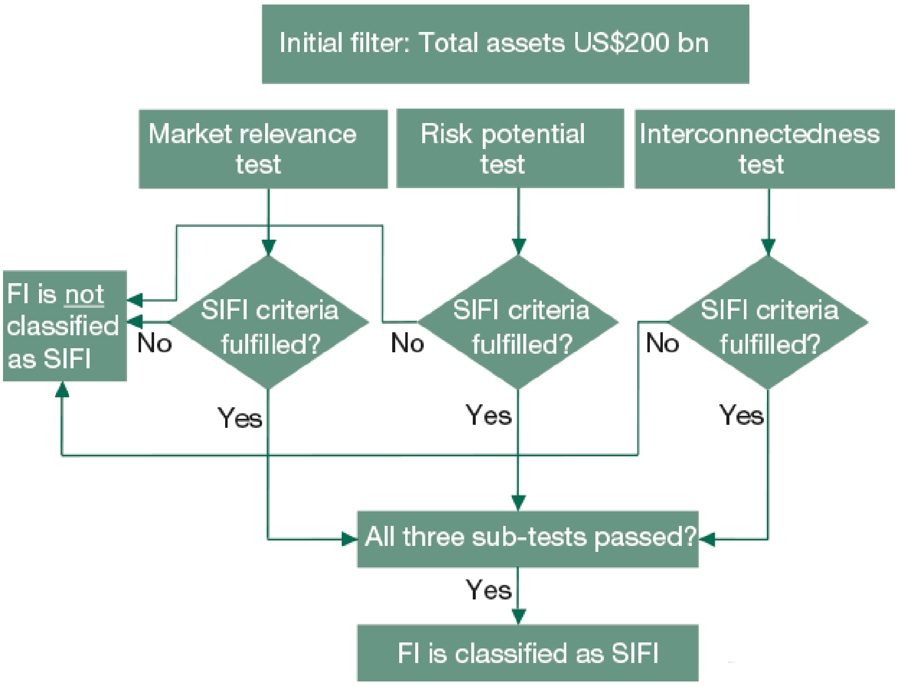
The concept of systemically important financial institutions (SIFI) has been introduced following the financial crisis of 2008. The Dodd-Frank Act – a legislative response to the financial crisis – enabled the establishment of the Financial Stability Oversight Council (FSOC), which has the authority to label financial institutions as systematically important. Systemically important financial institutions are defined as those financial institutions whose distress or disorderly failure would cause significant disruption to the wider financial system and economic activity (FSB, 2010; 2013). The main factors driving financial institutions to be deemed as systemically important are their size, complexity and interconnectedness with other entities within the financial system. These factors aim to address two problems associated with SIFIs: too-big-to-fail (TBTF) and too-connected-to-fail (TCTF).

The FSB currently publishes an annual list of globally systemically important institutions (G-SIFI), focusing on globally systemically important banks (G-SIB) with plans to incorporate insurers as well (FSB, 2019a; 2019b). Banks listed as G-SIBs[3] are then required to uphold to more rigorous regulatory requirements, namely to increase their capital buffer, total loss-absorbing capacity and higher standards with regards to resolution planning and meeting supervisory expectations (FSB, 2019a). The same set of principles are then downscaled from global perspective to regional and national levels. For example, the Croatian National Bank publishes a list of "Other systemically important credit institutions" imposing the additional capital requirements on these institutions[4].

[3] 2019 list of G-SIBs is available in the appendix
[4] 2019 list of Other systemically important banks in Croatia is available in the appendix

The supervision framework for systematically important financial institutions has been well defined and extensively elaborated. However, there are still suggestions for improvement of methodology. Brühl (2017) proposes a threefold SIFI test based on an institution's global market relevance, high level of risk potential and high level of interconnectedness. **Figure *10*** SIFI identification test depicts the proposed methodology with three identification tests required for a financial institution to be classified as systemically important.

Figure 10 SIFI identification test



Source: Brühl (2017)

3.2.3. Popular institution-level indicators

Institution-level measures capture the indicators of systemically relevant institutions, primarily banks and insurance companies, as well as market data. Market data is mostly used for potential predictions of systemic disruptions as market prices represent a forward-looking perspective. Three market measures of systemic risk deserve special attention, as they are used extensively by regulators: CoVaR, DCoVaR, MES, SES and SRISK. **Table *4*** Measures of systemic risk below presents these institution-level measures of systemic risk.

Table 4 Measures of systemic risk – Institution-level quantile approach

Indicator	Author	Measuring	Explanation
CoVaR	Tobias Adrian and Markus K. Brunnermeier (2008)	Systemic importance	**Conditional Value at Risk** measures the contribution of the specific institution to the VaR of financial system
DCoVaR	Tobias Adrian and Markus K. Brunnermeier (2014)	Systemic importance	**DCoVaR** measures the difference between CoVaR of the financial system conditional on an institution being in distress and the CoVaR conditional on the median state of the institution
MES	Acharya et al. (2009, 2010, 2012)	Systemic fragility	**Marginal Expected Shortfall** mesures the marginal contribution of an institution to systemic risk
SES	Acharya et al. (2009, 2010, 2012)	Systemic fragility	**Systemic Expected Shortfall** measures institution's propensity to be undercapitalized when the system as a whole is undercapitalized
SRISK	Brownlees and Engle (2011)	Systemic fragility	**SRISK** measures the institution's capital shortfall conditional on a severe market decline, as a function of its size, leverage and risk

Source: author's work based on De Bandt et al. (2013)

All of the measures mentioned above stem from one popular indicator in risk management, Value at Risk (VaR). VaR measures the maximum loss of a certain portfolio in a specified time period (e.g.1 month) and given the certain confidence level (e.g. 95%), expressed as a percentage. Conditional VaR (CoVaR) builds on this concept and measures the contribution of the specific institution to the VaR of financial system, indicating systemic importance of financial institution. DCoVaR, furthermore, measures the difference between CoVaR of the financial system conditional on an institution being in distress and the CoVaR conditional on the median state of the institution. Marginal Expected Shortfall (MES) measures the marginal contribution of an institution to systemic risk, while Systemic Excpected Shortfall (SES) measures an institution's propensity to be undercapitalized when the system as a whole is undercapitalized. Finally, SRISK measures the institution's capital shortfall conditional on a severe market decline, as a function of its size, leverage and risk.

4. BUSINESS INTELLIGENCE TOOLS AND ADVANCED ANALYTICS

4.1. Definitions of business intelligence and advanced analytics

Advanced analytics and business intelligence are both irreplaceable parts of any organization's decision-making process. With the exponential increase in data availability, diversity, and available computing power, it is more important than ever to utilize these tools properly. This chapter will shine a light upon the definitions of business intelligence and advanced analytics as well as discuss the distinction between the two terms.

4.1.1. Definition of business intelligence

Business intelligence, in a broad sense, can be understood simply as an organization's capability to utilize available information to achieve competitive advantage (Ćurko, 2002). Furthermore, as will be elaborated in the following chapter on historical development of BI and advanced analytics, these two terms both stem from the broader field of analytics. Richardson et. al. (2020) therefore provide a collective and comprehensive definition for analytics and business intelligence (ABI) as "easy-to-use functionality that supports a full analytic workflow - from data preparation to visual exploration and insight generation - with an emphasis on self-service and augmentation.". Easy-to-use functionality indicates that the learning curve to use a business intelligence solution should not be steep and should therefore be accessible to consumers with a non-technical background. A full analytic workflow incorporates all of the extract, transform, and load (ETL) data processing tasks as well as data visualizations. Ćurko, Pejić Bach & Radonić (2007) point out the three most commonly adopted technologies of BI: (i) data warehousing (DWH), (ii) online analytical processing (OLAP) tools and (iii) data mining. Generally speaking, BI tools traditionally focus on a hindsight view and use ETL functions to provide human-readable data visualizations on specified key performance indicators (KPIs).

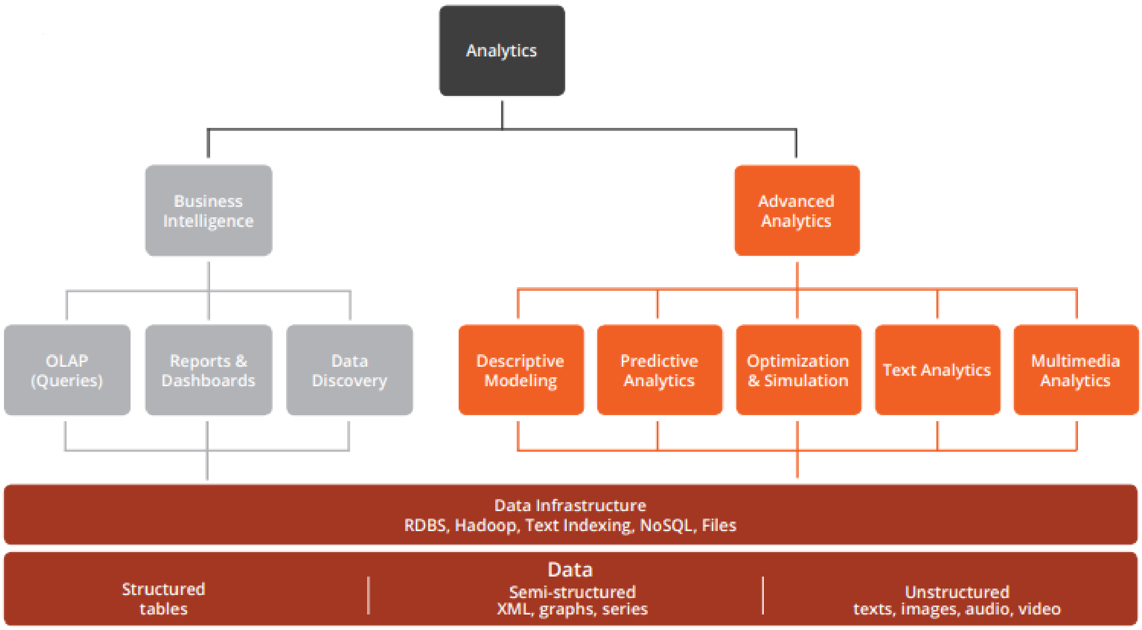
4.1.2. Definition of advanced analytics

Advanced Analytics build on top of traditional business intelligence solutions and serve as a broader term that encompasses sophisticated tools – usually beyond the scope of traditional BI tools - including the application of artificial intelligence (AI). Another important factor is that advanced analytics pertain to semi-autonomous or fully autonomous solutions (Gartner, 2020). This means that users who are not themselves experts in applying complex algorithms to drive insights can still utilize sophisticated techniques such as artificial intelligence, machine learning, pattern matching, forecasting, visualization, semantic analysis, sentiment analysis, network and cluster analysis, multivariate statistics, graph analysis, simulation, complex event processing and neural networks (Gartner, 2020). EBA (2020a) defines advanced analytics as a broad pool of techniques and tools which utilize big data to deliver predictive and prescriptive analysis. One can conclude that advanced analytics is a term used to describe a combination of statistical analysis methods and artificial intelligence applications to serve a function of providing insights within the scope of a certain business problem.

4.1.3. Distinction between business intelligence and advanced analytics

When describing analytics and business intelligence (ABI), Richardson et al. (2020) highlight 15 different capability areas: security, manageability, cloud, connectivity, data preparation, complexity, artefact catalog, automated insights, advanced analytics, data visualization, natural language querying, data storytelling, embedded analytics, natural language generation and reporting. It is clear that there is a need to combine these two terms into a single concept as the tools are not only used in coordination and simultaneously, but are also often integrated within the same software solution. However, this does not mean that the terms business intelligence and advanced analytics should be used interchangeably – on the contrary, there is a clear distinction. **Figure *11*** Business Intelligence vs. Advanced Analytics shows the relation between business intelligence and advanced analytics within the broader category of analytical tools.

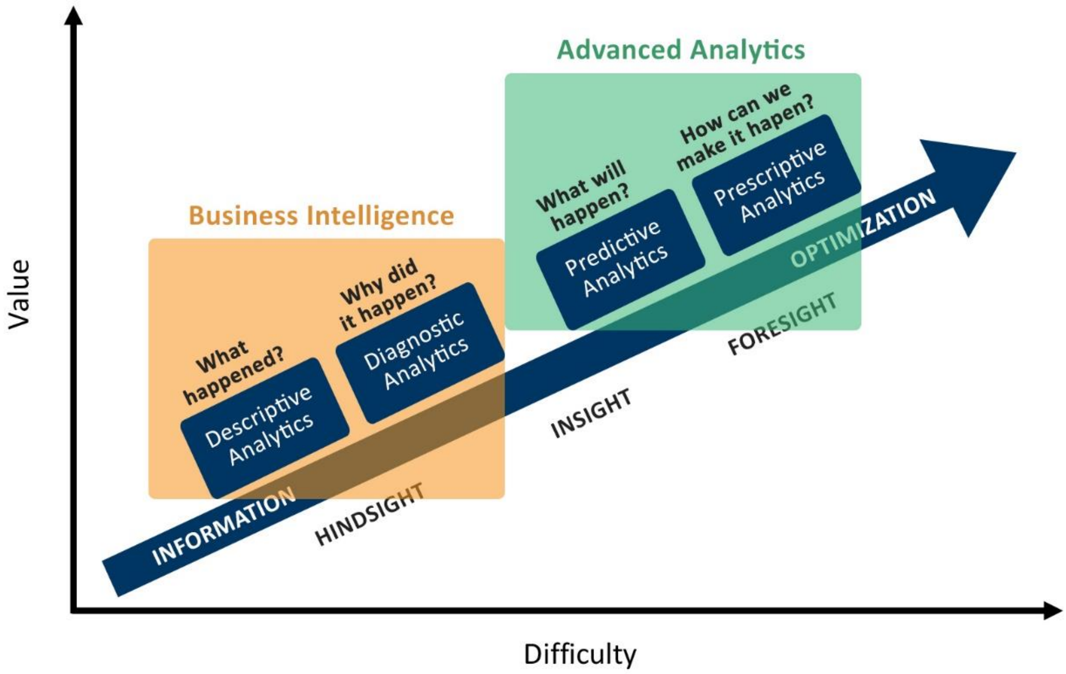
Figure 11 Business Intelligence vs. Advanced Analytics



Source: Rapidminer (2020)

Business intelligence tools utilize OLAP queries and dashboard reporting for data discovery. BI solutions, therefore, enable measurement of past performance through a set of automatic calculations and measures, as well as provide an easily readable presentation of large volumes of data. Advanced analytics effectively start where BI software ends. Specifically, AA enables automatic utilization of sophisticated methods for predictive and prescriptive modelling (Rapidminer, 2020). **Figure** ***12*** Data Analytics Maturity Model below illustrates this difference between business intelligence and advanced analytics. Business intelligence tools are mostly used for descriptive and diagnostic analytics by utilizing data external and internal to an organization. Essentially, BI tools are primarily concerned with performing hindsight analysis and deriving insights for future planning. Conversely, advanced analytics aim to provide foresight using predictive and prescriptive models leading to optimization and decision-making.

Figure 12 Data Analytics Maturity Model



Source: author's work based on Gartner (2020), Rapidminer (2020) and other sources

The end result of business intelligence tools are interactive dashboards which showcase a rearview orientation on business events analysis, consequently answering questions such as "What happened?", "When?" and "How many?". BI tools use different sets of predefined metrics to analyze past performance. However, the knowledge generation itself has to be done manually by business users. In contrast, advanced analytics automatically provide insights and utilize predictive modelling, statistical processing and optimization to answer questions about the future: "What will happen?" and "What will occur if specific variable changes value?" (Rapidminer, 2020).

4.2. Historical development of business intelligence and advanced analytics

The concepts of Business Intelligence (BI) and Advanced Analytics (AA) are very closely linked to one another and – as we shall see from this chapter – share a large chunk of common history. Much like systemic risk (which we traced as far back as the 17th century), Business Intelligence finds its historical roots with Richard Millar Devens who first coined the term in 1865 (Davis and Woratschek, 2015). Devens, the authors explain, used the term to describe how a banker profited by receiving and acting upon information about his environment before his competitors could. It took almost an entire century since then for the term Business Intelligence to gain traction in scientific literature once more. Many scholars (Davis and Woratschek, 2015; Grossmann and Rinderle-Ma, 2015; Pavkov, Poščić and Jakšić, 2016) commonly note that it was Hans Peter Luhn who once again re-coined the term in his 1958 article "A Business Intelligence System", thereby marking the beginning of its more contemporary development. These "prehistoric" events – as Grossmann and Rinderle-Ma (2015) humorously refer to them – ultimately led to the development of Decision Support Systems (DSS) and, some three decades later, to Business Intelligence as we know it today.

Before we delve deeper into modern Business Intelligence concepts and tools, one must first take a look at its early development in the context of DSS. Decision Support Systems mainly evolved early in the era of distributed computing with the introduction of IBM System 360 – the world's biggest and fastest computer at the time (Power, 2007; da Cruz, 2019). Power (2007) provides an interesting look at the computing advances brought on by IBM's hardware innovation: the IBM System 360, firstly, made it more practical and cost-effective to develop Management Information Systems (MIS) in large companies. This meant managers could now process accounting and/or transaction data and receive structured reports printed on a sheet of paper. Secondly, the data-processing capabilities brought on by the IBM computer spawned numerous scientific articles throughout the late 1960s and early 1970s which generated more public interest and led to further advances in the field. In 1971, for example, Michael Scott Morton published a groundbreaking book titled "Management Decision Systems: Computer-Based Support for Decision Making" in which he studied how computers and analytical models could help managers make key business decisions. Marketing and production managers in Scott Morton's study were given an MDS to coordinate production planning for laundry equipment. This utilization of a computer-based MDS was a pioneering implementation and research test of a model-driven research support system (Power, 2007). Indeed, it marked the beginning of a series of business- and performance-related tests which culminated during the 1990s, with the advent of the World Wide Web.

According to Power (2007): "Beginning in approximately 1995, the World Wide Web and global Internet provided a technology platform for further extending the capabilities and deployment of computerized decision support. The release of the HTML 2.0 specifications with form tags and tables was a turning point in the development of web-based DSS". These important innovations led to the development of OLAP (Online Analysis Processing) and

ROLAP (Relational Online Analytical Processing) – two analytical processing tools which formed the foundation of modern BI (Kateeb, Humayun and Bataweel, 2014; Davis and Woratschek, 2015). Pavkov, Poščić and Jakšić (2016) further solidify this claim by stating that this phase of BI development is often referred to as "BI 1.0". Furthermore, the 1990s not only saw developments in the area of data management, but also in data mining and predictive analytics (Grossmann and Rinderle-Ma, 2015). The authors go on to explain that all of these concepts started getting grouped under the name business analytics by the end of the 1990s, making it seem like BI was a collection of very loosely related and heterogeneous set of tools used to support a plethora of tasks within a business. "Hence" – the authors conclude – "it was necessary to consolidate the different lines of development and to focus again on the decision support perspective".

The dawn of the 21st century thus marked a distinct turning point as further technological development meant more specialized tools could be created in order to ease decision support across an entire organization. This transformation is referred to as "BI 2.0" and is characterized by an array of innovative technologies: (i) real-time data handling; (ii) SaaS; (iii) cloud computing; (iv) social networks; (v) linked data; and (vi) opinion mining (Trujillo and Maté, 2012). Grossmann and Rinderle-Ma (2015) further state that one can nowadays find a well-structured understanding of the business logic in almost all domain areas, thereby integrating workflow considerations and process mining into BI itself. Yet in the wake of this technological and data revolution, many organizations started experimenting with Advanced Analytics as a tool to help them stay competitive (Rose et al., 2017). The two concepts discussed within this chapter – BI and AA – only started to diverge as recently as 10 years ago. The authors note how AA go beyond traditional BI solutions to incorporate algorithmic techniques from machine learning, artifcial intelligence, natural language processing and other computer science disciplines. Although these techniques are becoming more and more prevalent (especially in larger, multinational corporations), they still represent a significant learning challenge and require in-depth knowledge to properly operate and analyze (Rose et al., 2017).

4.3. Classification of business intelligence tools and advanced analytics

As already noted in the previous chapter, there is a strong connection between BI tools and advanced analytics, but also a clear distinction. These concepts will be discussed in more detail in this chapter, presenting the popular BI tools and most common advanced analytics methods.

4.3.1. Comparison of different business intelligence tools

Business intelligence tools range from those offering full-stack solutions to the ones with solely visualization capabilities. The most popular BI tools are easy to integrate into the existing information technology infrastructure, provide scalable solutions and are simple to access for all users. Gartner (2020) provides a comprehensive tool to analyze vendors of leading business intelligence solutions and, more importantly, the products themselves. **Figure *13*** Gartner's Business Intelligence Magic Quadrant below shows how the most popular BI products compare to one another.

Figure 13 Gartner's Business Intelligence Magic Quadrant

Source: Gartner (2020)

Gartner (2020) uses its Magic Quadrant to analyze BI tools with respect to two aspects: completeness of vision and ability to execute. While ability to execute pertains to the capability of software to match current demand, completeness of vision stands for the preparedness for future changes in the demand and ability to add new features. Niche players are focused on a relatively small market segment and are currently not able to capture wider market. Challengers dominate the market with their products, but might be unprepared to meet the changing demand. Visionaries understand the market trends, but are not yet able to provide a competing product. Leaders are already capturing sizeable market with their competitive product and are also aware of the potentially disruptive changes in technology and demand (Gartner, 2020).

When inspecting the latest Gartner's magic quadrant, two specific products stand out, Tableau Software and Microsoft's Power BI. However, not all projects will require the same solution (Watson, 2009). Large-scale projects might need custom, tailor-made solutions because of the pure scale of the solution and resources needed for training, maintenance and change management. Other important issue, especially for national and supranational organizations, is information system security and concern about data privacy.

4.3.2. Advanced analytics methods

Advanced analytics has already figuratively been described as a catchall term for different statistical methods and artificial intelligence algorithms, which go beyond the scope of business intelligence solutions. Not only is it oftentimes confused with artificial intelligence, advanced analytics are almost inseparable from the concept of big data, which is a primary requirement for sophisticated modelling (FSB, 2017; BIS, 2018). Furthermore, advanced analytics incorporate various mathematical models and data transformation techniques. For example, even if the topic is limited to systemic risk, advanced analytics can refer to standard econometric models such as vector autoregression (VAR), systemic risk measures such as SRISK (Engle, 2018) , machine learning (ML) algorithms such as principal component analysis (PCA) (Nucera et al, 2016) and optimization models such as systemic risk minimization model (Castellano et al., 2020). One important distinctive characteristic of advanced analytics is that these models should be autonomous or semi-autonomous within the system (Gartner, 2020). Once developed, they should not require continuous oversight by professionals who implemented the model. This is different from the majority of machine learning and advanced statistical model algorithms, which are continuously revised by the authors. Out of these methods of advanced analytics, artificial intelligence and machine learning algorithms deserve special attention. The applications of AI and ML for analytics in securing financial stability will be discussed in more detail in the following chapters.

4.4. Applications of business intelligence and advanced analytics

4.4.1. Applications of business intelligence

Application of business intelligence tools does not always have the same end goal. Watson (2009) distinguishes three main BI targets according to the differences in terms of scope of the project, required resources, level of adoption by management, technical architecture, types and level of benefits the project will bring as well as impact on personnel and already established business processes. For specific projects, organizations will sometimes require a single BI application, for other BI infrastructure that will support both current and future tasks might be needed while some institutions will require full organizational transformation (Watson, 2009). Spremić (2017a) explains digital transformation as quick and thorough adaptation of its core business activities, including processes, structure and strategy.

There are many examples of application of business intelligence in corporations. **Figure *14*** Use cases for Business Intelligence in Corporations depicts the most common uses of BI solutions within corporations.

Figure 14 Use cases for Business Intelligence in Corporations

Source: BARC (2020)

The leading tasks require highly analytical approach and regular oversight, benefit from the interactive dashboard features, automation of ETL processes and reporting. Where business intelligence tools really stand out is the ability to incorporate both various types of data as well as new models for data analysis and graphical representation features. Probably the best recent example of utilizing visual representation part of BI solutions is the current global COVID-19 pandemic[5], incorporating geographical code data (Joao, 2020).

4.4.2. Applications of advanced analytics

The development of advanced analytics is highly dependent on the rapid developments in digital technologies. Spremić (2017b) distinguishes between basic, already existing digital technologies and emerging digital technologies, which will shape the business landscape of tomorrow. Big data and cloud computing are the single most crucial digital technology enabling advanced analytics, making it possible to access vast amounts of data and process the data efficiently.

Advanced analytics are applied in more and more industries within both businesses, nonprofits as well as governmental and supranational organizations. Henke et al. (2016) list almost completely exhaustive list of industries in their research on current and future use of advanced analytics, including healthcare, retail, education, public sector, life sciences, smart cities etc. Authors estimate a huge potential of $260B just in the sector of retail banking as a direct impact of data integration. The applications of advanced analytics will require trained personnel, which is not currently available on the labor market, specifically in the roles of data scientists, machine learning engineers, but also more traditional positions as database managers, engineers and security professionals. Henke & Kaka (2018) highlight the utilization of advanced analytics across different departments within large organizations, from marketing and sales to operations, human resource management and risk management. Advanced analytics is at the core of the Fourth industrial revolution and fuels the further increase in productivity, which will ultimately lead to disruption.

Utilization of advanced analytics is especially present in the financial sector – banks, insurance companies and investment management companies for example. The next chapter will go into more detail with regards to application of advanced analytics in financial sector and in regulatory agencies, with special focus on systemic risk supervision.

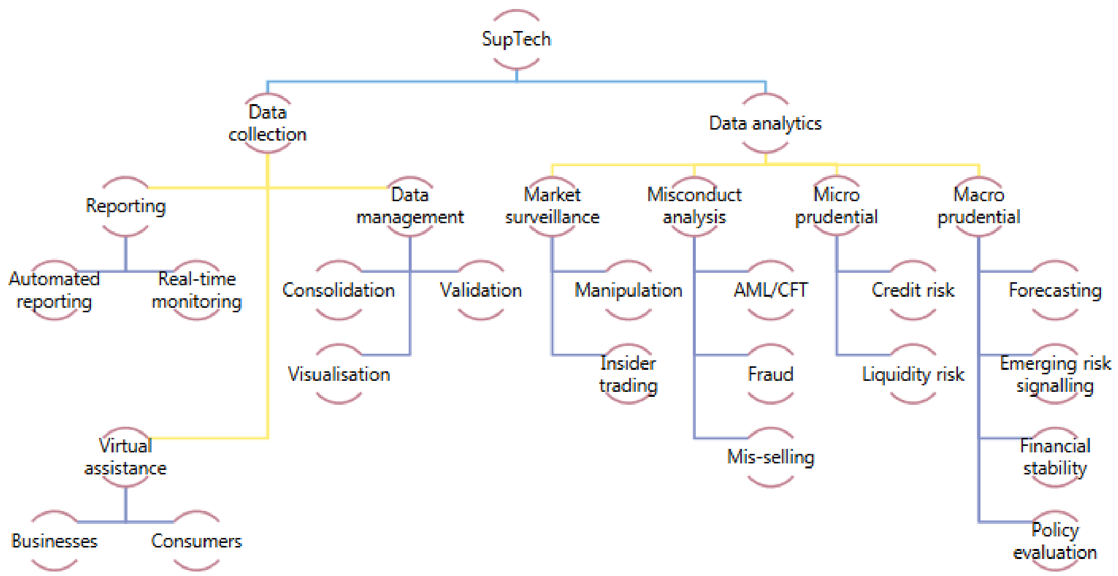
[5] See for example https://coronavirus.jhu.edu/map.html, Power BI version, Tableau version

5. UTILIZATION OF BUSINESS INTELLIGENCE TOOLS AND ADVANCED ANALYTICS IN SYSTEMIC RISK SUPERVISION

5.1. Overview of existing implementations

Business intelligence tools and advanced analytics will become one of the drivers of innovation in the fields of supervisory technology (SupTech) and regulatory technology (RegTech). Moreover, some technological solutions pertaining to this classification are already in use. Broeders & Prenio (2018) categorize the current use cases into data collection and data analytics. Authors recognize that SupTech already supports supervision by digitizing the processes such as reporting, integrating signalling systems and automatic forecasting. ***Figure 15*** Utilization of SupTech in Financial Supervision below illustrates the current use cases of SupTech.

Figure 15 Utilization of SupTech in Financial Supervision



Source: Broeders & Prenio (2018)

More specifically, business intelligence and advanced analytics have also found their way into systemic risk supervision. International regulatory, supervisory and academic institutions began implementing BI tools and applying advanced analytics to better utilize available data, automate solutions and increase efficiency of their researchers and practitioners. The remainder of this chapter will cover some of the implementations of business intelligence tools and advanced analytics to produce systemic risk supervision dashboards - visualization approach to systemic risk monitoring.

5.1.1. International supervisory organizations

One of the most detailed documents on systemic risk supervision tools is the International Monetary Fund's (IMF) user guide for "*SysMo*", a systemic risk-monitoring toolkit.[6] Based on this toolkit, IMF's *Global Financial Stability Report* [7] was developed - covering a range of topics from credit and emerging markets to the banking sector and the effect climate change has on equity prices. *SysMo* serves as one of the best set of guidelines in developing dashboard solutions for systemic risk supervision. It contains both an overview and synthesis of systemic risk measures, as well as a proposal of the supervision dashboard itself (Blancher et al., 2013). The supervision dashboard proposal can be found in ***Appendix* 4** Systemic Risk Monitoring Toolkit: IMF Sample Dashboard. In the United States, the Federal Reserve (FED) Bank of Cleveland's *Systemic Risk Indicator*[8] and the U.S. Department of Treasury Office of Financial Research's (OFR) *Bank Systemic Risk Monitor* are good examples of utilization of business intelligence tools. Cleveland FED's *Systemic Risk Indicator* tool was developed based on the research by Saldias (2013) and shows the changes in systemic risk in US financial services industry according to the widespread insolvency in the US banking system (FED, 2020). The most interesting dashboard among these, due to its interactive format and multiple sources of data, is the one by OFR.[9] The OFR's idea behind the interactive visualizations approach to monitoring financial stability is grounded in research. Flood et al. (2015) argue that visual analytics bring potential benefits for financial stability monitoring. Authors classify the visualization techniques as *static* or *dynamic*, and *noninteractive* and *interactive*, thus contriving four distinct categories. **Table *5*** Four categories of visualization techniques below lists the four visualization techniques and provides an example for each. Interactive-static visualization is the cornerstone of business intelligence dashboards, and is far more beneficial than the noninteractive-static counterpart is. Moreover, advanced analytics and business

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[6] See Blancher et al. (2013) and Appendix 4 Systemic Risk Monitoring Toolkit: IMF Sample Dashboard
7 See IMF (2020b)
[8] See FED (2020) and Appendix 5 Systemic Risk Indicator by Cleveland FED
[9] See OFR (2020) and Appendix 6 Bank Systemic Risk Monitor

intelligence tools enable knowledge discovery as well as dynamic visualizations such as movement of measured values through time. Flood et al. (2015) indicate that these tools enable better synthesis of information from huge, complex and often ambiguous datasets, thereby increasing analysts' productivity and refocusing their efforts on subject-matter research instead of data collection, manipulation and visualization.

Table 5 Four categories 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

Source: Flood et al. (2015)

OFR, therefore, utilizes interactive charts. These charts enable time-period and measurement of risk filtering, thus allowing for simultaneous presentation of multiple information sources on a given visual. On the example available in the Appendix 6 Bank Systemic Risk Monitor, year and indicator selection are enabled as filters via dropdown lists, G-SIB scores are shown on the x-axis while the level of Basel G-SUB capital surcharge is indicated by a legend and different colours.

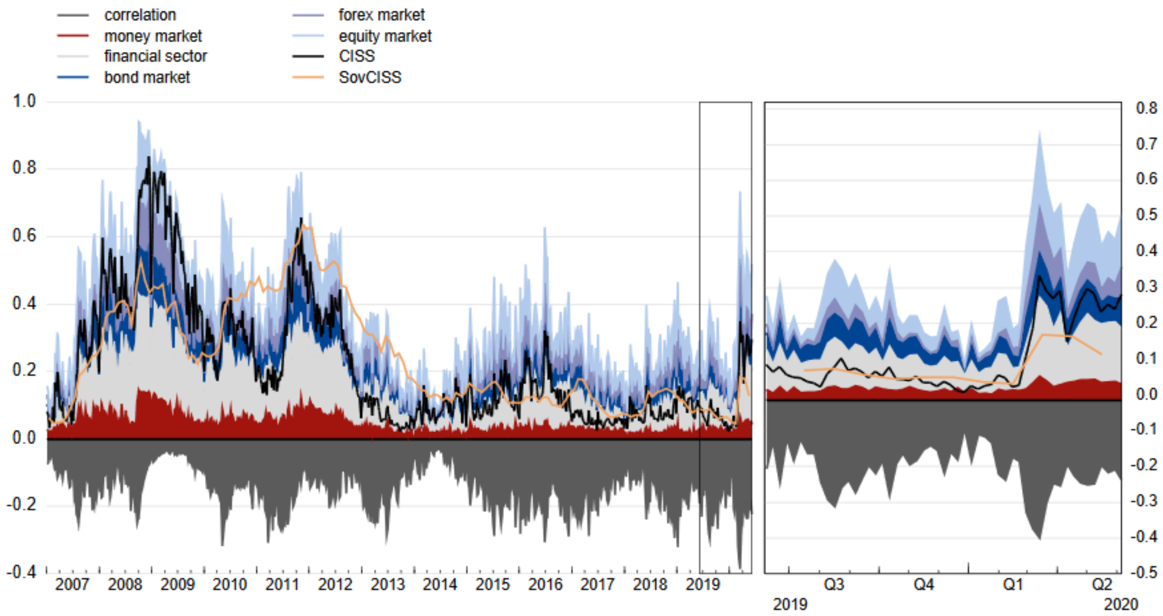
5.1.2. European supervisory and regulatory organizations

Some of the better-known examples of business intelligence solutions for systemic risk management by supervisory institutions in Europe include European Central Bank (ECB) and its European Systemic Risk Board (ESRB), which publishes *ESRB Risk Dashboard* [10] and European Banking Authority's (EBA) *Risk Dashboard*.[11] Both reports are available in .pdf formats for external purposes and, therefore, represent noninteractive-static visualizations according to Flood et al. (2015). EBA (2020b) provides a risk level approach by introducing heatmaps as a selected visual. Appendix 7 Risk Indicators Heatmap illustrates the utilization of heatmaps for risk monitoring purposes. In its risk dashboard, EBA uses a three-color *traffic lights* system to indicate low, medium and high risk-level for each specific indicator. Additionally, arrows pointing up, right or down can be utilized to signal a positive and negative

[10] See ESRB (2020a)
[11] See EBA (2020b) and Appendix 7 Risk Indicators Heatmap

trend, or stagnation (EBA, 2020b). Furthermore, the ESRB (2020a) uses eight distinct categories of risk in its quarterly published risk dashboard: interlinkages and composite measures, macroeconomic risk, credit risk, funding and liquidity, market risk, profitability and solvency, structural risk and risk related to central counterparties. ESRB (2020a) highlights the importance of composite indicators, by using Composite indicator of systemic stress (CISS) developed by Holló et al. (2012). **Figure *16*** CISS - Composite Indicator of Systemic Risk in Financial System illustrates the latest available data on CISS systemic risk indicator in the EU.

Figure 16 CISS - Composite Indicator of Systemic Risk in Financial System



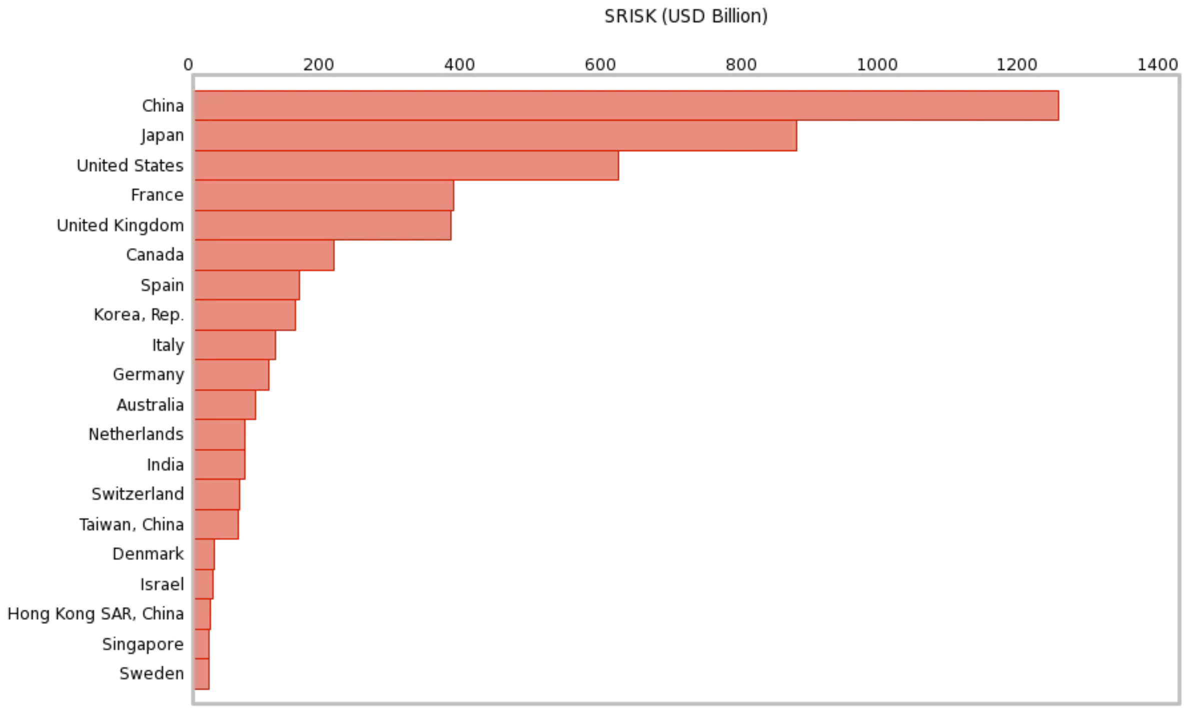
Source: ESRB (2020a)

The purpose of CISS is to measure the current state of financial distress and instability with a single indicator. CISS condenses the instability measure of banking and non-banking financial intermediaries, money markets, equity and debt markets and foreign exchange markets in a single statistic (Holló et al., 2012). However, it is important to reiterate that this indicator is backward-looking and showcases current state of the financial (in)stability, rather than predicting the future events.

5.1.3. Academic institutions

Regulatory institutions are not the only ones who demonstrate innovative approaches to systemic risk supervision. Academic organizations including research institutes and universities contribute significantly to the topic as well. Two of the leading academic institutions which base their research on systemic risk include the Volatility and Risk Institute with its Volatility Laboratory (V-Lab) and the Systemic Risk Centre (SRC). The SCR institute is co-hosted by London School of Economics (LSE) and University College London (UCL) and was co-founded by UK Financial Conduct Authority, European Central Bank, Central Bank of Iceland, Central Bank of Luxembourg and Banque de France in 2013 (SRC, 2020). The Volatility Laboratory (V-LAB) is based in New York, supported by NYU Stern and lead by Nobel Prize for Economics laureate Robert Engle. V-LAB provides a number of interactive charts which enable the selection of numerous different measures of systemic risk (V-LAB, 2020). **Figure** *17* Global Systemic Risk by Country - SRiSK illustrates one of these charts, showing SRISK measurement for countries in billion USD.

Figure 17 Global Systemic Risk by Country - SRiSK



Source: V-LAB (2020)

The greatest value added by V-LAB's approach to the systemic risk dashboard solution is its ability to interactively change underlying assumptions of tables and visualizions thereof. Appendix 8 V-LAB Interactive Parameterized Dashboard on Systemic Risk depicts the interactive options and parameterized values of the dashboard. Users can simply increase or decrease the variable for expected market decline from the default value, change the capital requirements per country, as well as filter specific banks. This level of flexibility and ability to change the input values enables analysts not only to quickly understand the dangers of current level of systemic risk in the financial system, but also to conduct further research based on different scenarios and ultimately analyse various outcomes and effects of specific macroprudential policies.

5.2. Potential future applications

While the current systemic risk monitoring processes sometimes include business intelligence tools, implementation of advanced analytics is still lacking behind. This chapter henceforth discusses the potential utilization of advanced analytics and machine learning in systemic risk supervision, focusing on new systemic risk measures and early warning systems on one side, and automation of macroprudential analysis on the other.

5.2.1. New systemic risk measures and early warning systems

Although current applications of BI tools provide a solid base for a systemic risk management and supervision toolkit, there is still a lot of room for improvement. One of the most valuable additions to systemic risk supervision toolkit, which could come from the scope of advanced analytics, is a set of effective early-warning systems. These systems have a goal of signaling potential crisis occurring, but are touted to be severely underdeveloped. ESRB (2020a), for example, explicitly states that its Risk Dashboard is comprised of a set of quantitative indicators and is not to be regarded as an early-warning system. Research suggests that the majority of systemic risk indicators perform poorly in predicting the upcoming financial crisis (Brownlees et al., 2020; Danielsson, 2017). However, new technologies and increasing availability of datasets enable continuous improvement of existing metrics and introduction of new indicators. Lang et al. (2019), for example, show promising results with their new early warning model – the domestic cyclical systemic risk indicator (d-SRI).

Moreover, there are many newly proposed indicators and measures for systemic risk that make use of advanced analytics. Kou et al. (2019) provide an extensive overview of the application of the machine learning methods in systemic risk supervision. **Table *6*** Machine Learning methods in Systemic Risk Supervision lists the current research on ML in systemic risk supervision by research objective. Kou et al. (2019) recognize four research objects in papers focusing on application of ML in systemic risk supervision: financial network, market sentiment, stability of financial industry and quantitative financial regulation. To address these research objects, authors use four main ML methods: network model, big data analysis, text mining and models more closely related to traditional statistical research and econometric models (Kou et al., 2019).

Table 6 Machine Learning methods in Systemic Risk Supervision

Objectives	Branch	Literatures	Methods	Data and areas
Financial network	Evolution of financial network	Allen and Gale, 2000; Souza, Silva, Tabak, and Guerra, 2016; Battiston, Farmer, and Flache, 2016; Haldane, 2015; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015; Haldane and May, 2011; Prasanna, Haldane, and Kapadia, 2011; Hu, Zhao, Hua, and Wong, 2012; Hu, Schwabe, and Li, 2015; Ferrara, Langfield, Liu, and Ota, 2016.	Multilayer networks; probability; economic theory, complexity theory, ecology, epidemiology and finance, etc.	BIS data; US banking system, the Bank of England, the European Union, Brazil, Japanese credit cooperatives and other emerging economies.
	Risk exposure and transmission	Stein, 2011; Hutchison, 2002; Shen, 2017; Giudici, Sarlin, and Spelta, 2017; Giudici and Spelta, 2016; Amini, Cont, and Minca, 2013; Bluhm and Krahnen, 2014; Choi, 2014; Billio et al., 2012; Cruz and Lind, 2012; Ladley, 2013; Betz, Hautsch, Peltonen, and Schienle, 2016; Souza, 2016; Cerchiello and Giudici, 2015; Carmassi and Herring, 2016; J.P. Li, Feng, Sun, and M. L. Li, 2012; Bernardi and Romagnoli, 2016; Chinazzi and Fagiolo, 2015.	Multivariate network; multivariate graphical models and Bayesian graphical models; inhomogeneous directed graphs; particle movement model; conditional graphical models, distorted copula-based probability, etc.	
	Financial network and real economic	Chang, Guerra, Lima, and Tabak, 2008; Gabbi, Iori, Jafarey, and Porter, 2014; Diebold and Yilmaz, 2014; Helwege and Zhang, 2016; Diebold and Yilmaz, 2014; Giudici and Parisi, 2017; Brunnermeier and Sannikov, 2014; Duca and Peltonen, 2013; Huang, Zhou, and Zhu, 2012; Calmès and Théoret, 2014.	Weighted directed graph; correlated stochastic processes; Dynamic Stochastic General Equilibrium (DSGE) model, etc.	
	The structure of financial network	Bargigli, Di Iasio, Infante, Lillo, and Pierobon, 2014; Battiston, Caldarelli, May, Roukny, and Stiglitz, 2016; Poledna, Molina-Borboa, Martínez-Jaramillo, Leij, and Thurner, 2015; Fukuyama and Weber, 2015.	Multilayer network, etc.	
Market sentiment	Correlation analysis of systemic risk and financial market	Choi, Chan, and Yue, 2017; Campbellverduyn, Goguen, and Porter, 2017; Flood, Jagadish, Kyle, Olken, and Raschid, 2011; Cui, 2015; Dong, Yang, and Tian, 2015; Smailović, Grčar, Lavrač, and Žnidaršič, 2014; Cerchiello and Giudici, 2016; Sarlin, 2016a; Sarlin, 2016b; Cerchiello, Giudici, and Nicola, 2016; Brunnermeier and Pedersen, 2009; Agliardi, 2018.	Big data analysis; web-based Business intelligence; Bayesian method; simulation and fuzzy systems, Value-at-risk, etc.	Financial words base; financial market, etc.
Market sentiment	Sentiment analysis in financial market	O'Halloran et al., 2015; Cerchiello and Giudici, 2016; Giudici et al., 2016; García, 2013; Price, Doran, Peterson, and Bliss, 2012; Tsai and Wang, 2013; Nyman, Gregory, Kapadia, Smith, and Tuckett, 2014; Chiang and Chen, 2015; Tsai and Wang, 2017; Meyer, Bikdash, and Dai, 2017; Tsai and Wang, 2017; Tromp, Pechenizkiy, and Gaber, 2017; García, 2013.	Big data analysis; text mining; regression and ranking methods. lexicon and sentiment analysis; Rule-Based Emission Model algorithm, etc.	Financial news; reports; twitter; laws, etc.
Stability of financial industry	Microstructures of financial market;	Arora and Rathinam, 2011; Bengtsson, 2014; Jin and Nadal De Simone, 2014; Wymeersch, 2010; Bluhm and Krahnen, 2014; Calmès and Théoret, 2013; Xiong et al., 2011; Walter, 2012; King and Maier, 2009; Liang, 2016; Bongini, Nieri, Pelagatti, and Piccini, 2017; Li, Liu, Siganos, and Zhou, 2016; Acharya, 2009; Acharya, Engle, and Richardson, 2012; Brownlees and Engle, 2011; Brownlees and Engle, 2017.	Statistical method; Conditional-Risk and Systemic Expected Loss (SES), GARCH and SRISK methods, agent-based computational finance, etc.	Chinese stock market; ver-the-counter (OTC) derivatives market; European securities market; endogenous asset markets and Market-oriented banking, etc.
	Financial tools, mechanisms and systemic risk,	Abedifar, Giudici, and Hashem, 2017; Calistru, 2012; Gaffeo and Molinari, 2016; Cox and Wang 2014; Acharya et al., 2012; Laeven, Ratnovski, and Tong, 2016; Calmès and Théoret, 2013; Balogh, 2012; Calabrese and Giudici, 2015; Chen, Wang, and & Yu, 2017; Hamdi, Hakimi, and Zaghdoudi, 2017; Bența et al., 2017; Crăciun, Bucerzan, Rațiu, and Manolescu, 2013; Liang, 2013.	Three-step importance sampling; regression analysis; logistic regression; stress testing, simulation analysis, etc.	Credit derivative markets, hedge fund, capital network and Shadow Banking, Tunisian banks, Romanian companies, etc.
Financial regulation	Quantitative policy analysis	Mustafa, Khursheed, and Fatima, 2018; Li, Spigt, and Swinkels, 2017; Posner and Weyl, 2013; Bosma, 2016; Clark and Jokung, 2015; Cao and Illing, 2010; Nucera, Schwaab, Koopman, and Lucas, 2016; Ashraf, Rizwan, and L'Huillier, 2016; Lupu, 2015; Fazio, Tabak, and Cajueiro, 2015; Fernández, González, and Suárez, 2016; Arthur, 2017; Khraisha and Arthur, 2018.	Benefit-cost analysis Causal test; correlation analysis, comparative analysis, etc.	Policies and laws of financial regulations.

Source: Kou et al. (2019)

New systemic risk measures, developed by applying machine learning algorithms and other methods of advanced analytics, aim to complement existing systemic risk models and to address their weak points. O'Halloran1 & Nowaczyk (2019), for example, propose an artificial intelligence approach to systemic risk management that would bridge the gap between microprudential and macroprudential systemic risk supervision. Nucera et al. (2016) use principal component analysis (PCA) to combine six different ranking methodologies into a single metric, while Kunovac & Špalat (2014) use PCA in the model for nowcasting Croatian GDP. All of these approaches, given the availability of data, will serve to improve the systemic risk supervision in the future.

5.2.2. Automation of macroprudential analysis

New digital technologies enable both better and more efficient supervision in two main ways. Firstly, by incorporating data that was previously unavailable and by introducing metrics based on the new methodologies and algorithms only recently discovered, additional insight into systemic risk supervision may be garnered. Secondly, existing systemic risk supervision efficiency can also be improved by automating current monitoring processes. The latter will be discussed in this subchapter. FSB (2017) predicts an increased utilization of artificial intelligence in Regulatory Technology (RegTech) and Supervisory Technology (SupTech). **Table *7*** Artificial Intelligence and Machine Learning in Supervision and Compliance below summarizes some of the possible applications of ML algorithms in RegTech, SupTech and macroprudential surveillance.

Table 7 Artificial Intelligence and Machine Learning in Supervision and Compliance

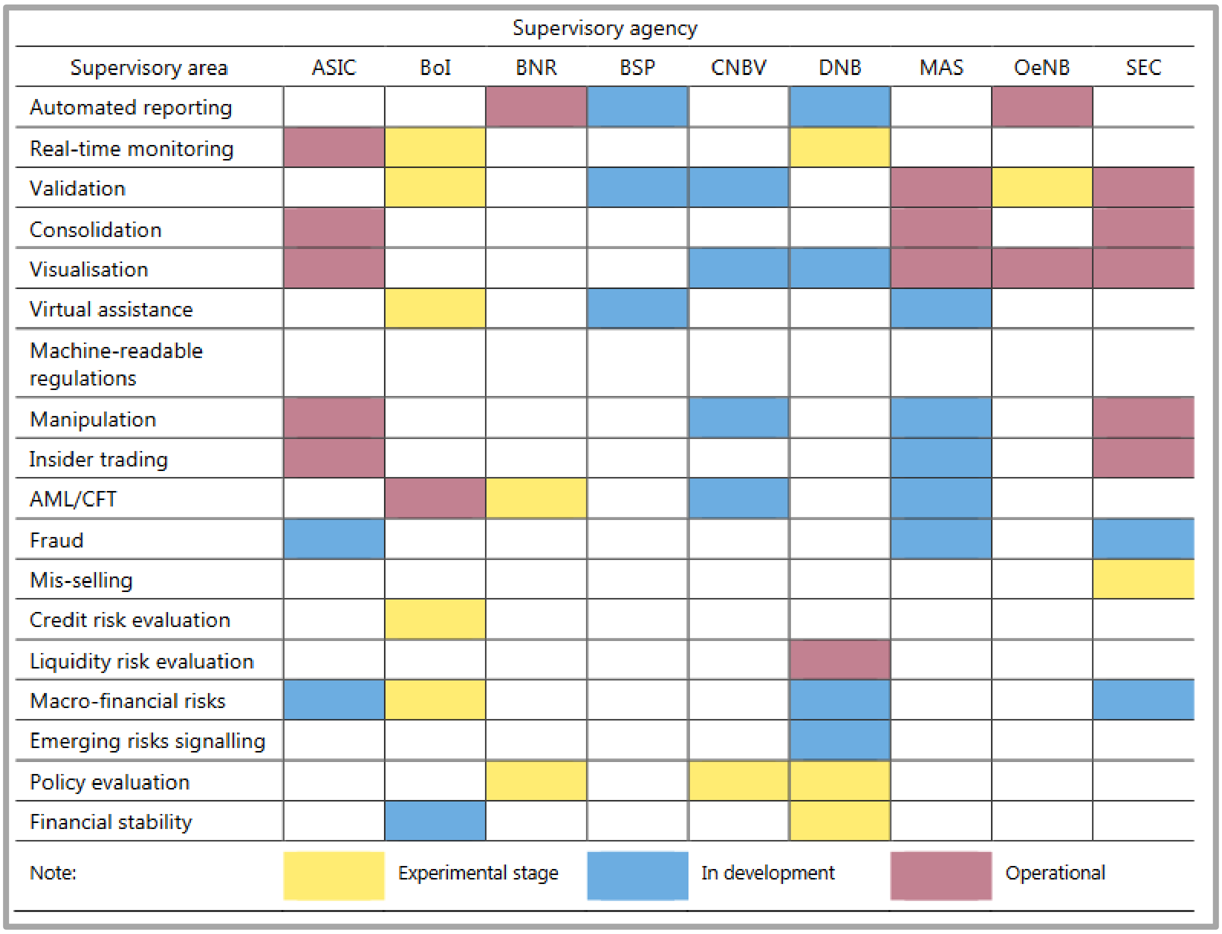
Field	Technology	Application
RegTech	Natural Language Processing (NLP)	Surveilance of e-mails, spoken word, instant messaging to detect miscoduct
	Computer Vision	Personal documentation processing automation
	Machine Learning (ML) Classification algorithms	Automatic risk-score calculation
Macroprudential surveillance		Data quality assurance
		More efficient data processing
		Automatic compliance, error detection
SupTech	Natural Language Processing (NLP)	Market sentiment analysis
	Predictive ML algorithms	Systemic risk identification
		Risk propagation channels analysis

Source: FSB (2017)

Apart from predictive algorithms such as early warning systems, supervisory institutions can benefit from the implementation of Natural Language Processing (NLP), Computer Vision and other ML algorithms which will result in an increased systemic risk monitoring efficiency (FSB, 2017). Machine learning can be used to detect data anomalies and aid practitioners and researchers to handle large amount of data with less errors, allowing them to focus on risk supervision instead of data preparation and processing. Proudman (2018) adds that advanced analytics will play an increasingly important role in systemic risk supervision and in the financial system as a whole, especially so in risk assessment and financial crime prevention and detection.

Variety and number of SupTech applications is constantly increasing, although the majority of advanced analytics and business intelligence tools implementations are still not in everyday use. Broeders & Prenio (2018) provide and showcase three different SupTech implementation phases by supervisory area and selected supervisory agencies. **Figure *18*** SupTech implementation phases below depicts these implementation phases.

Figure 18 SupTech implementation phases



Source: Broeders & Prenio (2018)

Broeders & Prenio (2018) differentiate between three implementation phases: *experimental stage*, *development stage* and *operational stage*. Some supervisory areas are not covered by SupTech even in experimental stage, such as the implementation of machine – readable regulations. Whereas policy evaluation is in the experimental stage in some supervisory agencies, visualization techniques are already utilized in day-today operations by few supervisory institutions.

5.3. Requirements and limitations of advanced analytics and business intelligence

Academics, researchers and practitioners keep developing better measures of systemic risk as well as new supervision tools. There are many drivers of this effort, be it the increased availability of data, higher collaboration between regulators or utilization of newly developed tools and algorithms made possible by cloud computing. This chapter discusses some of the key prerequisites for advanced analytics and business intelligence implementation, as well as the limitations of these tools and models.

5.3.1. Requirements

One of the basic requirements for both business intelligence and advanced analytics solution implementation is the availability of data, and its appropriate structure. In order to analyse systemic risk, Lo Duca et al. (2017) created a completely new database within ECB, with a dataset comprised of 50 systemic events and 43 residual events since 1970. To properly conduct research, develop new systemic risk measures and to implement new supervision tools, appropriate information technology infrastructure is needed. In most cases this includes databases, data warehouses, and OLAP cubes, processes and protocols necessary to import new data and satisfy data privacy and cybersecurity issues alike.

The other crucial prerequisite for implementation of BI and AA solutions is the lack of personnel with required skillset. Organizations need to have employees of various backgrounds who will be able to perform these tasks and interpret the results. These include data scientists, machine learning engineers, business intelligence engineers, database management professionals, and analytics translators (Henke & Kaka, 2018). This requires a combination of subject-matter skills, hard skills and soft skills. Subject-matter expertise pertains to specific knowledge on the topic of systemic risk which can be acquired through both formal education and professional experience. Hard skills include ability to use modern information and communication technology, i.e. programming languages and software required to conduct systemic risk supervision. Soft skills are equally important as they imply effective communication with both technical and non-technical personnel, and the ability to cooperate with external and internal parties to achieve a desired organizational goal.

5.3.2. Limitations

Utilization of business intelligence tools and advance analytics is not without its limitations. These limitations include issues outside of scope of BI tools and AA such as intrinsic mistakes in systemic risk measures, problems related to not ensuring that the IT infrastructure requirements for implementation are met, and finally the limitations of the models themselves.

The requirements for the implementation were discussed in the previous subchapter. It is worth reiterating that, if those prerequisites – including data availability and trained personnel – are not met, the BI and AA solutions cannot be implemented. Secondly, there might be some issues with the systemic risk measures themselves. Current systemic risk measures are unable to confidently predict the coming financial crisis – that is exactly the reason why supervisory agencies need versatile approaches using different categories of economic and financial indicators to monitor systemic risk. This is especially true for indicators serving as early warning systems. As aforementioned, the ESRB (2020a) provides an explicit disclaimer that its indicators are not to be interpreted as early warning systems, as they are based on historical data and have the purpose to provide a synthesis of market conditions rather than trying to predict the next event. Danielsson (2017) even goes as far as to say that ECB's Composite Indicator of Systemic Risk in Financial System (CISS) index is "too low before a crisis and too high after a crisis" – indicating that CISS does little to predict the upcoming financial crisis. Idier et al. (2013) assessed the other popular systemic risk indicator in supervisory institutions, Marginal Expected Shortfall (MES) and have concluded that it did not perform better than standard risk metrics like tier one solvency ratio. Brownlees et al. (2020), backtested the systemic risk measures during eight financial panics in the era before the FDIC insurance and found that CoVaR and SRISK were only somewhat effective at predicting the financial crisis. These systemic risk measurement limitations are important to keep in mind when analyzing BI and AA implementations by supervisory agencies. While business intelligence tools and advance analytics cannot immediately overcome the limitation of specific metric, but they can help supervisors better understand these issues and can also aid in addressing them in the future.

6. A CASE STUDY ON THE CROATIAN FINANCIAL SYSTEM

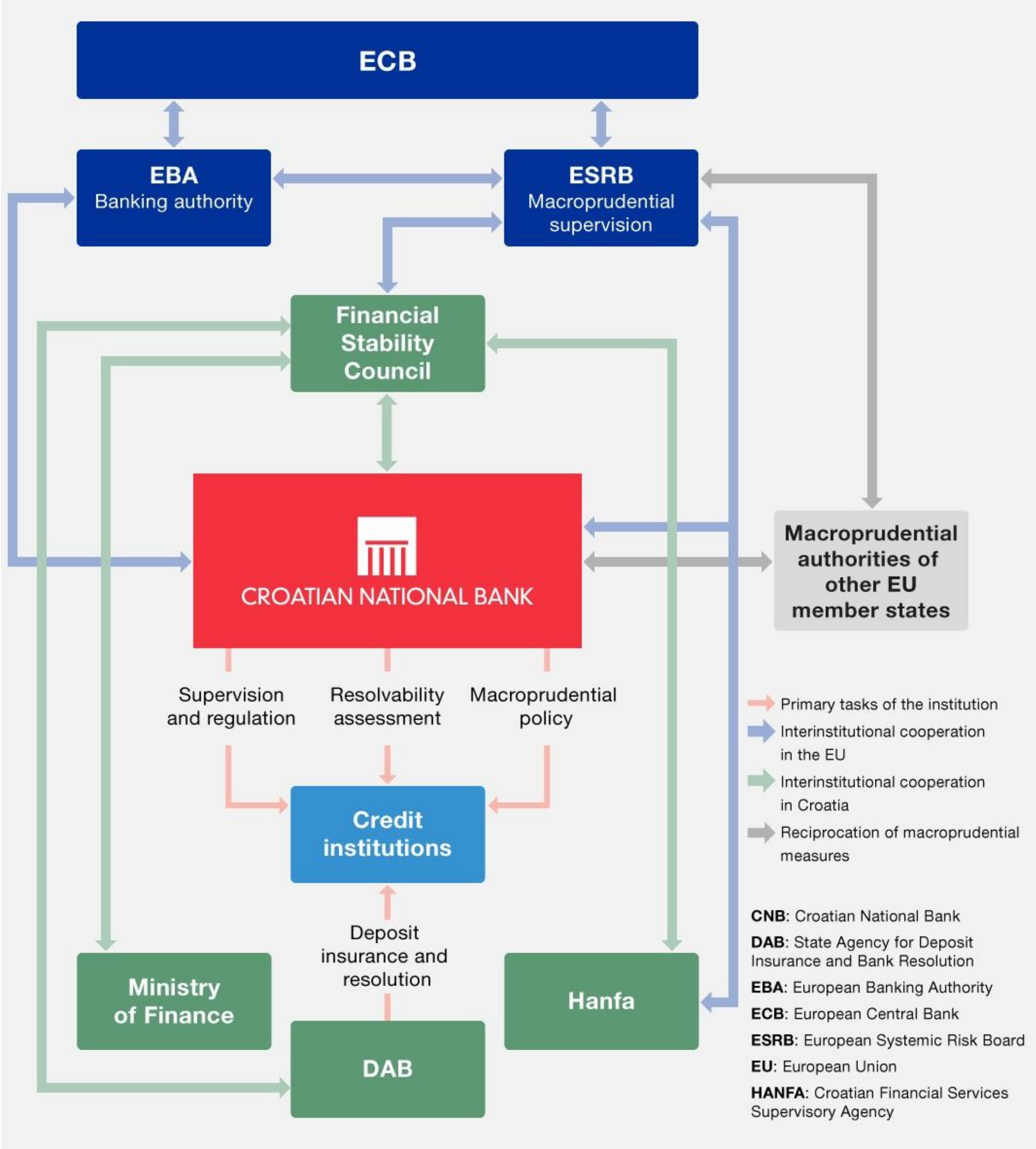
This chapter will provide an overview of macroprudential reporting in Croatia with special focus on the utilization of business intelligence tools and advance analytics. Firstly, the current macroprudential and systemic risk reporting practice by Croatian National Bank (HNB) and Croatian Financial Services Supervisory Agency (HANFA) will be reviewed. Secondly, a case study on Croatian financial system will be conducted and a business intelligence solution provided.

6.1. Current practices of systemic risk reporting in Croatia

Croatian financial system is a bank-centric financial system - where banks hold almost 70% of total assets in the financial sector (Krišto et al., 2018). The main institution responsible for systemic risk is the Croatian National Bank (HNB), which oversees the banking financial sector. The other important regulator is Croatian Financial Services Supervisory Agency (HANFA), which supervises the non-banking financial sector. Both HNB and HANFA are members of the Croatian Financial Stability Council, alongside Ministry of Finance (MF) and State Agency for Deposit Insurance and Bank Resolution (DAB).

Figure *19* Financial Stability and Systemic Risk Supervision in Croatia below illustrates the cooperation between HNB, HANFA and other institutions to ensure financial stability in Croatia. Both HNB and HANFA publish a dedicated reports on macroprudential diagnostics and systemic risk supervision respectively. The remainder of this chapter will provide a brief review of these documents, including their scope, measures used and frequency of publication.

Figure 19 Financial Stability and Systemic Risk Supervision in Croatia

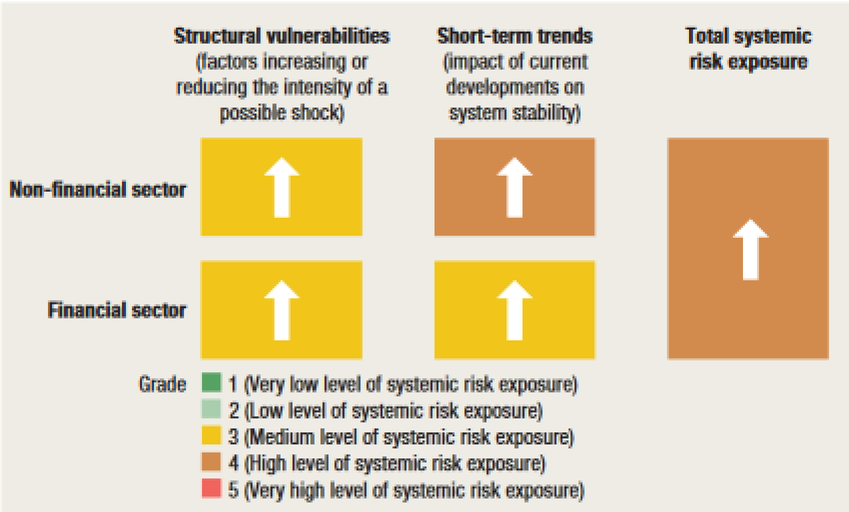


Source: HNB (2020c)

6.1.1. Croatian National Bank

HNB (2020b) publishes *Macroprudential Diagnostics* three times a year since 2017, focusing on “systemic vulnerabilities and risks which could jeopardize the stability of the domestic financial system”. HNB’s publication dedicated to systemic risk is concise and clear, but the report - condensed to only 20 pages and 4 graphs - does not properly reflect the importance of systemic risk and financial stability. It is worthwhile mentioning that HNB also publishes much more detailed monthly periodical *Bulletin*, covering macroeconomic overview of the real, monetary, fiscal and external sectors. *Macroprudential Diagnostics* includes a risk map indicating the level of systemic risk and its trend. The indicators cover structural vulnerabilities and short-term changes in system stability for financial and non-financial sector.

Figure 20 Croatian National Bank's Risk Map - Q1 2020



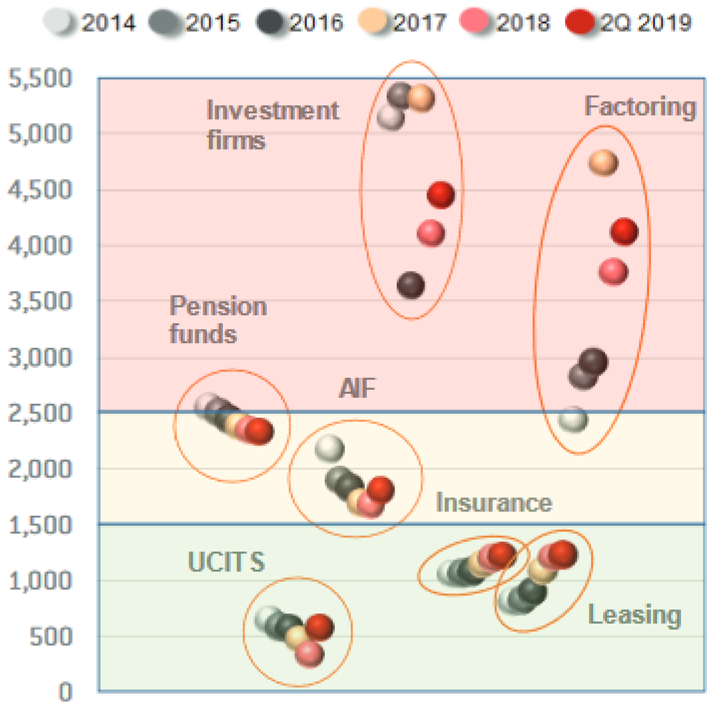
Source: HNB (2020b)

In the **Figure *20*** Croatian National Bank's Risk Map - Q1 2020 above, the level of the risk is indicated by color and classified into five categories, ranging from *very low* to *very high*. Additionally, the arrows indicate the trend of the risk compared to the last update in Q3 2019. As can be seen, HNB grades the level of total systemic risk exposure in Q1 2020 as high, which is an upward trend from Q3 2019.

6.1.2. Croatian Financial Services Supervisory Agency

HANFA (2020) started publishing *Macroprudential Risk Scanner* - its quarterly report on systemic risk - in 2019 with the aim of identifying, assessing and monitoring systemic risk in the non-banking financial sector. The report starts with a macroeconomic overview, followed by the assessment of systemic risk in financial services – covering all the relevant sectors under HANFA's domain. Detailed focus is given to market concentration, measures of interconnectedness, market risks, profitability and capitalization, liquidity risks and operational risks (HANFA, 2020). Overall, *Macroprudential Risk Scanner* provides a very good overview of the systemic risk in the Croatian non-banking financial sector, especially with regard to market concentration and interconnectedness between financial institutions. **Figure *21*** Market Concentration of Croatian non-Banking Financial System (HHI Index) gives an overview of market concentration within different sectors under HANFA's supervision using Herfindahl–Hirschman Index (HHI).

Figure 21 Market Concentration of Croatian non-Banking Financial System (HHI Index)



Source: HANFA (2020)

Both HNB's and HANFA's approaches to systemic risk supervision serve as a good starting point for further analysis. Business intelligence tools and advanced analytics could further improve the supervision process by enabling practitioners an access to an interactive and automated software solution. The following two subchapters will briefly present an example of such a tool.

6.2. Heatmap approach to systemic risk reporting

A beneficial addition to HNB's and HANFA's systemic risk supervision tools would be an expansion of the heatmap approach, which HNB utilizes for systemic risk exposure (**Figure *20***). A heatmap can be thought of as an analytical tool for assessing and monitoring risk exposure at a certain point in time. Heatmap assigns a risk level – represented by a single colour - to each of the data points for all of the given variables. The benefit of heatmap as a visualization tool is that it enables monitoring of exposures and vulnerabilities that can have systemic impact for a wide range of metrics in a systematic and transparent manner. The heatmap approach is a great way of representing different risk-levels for large sets of variables. Moreover, its use is seen extensively in systemic risk supervision (Bank of Ireland, 2017; Mencía. & Saurina, 2016; EBA, 2020b; Arbatli & Johansen, 2017; Ryan, 2017; HNB, 2020b).

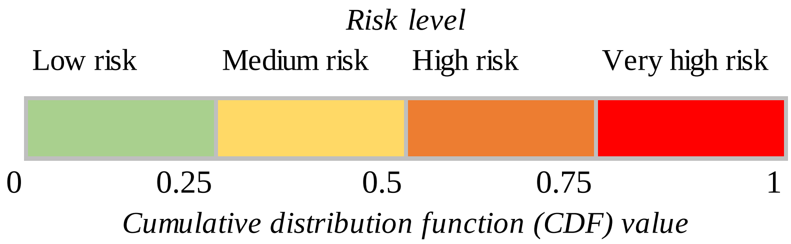
The heatmap approach requires a concise risk definition and assessment for a wide array of variables. A four – colour scheme is proposed, indicating different risk levels: *green – low risk*, *yellow – medium risk*, *orange – high risk* and *red – very high risk*. Following Mencía. & Saurina (2016), a distinction is made between one-tailed and two-tailed indicators. To determine the risk threshold for each of the risk categories, three distinct methods are used: cumulative distribution function (CDF) for one-tailed indicators, standard deviation and Z-score approach for two-tailed indicators, and pre-determined (hard-coded) thresholds for other indicators.

One-tailed indicators include those variables which always signal lower risk with lower values and higher risk with higher values, and vice versa. In other words, these are the metrics which are always better when they are lower or always better when they are higher. One example could be capitalization – the higher the capitalization of a financial institution, the lower the risk. Similarly, other examples can include liquidity and solvency ratios. Following the methodology used by Arbatli & Johansen (2017) for one-tailed indicators risk-level assessment, cumulative distribution function (CDF) is utilized to determine the risk level. Applying the CDF calculation by Holló et al. (2012), for each time series of the indicator $(x_1, x_2, \dots ,\ x_t\ , \dots , x_N)$, observations are ranked in ascending order from the lowest to the highest $(x^{(1)} \leq\ x^{(2)} \leq\ \dots \leq x^{(r)} \dots \leq\ x^{(N)})$ if higher values indicate more risk or in descending order from the highest to lowest if higher value indicates lower risk. N stands for the total number of observations, the subscript t denotes time and the superscript r refers to the ranking number assigned to a particular realisation of x_t. The normalised indicator Z_t is then constructed on the basis of the empirical CDF:

$$Z_t = F_N(x_t) = \begin{cases} \dfrac{r}{N}\ for\ x^{(r)} \leq\ x_t <\ x^{(r+1)} \\ 1\ for\ x_t \geq\ x^{(N)} \end{cases} \quad , r =\ 1, 2, \dots , N-1$$

The normalized indicator Z_t then represents the share of the observations that are less or equal to x_t, or the number of observations not exceeding x_t divided by the number of total observations (Holló et al., 2012). If a normalised indicator equals 0.2, this in fact means that 20% of the historical values are less than or equal to x_t. The highest values of the indicator therefore take on the normalized value of 1. The normalized indicators can then be mapped to the colour scheme, as visible from **Figure *22*** One-tailed indicator risk level.

Figure 22 One-tailed indicator risk level



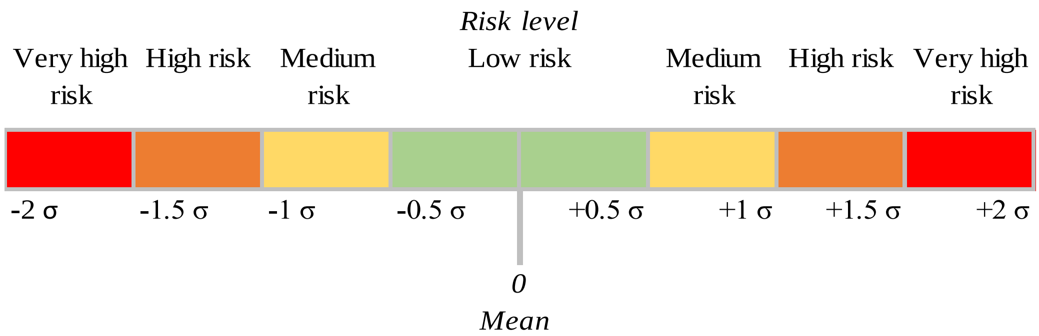
Source: author's work based on Mencía & Saurina (2016) and Arbatli & Johansen (2017)

Two-tailed indicators include those variables for which higher deviation from the average value indicates higher risk. Examples include various variables for which volatility is used to measure risk. The best example are equity prices – high volatility and abnormal change of price in each direction would indicate higher risk. Following Ryan (2017), the standard deviation approach is used for two-tailed indicators. Standardization with Z-score measures how many standard deviations an observation stands from the mean of the variable distribution. For observed value x_i with n observations, a mean of μ and a standard deviation of σ, Z-score will be calculated as:

$$Z_i = \frac{x_i - \mu}{\sigma}$$

The colour scheme is as shown in **Figure *23*** Two-tailed indicator risk level below. Standardized indictor Z has a mean $\mu = 0$ and standard deviation $\sigma = 1$. Extreme observation values on each end of the tail would be categorized with very high risk level, while observation values closer to the mean would be classified as less risky.

Figure 23 Two-tailed indicator risk level



Source: author's work based on Mencía & Saurina (2016) and Ryan (2017)

The final, third set of indicators either follow a separate methodology or just fall into pre-determined (hard-coded) thresholds. These are usually variables for which a specific target value - such as inflation or debt ratio – already exists.

By following this approach, heatmaps containing hundreds of variables can be generated and automatically periodically refreshed using business intelligence tools. Examples of heatmap dashboard implementations in macroprudential diagnostics by supervisors can be seen in ***Appendix 9*** *Heatmap example: Norwegian Central Bank* and **Appendix *10*** Heatmap example: Bank of Ireland.

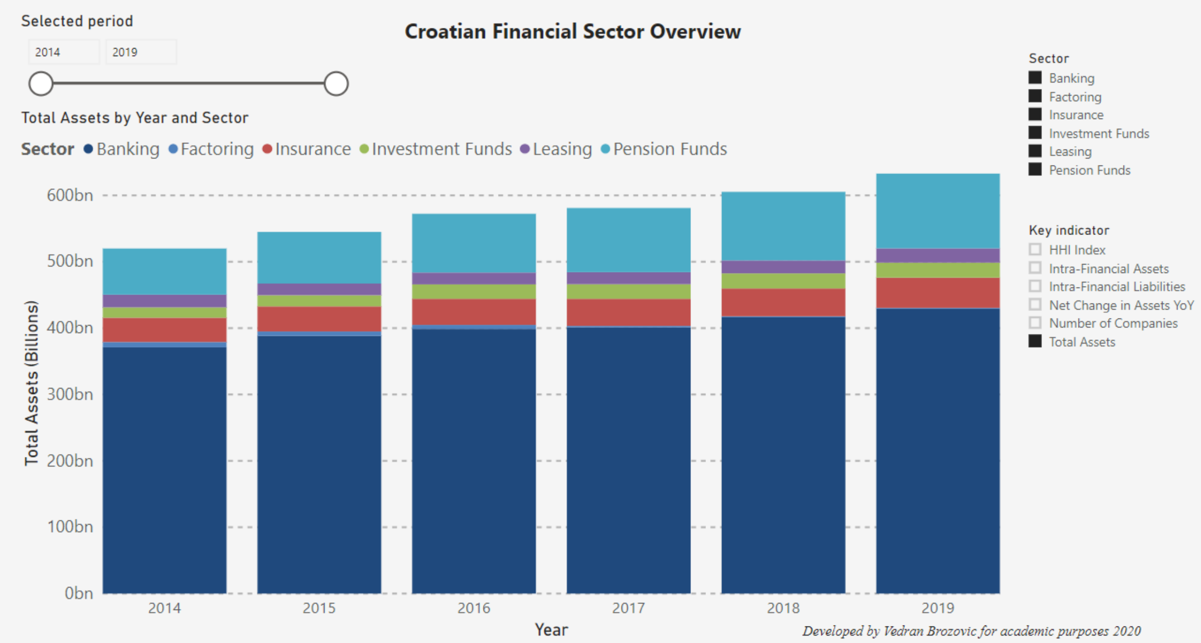
6.3. Business intelligence implementation

This chapter will illustrate some of the possible business intelligence solutions by displaying examples of interactive dashboard visualizations in systemic risk supervision on the example of the Croatian financial system. All of the displays are actual business intelligence examples which utilize data from HNB, HANFA, ECB and other publicly available sources. The software used to generate these models is Microsoft Power BI.

6.3.1. Croatian financial system overview by sectors

Arguably the best way to facilitate the analysis of the Croatian financial sector would be by taking a look at its key aspects such as size, composition and overall trends on the domestic financial markets. **Figure *24*** Croatian financial system overview by sectors illustrates the entire financial sector of Croatia displaying aggregate total assets of banking sector, pension funds, insurance companies, investment fund companies, leasing and factoring companies.

Figure 24 Croatian financial system overview by sectors



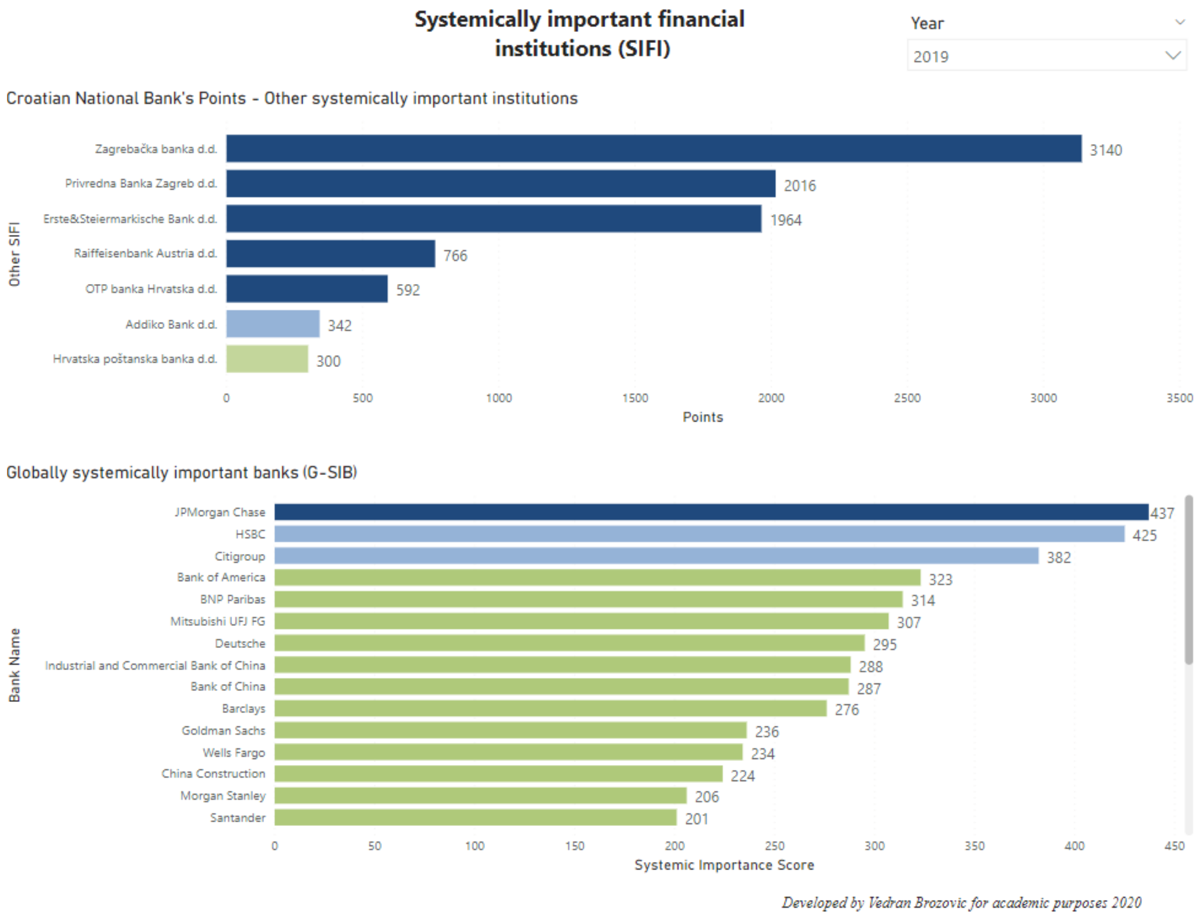
Source: author's work using publicly available data from HNB and HANFA

Apart from total assets, users are able to quickly change view to Herfindahl–Hirschman Index (HHI) or any other available metric via filter on the right side.

6.3.2. Implementation for systemically important financial institutions

Other useful dashboard solution displays systemically important financial institutions (SIFI). **Figure** *25* Systemically important banks - Croatia and worldwide below illustrates globally systematically important banks (G-SIB) and other systemically important institutions side by side. Systemic importance scores are presented and graphically indicated, while the coloring scheme differentiates between different levels of capital buffer and surcharge. The same dashboard can be used to analyze banks by many other metrics, including interconnectedness score, intrafinancial assets, intrafinancial liabilities, substitutability score, complexity score etc.

Figure 25 Systemically important banks - Croatia and worldwide

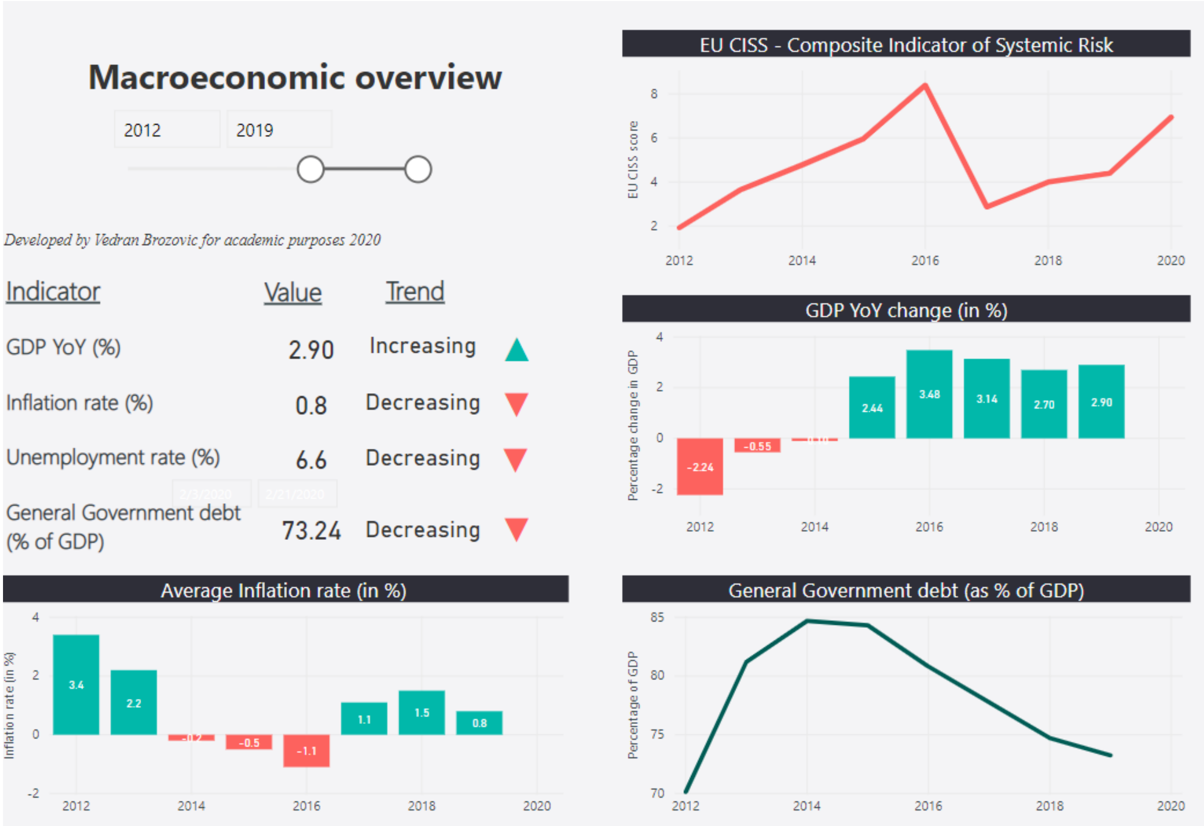


Source: author's work based on HNB and OFR data

6.3.3. Macroeconomic overview and systemic risk measures

Finally, **Figure** ***26*** Macroeconomic Overview & CISS displays how selected macroeconomic indicators can be presented following the example of EBA (2020b). Dashboard includes both current value of selected macroeconomic indicators as well as the trend, i.e. direction of change compared to the last data point. Furthermore, EU Composite indicator of systemic risk is included in the dashboard, displaying the functionality of simultaneous filtering of data from different sources.

Figure 26 Macroeconomic Overview & CISS



Source: author's work based on HNB and ECB data

7. CONCLUSION

Systemic risk supervision became an increasingly important topic since the global financial crisis in 2008. Regulatory response was unprecedented on the global scale. Thousands of pages of new regulations and macroprudential policies were published. Specialized councils, international organizations and research institutes were formed to tackle the potentially devastating consequences of another systemic risk event. While policymakers, researchers and systemic risk supervision practitioners now enjoy more resources than ever, the progress in risk identifying, risk assessment and monitoring is still slow without the implementation of new information technologies. Due to the high interconnectedness and complexity of financial system, it crucial to take advantage of technological advances in supervisory and regulatory processes. Supervisory technology (SupTech) and regulatory technology (RegTech) are becoming one of the fastest growing industries when it comes to implementation of digital technologies. At the core of this transformation lie business intelligence (BI) tools and advances analytics.

Business intelligence tools and advanced analytics will enable the introduction of new systemic risk measures, allow for increased efficiency in systemic risk analysis, reduce errors in data collection and processing, and automate some of the tasks in supervision. Among the prerequisites for business intelligence and advance analytics solutions are data availability and information technology infrastructure – including structured databases, data warehouse (DWH) and online analytical processing (OLAP) cubes. On top of the technical requirements, perhaps even more important is the need for trained personnel. Data scientists, machine learning engineers, business intelligence engineers and analytics translators are just some of the jobs of the new century required to carry out proper business intelligence and advance analytics implementations. Acquiring both formal education and relevant professional experience in this field is no easy task, but an interdisciplinary approach is necessary for successful utilization of business intelligence tools and advanced analytics in systemic risk supervision.

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CURRICULUM VITAE

Vedran Brozović is a full-time Master's degree student currently finishing his studies in Managerial Informatics at the Faculty of Economics and Business, University of Zagreb. During both his undergraduate and graduate studies at FEB Zagreb, he sought to expand his knowledge by attending numerous summer schools and international student competitions. His proactivity and curiosity took him on study visits and competitions throughout Europe, including: Ljubljana (Slovenia), Utrecht (Netherlands), Enschede (Netherlands), Stockholm (Sweden), Vilnius (Lithuania), Moscow (Russia) and St. Gallen (Switzerland) where he earned numerous accolades. Since the 2016/17 academic year, he has held multiple Student Teaching Assistant roles across various Departments: the Department for Mathematics, the Department for Informatics, the Department for Managerial Economics and the Department for International Business and Trade. As a Student Teaching Assistant, Vedran has given valuable study support to both lecturers and students on multiple diverse courses. His academic success has won him a plethora of student excellence scholarships from both the University of Zagreb in 2015/16 and 2016/17, as well as the City of Zagreb in 2018 and 2019 respectively. Vedran, moreover, received two Dean's and two Rector's awards throughout his studies. His seminar paper "*Capital Structure Determinants: Empirical Evidence from Zagreb Stock Exchange 2016*" won him his first Dean's award, subsequently followed by a Rector's award for a group scientific paper titled "*Empirical Research on Sharing Economy in Croatia: Youth Habits and Their Satisfaction with Ride-hailing Services*". In addition to his studies, Vedran gained practical business experience working for five major companies and institutions: Amazon, Ernst & Young, PBZ Invest, the Croatian National Bank and IKEA Croatia. After completing his internship at Amazon in 2019, he returned to Luxembourg as a full-time employee in 2020 working in a central EU Financial Planning & Analytics Tech team. His expertise in finance was further honed whilst working as a consultant at Ernst & Young within the Financial Services & Risk Management Advisory and IT Advisory departments. In his free time, Vedran plays basketball competitively: he used to play for basketball club Cibona and has won a gold and a bronze medal in the Croatian junior basketball championships. Vedran continues to play basketball, representing his Faculty in university leagues and Amazon in corporate leagues.

APPENCIDES

Appendix 1 Overview of Measures of Systemic Risk

Institution-Level Measure	
Market Data	**Balance Sheet and Regulatory Data**
Tail Risk • Hartmann, *et al.* (2005) • Forbes (2012) **Quantile Approach** • Acharya *et al.* (2011) – *MES, SES* • Adrian and Brunnermeier (2011) – *CoVaR* • Brownless and Engle (2011) – *SRISK* **Default Probability** • Gray and Jobst (2011) • Huange *et al.* (2009) – *Distress Insurance Premium* • Segoviano and Goodhart (2009) - *Banking Stability Measures* **Statistical causality** • Billio *et al.* (2010)	• BCBS (2010) - *G-SIBs* • Brunnermeiere *et al.* (2012) – *Liquidity Mismatch Index* • Greenwood *et al.* (2012) • IAIS (2012) – *G-SIIs* • Jobst (2012)
Financial Markets and Infrastructures	
Non-banks & Financial markets	**Payment, clearing and settlement systems**
• Gorton and Metrick (2010) – *LIB-OIS spread* • Schmidt *et al.* (2012)	• Galbiati and Soromaki (2012)
Synthetic and interconnection indicators	
Synthetic indicators	**Interconnection indicators**
Synthetic Indicators • Hollo *et al.* (2012) – *CISS* • Kritzman and Li (2010) – *Mahalanobis Distance* **Macroeconomic Indicators** • Aikman *et al.* (2009) – *RAMSI* • Niccolo and Luccheta (2011) – *GDP-at-Risk, FSaR* **Early-Warning Systems** • Babecky *et al.* (2012) • Barone-Adesi *et al.* (2011) • Jahn and Kick (2012) • Schwaab *et al.* (2011)	• Alves *et al.* (2013) • Fourel *et al.* (2013) • Gouriéroux *et al.* (2012) • Karas and Schoors (2012) – *K-shell* • Squartini *et al.* (2013) • Upper (2011) • Bastos Santos *et al.* (2012) – *Default Impact, Contagion Index*

Source: De Bandt et al. (2013)

Appendix 2 List of 2019 G-SIBs by FBS

Bucket	G-SIBs in alphabetical order within each bucket
5 **(3.5%)**	(Empty)
4 **(2.5%)**	JP Morgan Chase
3 **(2.0%)**	Citigroup HSBC
2 **(1.5%)**	Bank of America Bank of China Barclays BNP Paribas Deutsche Bank Goldman Sachs Industrial and Commercial Bank of China Mitsubishi UFJ FG Wells Fargo
1 **(1.0%)**	Agricultural Bank of China Bank of New York Mellon China Construction Bank Credit Suisse Groupe BPCE Groupe Crédit Agricole ING Bank Mizuho FG Morgan Stanley Royal Bank of Canada Santander Société Générale Standard Chartered State Street Sumitomo Mitsui FG Toronto Dominion UBS UniCredit

Source: FSB (2019a)

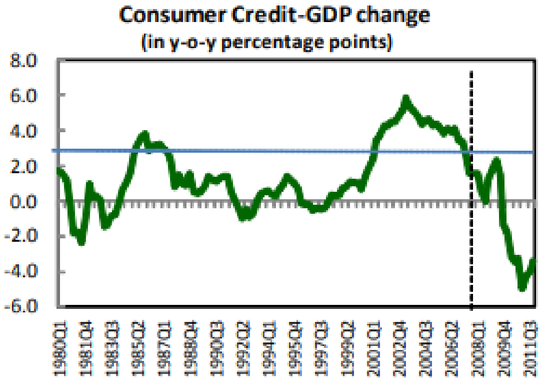
Appendix 3 List of 2019 Other systemically important banks in Croatia

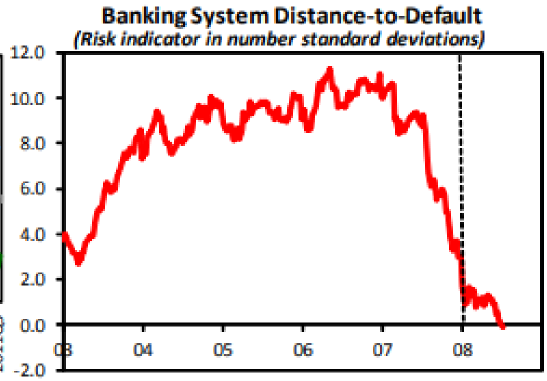
Other systemically important institution	Points	Add. Capital requirements
Zagrebačka banka d.d., Zagreb	3140	2,0%
Privredna banka Zagreb d.d., Zagreb	2016	2,0%
Erste&Steiermärkische Bank d.d., Rijeka	1964	2,0%
Raiffeisenbank Austria d.d., Zagreb	766	2,0%
OTP banka Hrvatska d.d., Split	592	2,0%
Addiko Bank d.d., Zagreb	342	1,0%
Hrvatska poštanska banka d.d., Zagreb	300	0,5%

Source: HNB (2019)

Appendix 4 Systemic Risk Monitoring Toolkit: IMF Sample Dashboard

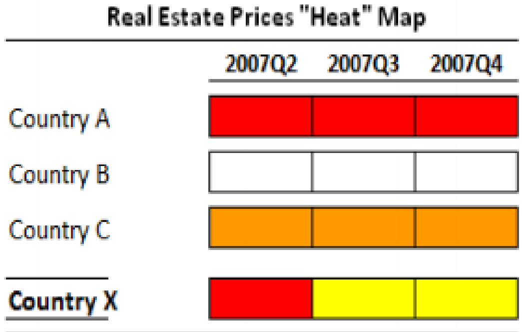
A. Is excessive risk building up in financial institutions?





Summary: Credit growth has slowed down and banking stability is falling fast, and below 2003 levels at end-2007. Systemic risk is starting to unwind.

B. Are asset prices growing too fast?

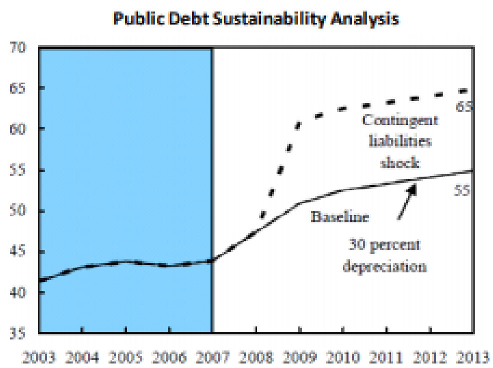


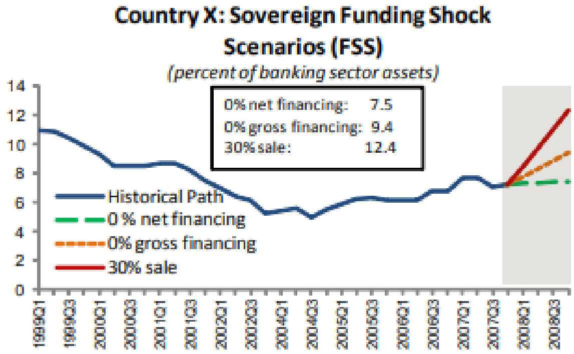
Equity Market Misalignments
Deviation Between Market and Model Prices
Dec, 2007

	Dividend Discount Model	Arbitrage Pricing Theory (APT) Model Local	APT Global
Country A	-3.2	-0.1	-1.5
Country J	-2.3	1.3	-1.4
Country N	-4.1	3.8	-1.2
Country X	-1.7	1.0	-1.4

Summary: There are mixed signals from asset markets at end-2007.

C. How much is sovereign risk a source of systemic risk?



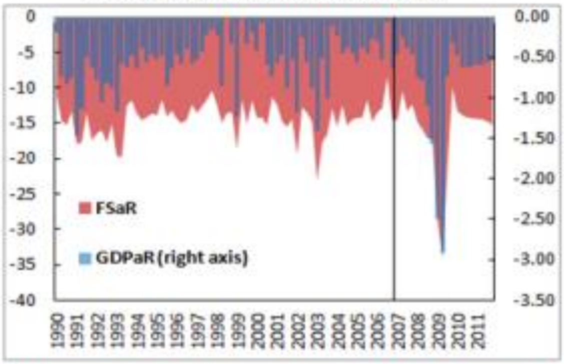


Summary:There are clear signals that fiscal risk are increasing, especially from financial sector-related contingent liabilities.

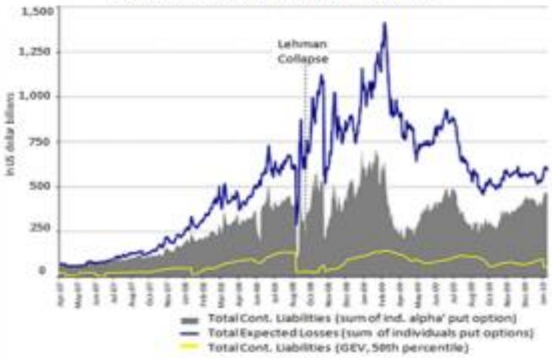
Source: Blancher et al. (2013)

D. What are the amplification channels among sectors and through the broader domestic economy?

GDP-at-Risk and Financial Stability-at-Risk

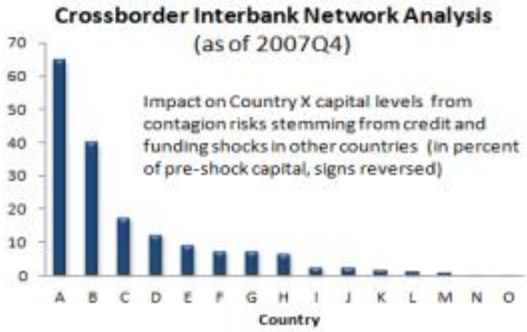


Systemic Contingent Claims Analysis

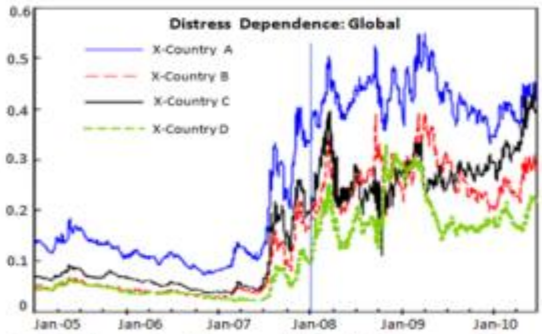


Summary: There is limited evidence that financial sector shocks are spilling over into the real sector at this stage, although spillover risk within financial institutions is slowly rising.

E. What are the amplification channels through crossborder spillovers?



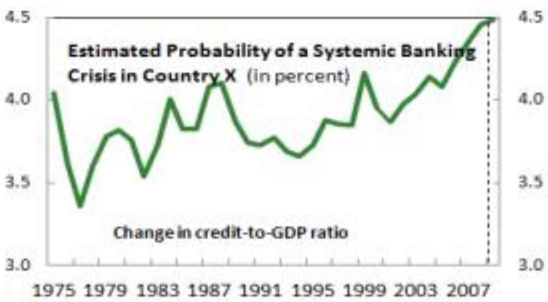
Joint Distress Indicators



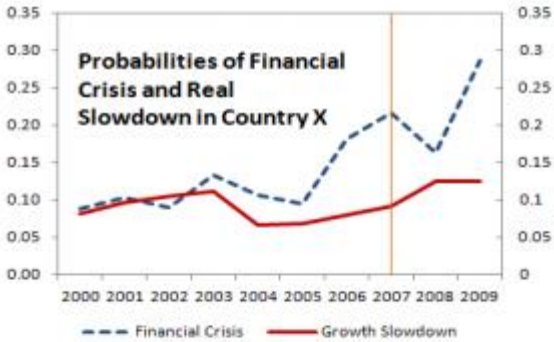
Summary: Country X continues to be strongly connected to the rest of the world, both in terms of actual balance sheet linkages of banks and potential spillover risks from market contagion.

F. What is the probability of a systemic financial crisis?

Credit-Based Crisis Probability Model



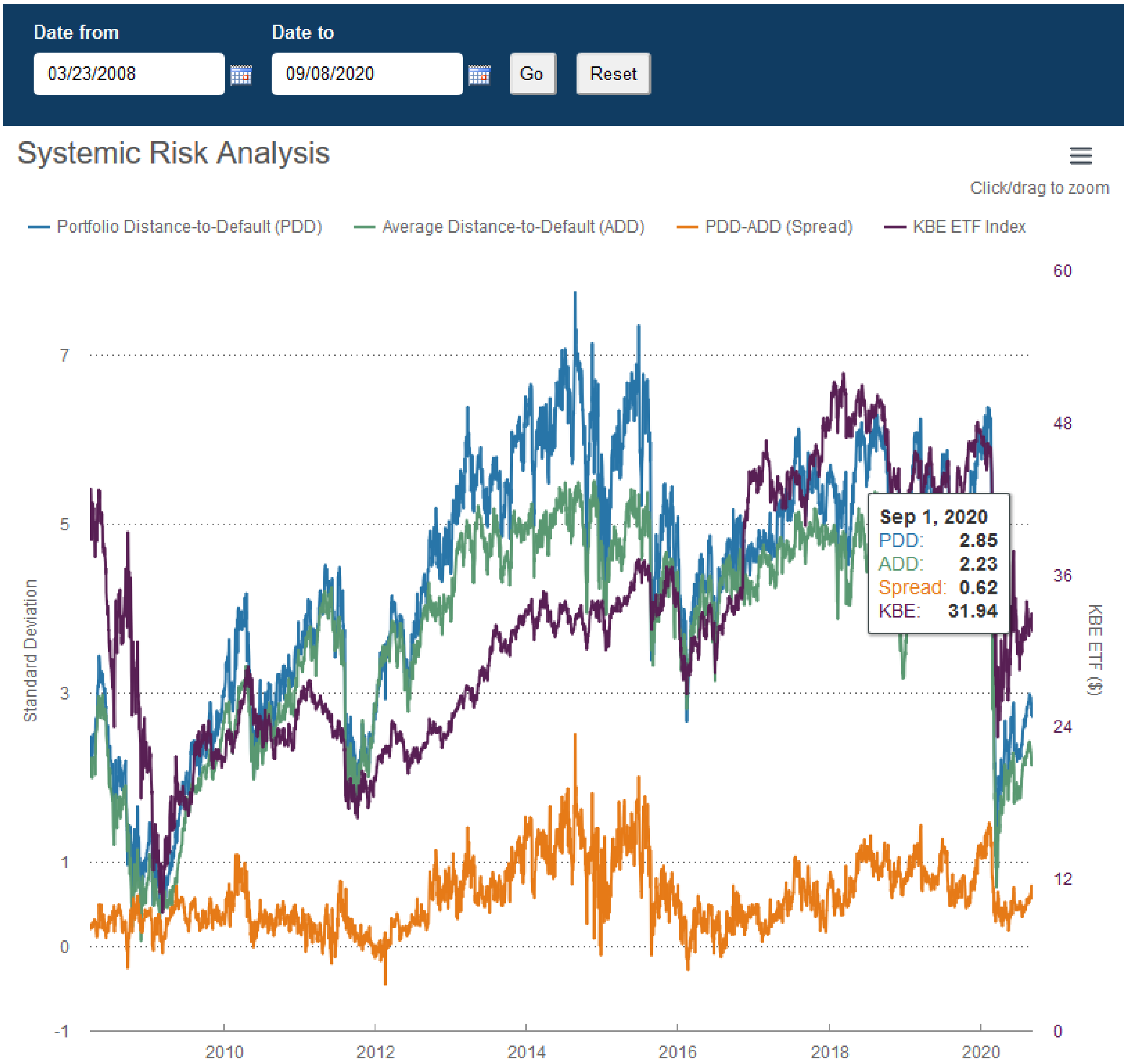
General Crisis Probability Model



Summary: The estimated likelihood of a systemic crisis has increased, but is still small.

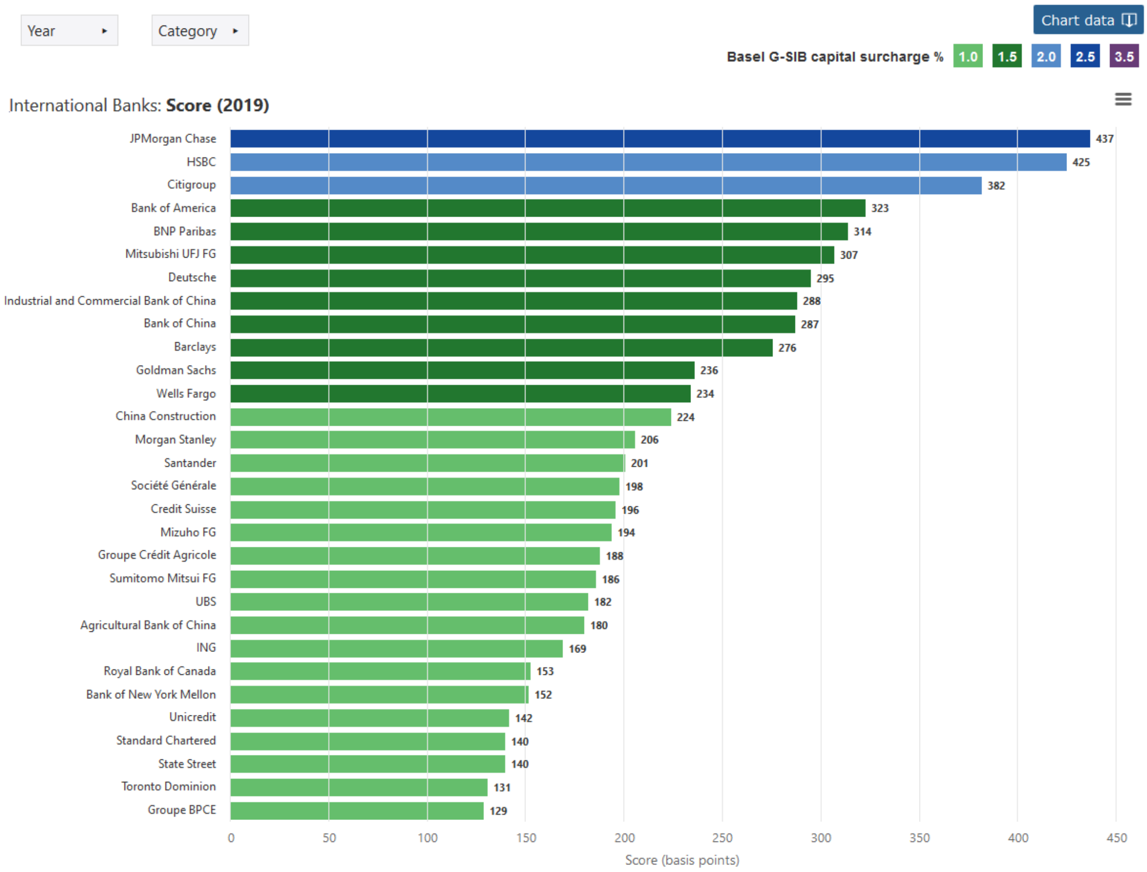
Source: Blancher et al. (2013)

Appendix 5 Systemic Risk Indicator by Cleveland FED



Source: FED (2020)

Appendix 6 Bank Systemic Risk Monitor



Source: OFR (2020)

Appendix 7 Risk Indicators Heatmap

	RI	Threshold	Traffic light: Current vs previous quarters for the worst bucket	201603	201606	201609	201612	201703	201706	201709	201712	201803	201806	201809	201812	201903	201906	201909	201912	202003
Solvency	Tier 1 capital ratio	> 15%		28.8%	29.7%	39.6%	55.5%	49.3%	50.5%	59.4%	67.0%	57.9%	55.3%	59.9%	64.8%	59.5%	63.5%	64.6%	71.7%	46.5%
		[12% - 15%]		63.4%	62.3%	52.5%	35.5%	43.9%	39.7%	38.2%	32.0%	41.2%	43.5%	38.8%	33.8%	39.5%	35.9%	34.6%	28.3%	53.1%
		< 12%		7.9%	8.0%	7.9%	9.0%	6.8%	9.8%	2.3%	1.0%	0.9%	1.3%	1.3%	1.3%	1.0%	0.5%	0.8%	0.0%	0.4%
	CET1 ratio	> 14%		22.0%	22.8%	27.5%	34.3%	41.1%	40.0%	46.3%	52.7%	41.7%	47.3%	46.9%	42.1%	45.1%	47.9%	42.3%	50.4%	40.4%
		[11% - 14%]		73.7%	72.6%	68.1%	61.2%	55.7%	52.0%	53.1%	47.0%	58.0%	47.0%	52.6%	57.2%	54.3%	51.5%	57.2%	49.6%	59.6%
		< 11%		4.3%	4.6%	4.5%	4.6%	3.2%	8.0%	0.5%	0.3%	0.3%	5.8%	0.5%	0.7%	0.6%	0.5%	0.5%	0.0%	0.0%
	Leverage ratio	> 8%		n.a.	n.a.	4.2%	4.6%	4.3%	4.3%	4.3%	4.6%	4.5%	4.1%	4.4%	5.0%	4.1%	4.3%	4.1%	5.3%	5.9%
		[5% - 8%]		n.a.	n.a.	47.4%	54.5%	45.9%	52.4%	57.2%	57.5%	53.9%	52.6%	54.7%	59.7%	53.1%	51.4%	53.2%	60.7%	48.9%
		< 5%		n.a.	n.a.	48.4%	40.9%	49.8%	43.3%	38.5%	37.9%	41.7%	43.3%	40.9%	35.4%	42.8%	44.3%	42.7%	34.0%	45.2%
Credit Risk & Asset Quality	Ratio of non-performing loans and advances (NPL ratio)	< 3%		37.7%	42.8%	42.1%	39.5%	40.1%	44.6%	51.4%	60.5%	60.7%	60.8%	61.9%	67.3%	67.7%	74.1%	74.0%	75.8%	67.2%
		[3% - 8%]		48.8%	44.0%	44.5%	47.3%	46.4%	42.8%	36.2%	28.5%	32.1%	32.9%	34.3%	29.6%	29.5%	23.0%	23.1%	21.3%	29.0%
		> 8%		13.5%	13.1%	13.3%	13.2%	13.5%	12.6%	12.4%	11.1%	7.3%	6.4%	3.8%	3.2%	2.9%	2.9%	2.9%	3.0%	3.8%
	Coverage ratio of non-performing loans and advances	> 55%		10.5%	10.7%	10.9%	16.9%	9.7%	11.2%	12.9%	9.3%	25.7%	20.3%	20.2%	15.1%	14.4%	14.3%	19.7%	19.8%	16.5%
		[40% - 55%]		48.3%	50.3%	49.0%	43.7%	52.2%	50.5%	48.5%	51.6%	33.5%	36.9%	36.3%	51.1%	43.4%	53.3%	37.9%	38.8%	61.6%
		< 40%		41.2%	38.9%	40.2%	39.4%	38.1%	38.3%	38.6%	39.1%	40.8%	42.8%	43.4%	33.7%	42.2%	32.5%	42.4%	41.4%	21.9%
	Forbearance ratio for loans and advances	< 1.5%		41.4%	42.7%	50.6%	51.5%	53.9%	52.3%	52.3%	59.4%	58.0%	62.1%	64.9%	66.2%	66.5%	67.3%	68.0%	68.3%	67.2%
		[1.5% - 4%]		37.1%	36.2%	24.5%	21.0%	24.7%	27.2%	27.3%	23.3%	25.2%	21.9%	24.9%	26.2%	27.3%	27.5%	27.1%	26.7%	26.4%
		>4%		21.5%	21.2%	25.0%	27.5%	21.5%	20.6%	20.4%	17.3%	16.8%	16.0%	10.2%	7.5%	6.1%	5.2%	4.9%	5.0%	6.3%
Profitability	Return on equity	> 10%		3.1%	6.0%	6.6%	5.3%	11.6%	12.0%	15.1%	12.4%	12.2%	13.2%	9.6%	6.1%	10.1%	12.5%	9.8%	2.2%	2.6%
		[6% - 10%]		42.3%	49.4%	36.8%	40.4%	45.4%	47.6%	48.1%	34.4%	52.1%	53.9%	53.3%	55.5%	47.9%	60.2%	54.6%	42.1%	8.4%
		< 6%		54.6%	44.6%	56.6%	54.3%	43.0%	40.3%	36.8%	53.2%	35.7%	32.9%	37.1%	38.4%	42.0%	27.3%	35.7%	55.6%	89.0%
	Cost to income ratio	< 50%		12.1%	9.9%	9.4%	10.7%	13.8%	14.7%	13.6%	10.2%	9.3%	9.4%	9.5%	10.2%	8.2%	8.9%	8.6%	9.1%	12.8%
		[50% - 60%]		16.9%	26.2%	23.8%	13.6%	9.0%	16.9%	18.5%	16.9%	17.5%	18.7%	15.7%	16.2%	18.1%	12.9%	22.2%	16.6%	7.1%
		> 60%		71.0%	63.9%	66.8%	75.8%	77.2%	68.4%	67.9%	72.9%	73.2%	72.0%	74.8%	73.7%	73.6%	78.3%	69.2%	74.3%	80.2%
Funding & Liquidity	Loan-to-deposit ratio for households and non-financial corporations	< 100%		26.9%	28.3%	29.4%	29.4%	31.6%	35.3%	35.1%	35.6%	35.3%	35.0%	34.7%	34.6%	34.9%	35.0%	35.3%	36.1%	13.3%
		[100% - 150%]		59.6%	58.2%	56.6%	55.2%	54.6%	50.9%	51.8%	51.5%	51.7%	52.0%	52.4%	50.8%	51.9%	51.8%	51.5%	50.8%	69.9%
		> 150%		13.5%	13.5%	14.0%	15.3%	13.8%	13.8%	13.1%	12.9%	13.0%	13.0%	12.9%	14.6%	13.3%	13.3%	13.1%	13.1%	16.8%

Risk measure	Developments: Risk level – Last risk dash-board	Developments: Risk level – Current	Developments: Short-term outlook	Description
Asset quality				Asset quality is a key concern amid the COVID-19 outbreak. First indications of a deterioration is reflected in banks' rising costs of risk. However, costs of risk are widely dispersed among banks, not least depending on the geographical and sectoral composition of their loan portfolios. Further asset quality related aspects include the wide application of borrowers for payment moratoria. New lending was mainly restricted to the use of existing credit lines and introduction of government guarantee schemes have driven banks' increasing lending volumes. **Short-term outlook:** Asset quality is expected to deteriorate. The impact will depend on banks' composition of loan portfolios, with consumer and SME lending being presumably among the most vulnerable exposures. Within corporate exposures, sectors more affected by the pandemic – such as the transportation and accommodation & food services sectors – might also be more susceptible to losses than others (e.g. the pharmaceutical and telecommunications sectors). The impact on asset quality will also depend on how the pandemic further unfolds, and how quickly stakeholders accommodate to the new situation. It remains to be seen to which degree extensive monetary and fiscal stimulus programmes as well as payment moratoria and public guarantee schemes will help to soften the deterioration in asset quality.

Source: EBA (2020b)

Appendix 8 V-LAB Interactive Parameterized Dashboard on Systemic Risk

Systemic Risk Analysis (Global Dynamic MES) of World Financials

WHAT'S ON THIS PAGE?

Predicted System Capital Shortfall for a 40% market decline: $1,404,408.08 million

Systemic Risk Analysis Welcome Page

Last update: Saturday, September 19th, 2020

SRISK Graph

Systemic Risk Rankings for 2020-09-18   View changes

Institution	SRISK %	SRISK ($ m)	LRMES	Beta	Cor	Vol	Lvg
BNP Paribas SA	8.89	124804.8	36.66	0.89	0.36	32.81	56.14
Credit Agricole SA*	7.23	101591.5	38.23	0.94	0.39	32.14	78.30
HSBC Holdings PLC	6.83	95903.4	29.45	0.68	0.42	29.74	34.85
Societe Generale SA	5.60	78625.4	41.24	1.04	0.33	40.51	122.93
Barclays PLC	5.42	76163.6	37.20	0.91	0.23	36.04	73.09
Banco Santander SA	5.38	75605.1	43.70	1.12	0.40	38.63	51.81
Deutsche Bank AG	5.21	73191.7	42.53	1.08	0.35	33.26	81.64
Natwest Group PLC	3.04	42725.9	36.15	0.88	0.27	38.58	62.99
Lloyds Banking Group PLC	3.02	42376.5	37.71	0.93	0.29	43.32	44.97
UniCredit SpA	2.80	39313.1	33.71	0.80	0.38	35.23	48.01

Rows per page: 10   1-10 of 308

Geographic Area

Region	Cap Req
Africa	8.0%
Americas	8.0%
Asia	8.0%
Europe	5.5%

RESET

Country

All

Separate Accounts

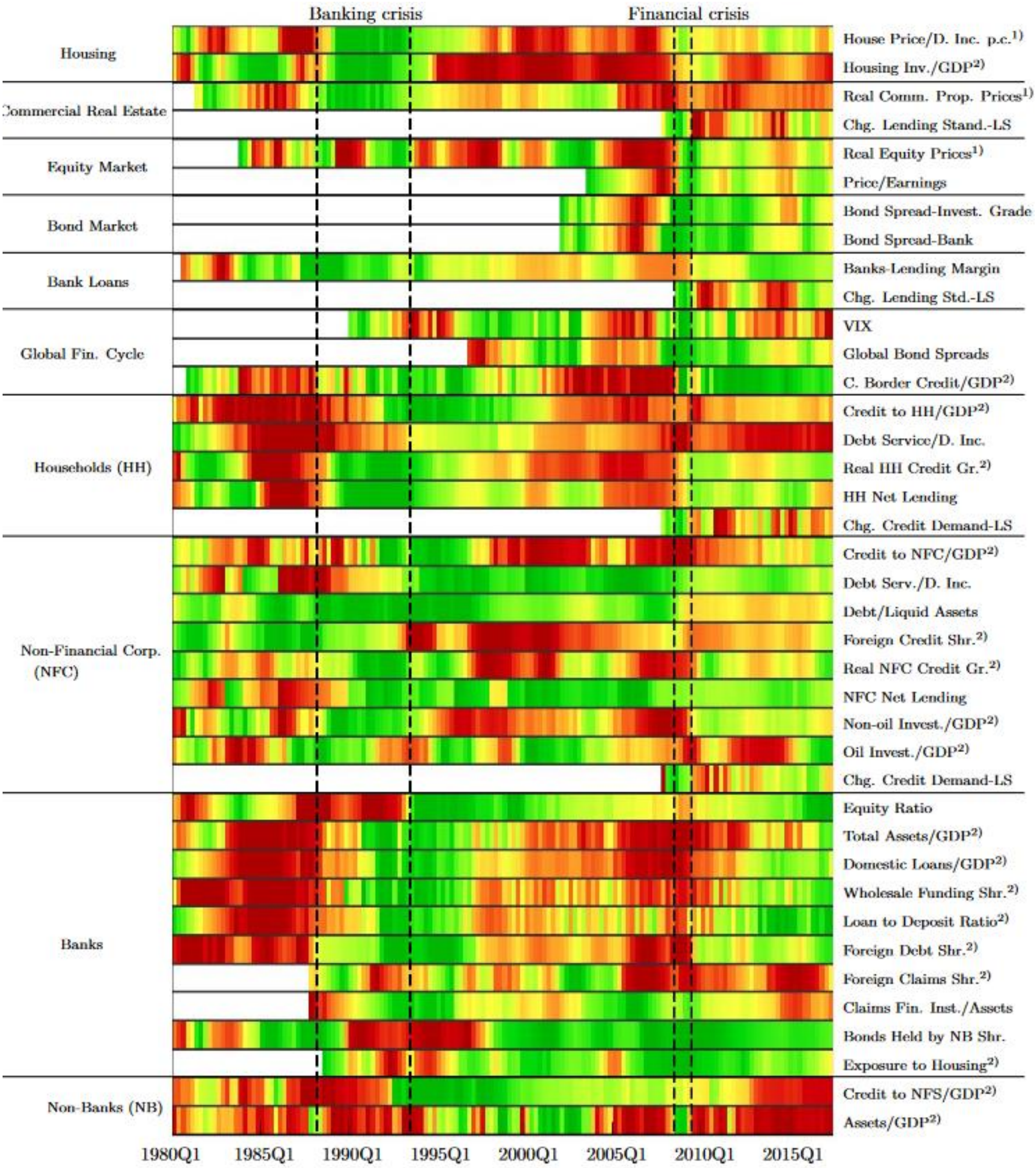
% to include: 40%

RESET

RESET OPTIONS

Source: V-LAB (2020)

Appendix 9 Heatmap example: Norwegian Central Bank



Source: Arbatli & Johansen (2017)

Appendix 10 Heatmap example: Bank of Ireland

Systemic Risk Heatmap

>1.5 SDs below	>1.0 SDs below	>0.5 SDs below	Threshold	>0.5 SDs above	>1.0 SDs above	>1.5 SDs above

Intermediate objective		Indicator	Threshold	Risk level	Latest observation	Latest observation date	6 month change	Annual change
Objective 1: Mitigate & prevent excessive credit growth and leverage	Aggregate credit and leverage	Standardised credit gap	Lower threshold for CCyB setting (BCBS 2010)		-63.9pps	Mar-17	-1.2 pps	-26.1 pps
		Private-sector credit growth	Historical average		-1.8%	Aug-17	1.1 pps	1.9 pps
		National credit-to-GNI* gap	Lower threshold for CCyB setting (BCBS 2010)		-83.8pps	Mar-17	-10.4 pps	-1.5 pps
		Leverage ratio - Irish historical comparison	Historical average		5.9%	Aug-17	0.0 pps	-0.2 pps
		Leverage ratio - European comparison	European average		9.2%	Dec-16	-0.9 pps	-1.3 pps
	Asset prices	Residential property price growth	MIP threshold		11.4%	Jun-17	2.4 pps	5.9 pps
		Residential property price-to-rent ratio	Historical average		17.31	Jun-17	1.7%	3.3%
		Residential property price-to-income ratio	Historical average		3.99	Jun-17	1.4%	3.9%
		Res. real estate misalignment measure	Zero		-17.5%	Mar-17	-2.1 pps	-1.2 pps
		Residential property turnover	European average		2.3%	Dec-16		0.1 pps
		Residential property stock / 1,000 adults	European average		428.2	Dec-16		-2.0%
		Residential property completions/ stock	European average		0.7%	Dec-16		0.1 pps
		Commercial real estate price growth	Historical average		5.1%	Jun-17	-2.3 pps	-8.9 pps
		CRE price-to-rent index	Historical average		96.0	Jun-17	-0.4%	-0.6%
		CRE price misalignment measure	Zero		1.2%	Jun-17	6.3 pps	4.9 pps
		ISEQ 3 month MA QoQ growth	Historical average		-2.7%	Sep-17	-9.2 pps	0.5 pps
	Sectoral credit and leverage	Total domestic credit - herfindahl	Historical average		0.5	Jun-17	1.5 pps	2.7 pps
		Household debt gap	Lower threshold for CCyB setting (BCBS 2010)		-48.2pps	Mar-17	-9.9 pps	-4.7 pps
		Household credit growth	Historical average		-1.7%	Aug-17	0.5 pps	1.3 pps
		Domestic NFC debt gap	Lower threshold for CCyB setting (BCBS 2010)		-35.7pps	Mar-17	-0.5 pps	3.1 pps
		Domestic NFC credit growth	Historical average		-2.0%	Aug-17	2.7 pps	3.5 pps
		Property-related lending (% share of total)	Historical average		68.3%	Jun-17	0.6 pps	0.3 pps
		CRE related credit growth	Historical average		-9.0%	Jun-17	3.4 pps	1.5 pps
		Residential fixed cap. formation/GNI*	European average		3.6%	Jun-17	0.6 pps	0.0 pps
Objective 2: Prevent excessive maturity mismatch & market illiquidity	Balance sheet mismatch and liquidity	Loan-to-deposit ratio	Historical average		93.0	Aug-17	-0.5%	-2.0%
		Non-deposit funding	European average		23.0%	Dec-16		-3.7 pps
		Share of funding from ESCB	Pre-crisis average (pre-2008)		1.4%	Aug-17	0.1 pps	0.2 pps
		Overnight interbank borrowing volume 1M avg.	No threshold established		0.0	Jun-17	0.0%	-100.0%
		Overnight interbank borrowing int rate 1M avg.	No threshold established		-0.4%	Nov-16	0.0 pps	-0.3 pps
		Overnight interbank borrowing spread 1M avg.	No threshold established		0.0%	Nov-16	0.0 pps	-0.1 pps
		Liquidity coverage ratio	European average		134.1%	Dec-16		8.4 pps
	Market conditions	EURIBOR OIS 3M Spread - 1 quarter max (bps)	Historical average		-0.001 bps	Sep-17	0.013 bps	0.033 bps
		Irish composite stress index - 1 quarter max	Historical average		0.08	Jun-17	9.6%	-33.2%
		CISS euro area - 1 quarter max	Historical average		0.06	Sep-17	-29.8%	-79.7%
		Euro NFC spreads - 1 quarter avg (bps)	Historical average		-0.1 bps	Sep-17	-0.2 bps	0.1 bps
		Euro financials spreads - 1 quarter avg (bps)	Historical average		-0.1 bps	Sep-17	-0.2 bps	0.0 bps
		Euro gov spreads - 1 quarter avg (bps)	Historical average		-0.1 bps	Sep-17	-0.2 bps	0.0 bps
Objective 3: Limit direct and indirect exposure concentration	Large exposures	Total LE / own funds - All banks	European average		319.2%	Jun-17	-23.2 pps	-33.0 pps
		Total LE / own funds - Retail banks	European average		218.4%	Jun-17	-26.0 pps	-40.6 pps
		10 largest LE / own funds - All banks	No threshold established		137.5%	Jun-17	-0.8 pps	-28.9 pps
		10 largest LE / own funds - Retail banks	No threshold established		141.7%	Jun-17	-14.2 pps	-33.6 pps
		LE to NFCs/ own funds - All banks	No threshold established		13.0%	Jun-17	-1.7 pps	-5.7 pps
		LE to NFCs/ own funds - Retail banks	No threshold established		8.1%	Jun-17	-2.4 pps	-2.9 pps
		LE to credit inst./own funds - All banks	No threshold established		103.9%	Jun-17	-12.7 pps	-6.0 pps
		LE between dom. retail banks / own funds	No threshold established		2.6%	Jun-17	-0.4 pps	-0.3 pps
		LE between dom. retail banks - total EURbn	No threshold established		€0.8 bn	Jun-17	-13.6%	-12.2%
	Sectoral concentration & interconnectedness	Total domestic credit - herfindahl	Historical average		0.5	Jun-17	1.5 pps	2.7 pps
		Property-related lending (% share of total)	Historical average		68.3%	Jun-17	0.6 pps	0.3 pps
		Interbank loans/total financial assets	European average		3.3%	Dec-16		-0.6 pps
		% funding from interbank deposits	European average		7.8%	Dec-16		-1.9 pps
		Static delta coVar	Historical average		0.07	Jun-17	10.9%	6.1%
Objective 4: Reduce the potential for systemically important banks to adopt destabilising strategies and to mitigate the impact of such actions	Size	Domestic bank assets-to-GNI*	European average		119.9%	Dec-16	-10.7 pps	-24.0 pps
		Total O-SII assets to GNI*	European average		192.4%	Jun-17		-19.2 pps
	Interconnectedness	LE to credit institutions - All banks	No threshold established		€57.3 bn	Jun-17	-13.5%	-5.3%
		LE to credit institutions - Retail banks	No threshold established		€14.6 bn	Jun-17	-12.9%	-14.8%
		LE to Irish gov - All banks	No threshold established		€38.7 bn	Jun-17	-9.0%	-17.6%
		LE to Irish gov - Retail banks	No threshold established		€28.4 bn	Jun-17	-15.7%	-26.2%
		Interbank loans/total financial assets	European average		3.3%	Dec-16		-0.6 pps
		% funding from interbank deposits	European average		7.8%	Dec-16		-1.9 pps
	Concentration	Market share top 5 inst: priv sector lending	Post-crisis average		87.6%	Aug-17	0.7 pps	0.4 pps
		Market share top 5 inst: priv sector deposits	Post-crisis average		81.0%	Aug-17	1.6 pps	1.3 pps
		Market share top 5 inst: NFC lending	Post-crisis average		90.6%	Aug-17	0.5 pps	-0.5 pps
		Market share top 5 inst: SME lending	Post-crisis average		96.9%	Jun-17	0.7 pps	-0.2 pps
		Market share top 5 inst: HH lending	Post-crisis average		93.3%	Aug-17	-0.2 pps	1.0 pps
		Market share top 5 inst: OFI lending	Post-crisis average		82.4%	Aug-17	1.0 pps	-0.2 pps
		Share of the 5 largest inst: total assets	European average		44.3%	Dec-16		-1.7 pps
		Total LE / own funds - All banks	European average		319.2%	Jun-17	-23.2 pps	-33.0 pps
	Complexity	Derivatives (notional value) to total assets	European average		77.2%	Dec-16		-12.8 pps
		Share non-loan assets	European average		27.9%	Dec-16		-0.2 pps
		Share non-interest income	European average		20.2%	Dec-16		-0.5 pps

Source: Bank of Ireland (2017)

GLOSSARY

AA - advanced analytics

ABI – analytics and business intelligence

AI - artificial intelligence

BCBS – Basel Committee on Banking Supervision

BI - business intelligence

CDF – cumulative distribution function

CISS – Composite Indicator of Systemic Risk

CoVaR – Conditional Value at Risk

DAB – Croatian State Agency for Deposit Insurance and Bank Resolution

DB –database

DWH – data warehouse

EBA – European Banking Authority

ECB – European Central Bank

EIOPA – European Insurance and Occupational Pensions Authority

ESA - European Supervisory Authority

ESFS - European System of Financial Supervision

ESMA – European Securities and Markets Authority

ESRB – European Systemic Risk Board

ETL – Extract, Transform, Load

FDIC - Federal Deposit Insurance Corporation

FED – Federal Reserve Board

FSB – Financial Stability Board

G-SIB – Globally Systematically Important Banks

G-SIFI – Globally Systematically Important Financial Institution

HANFA - Croatian Financial Services Supervisory Agency

HHI - Herfindahl–Hirschman Index

HNB – Croatian National Bank

IAIS – International Association of Insurance Supervisors

IMF – International Monetary Fund

IOSCO – Organization of Securities Commissions

KPI – key performance indicator

MES – Marginal Expected Shortfall

ML - machine learning

NCAS – National Competent Authorities

NLP – Natural Language Processing

OECD – Organisation for Economic Co-operation and Development

OFR – Office of Financial Research (U.S. Department of Treasury)

OLAP – online analytical processing

PCA – principal component analysis

RegTech – regulatory technology

SES – Systemic Expected Shortfall

SIFI – Systematically Important Financial Institution

SRC – Systemic Risk Centre

SupTech – supervisory technology

TBTF – too-big-to-fail

TCTF – too-connected-to-fail

VaR – Value at Risk

VAR – vector autoregression

V-LAB – Volatility Laboratory (NYU Stern)

WB – World Bank