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Three essays on the nature of systemic risk

Mathis Mourey

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THÈSE

Pour obtenir le grade de

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Présentée par

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préparée au sein du **Laboratoire Centre d'Etudes et de
Recherches appliquées à la gestion**
dans l'**École Doctorale Sciences de gestion**

Trois essais sur la nature du Risque Systémique

Three essays on the nature of Systemic Risk

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**Three essays on the nature of
Systemic Risk**

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L'Université n'entend donner aucune approbation ou improbation aux opinions émises dans cette thèse. Celles-ci doivent être considérées comme propres à leur auteur.

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'There are two ways to write error-free programs; only the third one works.'

Alan Perlis

General Introduction

Understanding and taming the chronic instability of the financial system has been a life-long pursuit for financial academics and regulators. This search is, however, profoundly unfair. Unlike ‘exact’ sciences as physics or mathematics, finance is intrinsically linked to the human behavior. One could easily imagine how hard it would have been to discover a law of universal gravitation, as Newton did, if gravity around people would change depending on their mood. It is however, the ungrateful task of financial economists to unravel why, and how, financial crises occur, regardless of the task’s difficulty.

Before jumping in the core of this dissertation, a few points needs to be clarified. The common sense that financial crises are inherently bad is not obvious. Calomiris and Kahn (1991) show that the economy can actually benefit from bank runs, in the way that there allows to ‘salvage’ some of the bank value. Similarly, some countries exposed to financial crises, have been experiencing a greater growth than countries enjoying stability (Ranci ere, Tornell, & Westermann, 2008). As recent historical research (Barth el emy, Binet, & Pentec ote, 2020) shows, most countries and economics are recovering from these shocks at some point. The losses in GDP per capita, rise in unemployment, or even decreases in international trade (Reinhart & Rogoff, 2009) will end up being recovered, and hence where lies the need to protect the economy from crises? The reasons are numerous, but foremost it is because some economies do not recover. Moreover, essential firms in the economy may fail, and will not recover once bankrupted. Some peculiar phenomena, as self-fulfilling bank runs have the power to force the default of perfectly healthy banks. The failure of healthy banks has then tremendous implications for the well-functioning of the interbank market, and will lead to severe spillovers on the real economy (Diamond & Dybvig, 1983; Madi es, 2006). The impacts of financial crises will tend to impact

aggregate consumption, unemployment level, and output. The decrease in these variables leads to a reduction of aggregate demand, thus will tend to furthermore stress the financial system by lowering the value of collateral assets and asset prices (Freixas, Laeven, & Peydró, 2015). Financial crises also translates in increased fiscal costs stemming from the measure put in places to support the financial system, while also increasing public debt (Atkinson, Luttrell, & Rosenblum, 2013; Laeven & Valencia, 2020).

Despite the few advantages financial crises provide, it appears clear that taming them is the way to go. However, how can we prevent such crises from happening, especially since they are so frequent, and inherently linked to the functioning of financial markets? It is now widely known that financial markets are difficult, not to say impossible, to predict. The work of Fama (1970) on the [Efficient Market Hypothesis \(EMH\)](#) is derived from that very characteristic. In fact, theory often comes as a solution to approaching complex problems. As, Nobel Prize Winner, James Tobin put it: *‘The terms in which a problem is stated and in which the relevant information is organized can have a great influence on the solution’* (Tobin, 1966). Indeed, theory has the advantage to redefine a given problem, hence allowing us to get a new perspective. However, theory does not always allow for the optimal solution¹. For a long time the neoclassical view has been considered has the correct one. However, financial markets evolved and grew up to a point where the neoclassical theory cannot follow. Minsky (1986) presents the two systems of prices in a capitalistic economy: the price level of current output and the capital asset’s price level. When the price level of capital assets becomes high, relatively to the one of current output, the economic environment is favorable for investment, and reciprocally. Thus, the movements of these two system of prices constitute the business cycles, and from the business cycles emerged the [Financial Instability Hypothesis \(FIH\)](#) proposed by Minsky (1992).

The work of Minsky (1992) had the advantage of proposing a new framework on how recessions, economic depressions, and financial crises emerge; and the [FIH](#) proved itself useful in explaining a large share of financial crises, up to the point of

¹Minsky (1986) considers theory as a double edged sword, which, from one side, allows to redirect the focus of the regulators on specific matters, while, at the same time, blinds them from other mechanisms or characteristics of the problem considered.

naming the burst of a crisis, the ‘*Minsky Moment*’. Despite the success of Minsky’s work in the early 2000s, financial crises continued to occur. Among these unusual events, lies an even more peculiar phenomenon: *Systemic Crises*. Such events are especially characterized by the negative externalities on the real economy they lead to. While no proper, common, definition of **Systemic Risk (SR)** has been agreed upon, it is widely accepted that the risk of spillover, from the financial system to the real economy, is one of its main component (Aglietta, 1993; De Bandt & Hartmann, 2000; IMF, 2009). Etymologically, the concept finds its roots in the word ‘*System*’. It relates to the inherent risk a considered system carries. In our case, we consider the financial system. Historically, the concept stems from the failure of the German bank, *Herstatt* in 1974. The failure of this bank caused havoc on the foreign exchange market, and forced the interbanking settlement system in New York to stop for few days. It is remembered as the first systemic failure, in the sense that no regulator had imagined the extent of disruption that a single institution could cause. In other words, it revealed the systemic implications of a large financial institution. Fortunately, Herstatt was a, relatively, small institution and, hence, its failure had limited consequences. However, it created the interest on the kind of disruption one institution could cause. Aglietta (1993) presents three main possible negative externalities. First, the failure of payment systems could lead to bank runs, the increase of transaction costs or the decrease in money availability. Second, extreme financial fragility of lending institutions, which could results in a credit crunch, or a sudden stop in lending activity due to a sharp increase in borrowing costs. Finally, a divergence between capital assets values and their fundamental value, causing speculative bubbles, sudden crashes or spillover effects over multiple markets. A Systemic Crisis is significantly worse than most extreme financial events due to the severity of the possible consequences, as stated above. The failures of large banking institutions in the late 2007 (Lehman Brothers, Bear Stearns, Countrywide Financials, etc.) and the Subprime crisis that followed are a striking example of how bad a **Systemic Event (SE)** can turn out to be. Taming such events is not a luxury that only regulators with time to spare² should pursue. It is a challenge that must be tackle for the benefit of the economy and society.

It is however a blessing in disguise. The problem will not be solved without

²Given such mythical creatures actually exist.

taking an uncompromising look at how our current economy functions and how well our theories explain its mechanisms and the phenomena arising from it. As Minsky (1986) had already realized, our current view on the functioning of the economy is unable explain the endogenous build-up of imbalances leading to financial instability. The issue of SR is an opportunity to adapt our models and change our outdated views on the role of financial markets in our economy.

This introduction is structured in the following way. We first expose our inherent motivations for studying SR. We will do so by presenting the lack of a commonly accepted definition and the variety of measures proposed over the years, as well as by highlighting the gaps in the current prudential regulation. In a second time, we expose our research objectives. Finally, we detail the content of this dissertation.

Research Motivations

The destructive potential of Systemic Crises presented above already constitutes a sufficient reason to study SR. Nevertheless, other reasons must also be considered. We will first discuss the lack of agreement in defining SR and how it led to a plethora of measures. Furthermore, we will present the current prudential regulatory framework and expose its gaps, themselves stemming from the uncertainty of the definition of SR.

Definitions & Measures

Historically, banking has been at the core of the definition of SR. The case of Herstatt and the early cases of bank panics³ have shown the systemic importance of lending institutions. More especially, it showed banks' exposure to the confidence of their depositors. Such event have fueled the academic interest in the systemic importance of banks, leading to pioneer work on deposit insurance (Bryant, 1980; Cooper & Ross, 2002) and its effect on the financial health of banks (Diamond & Dybvig, 1986, 1983). However, SR is not limited to lending institutions exclusively. It relates also to payment systems and the stock markets (Aglietta, 1993, 1998), and is carried through multiples types of financial institutions. As financial markets evolved over

³Among the most famous cases, we find the *1907 Bankers' Panic* in the U.S., the Norwegian banking crisis in 1988, or the Russian and Argentinian panics in 1998.

time, SR followed, and transformed, thus SR is no longer a bank-focused concept. It is now intrinsically linked to the interconnexion between financial institutions and the complexity of financial markets. In order to bring clarity regarding SR definition, Benoit, Hurlin, and Perignon (2019) proposes a comprehensive literature review on the concept of SR and its measure, while Smaga (2014) present conceptually SR and categorize its existing definitions.

The changes in the financial system transformed SR. Consequently, the definitions drifted away of banking, to become more general. Each definition proposed in the literature focuses on particular aspect of SR. Mishkin (1992) and Aglietta and Moutot (1993) believe that SR resides in the disruption of proper allocation of funds/risks in an economy⁴. Other authors prefer to focus on the contagion effect and the transmission of distress from one agent to another (Rochet & Tirole, 1996; De Bandt & Hartmann, 2000). In particular, De Bandt and Hartmann (2000) separates systemic crises, in two categories. Horizontal crises affect only the financial system. While, vertical crises are financial events that end up influencing the real economy. These negative impacts on the real economy, commonly called *negative externalities*, are one of the central feature of recent systemic crises. The IMF (2009) and the report of the Group of Ten (2001) propose definitions that are centered on that concept. Such definitions makes the construction of a coherent measure particularly hard, as the crisis is determined *ex-post* to be systemic⁵. Due to that limitation, recent definitions aimed to be more ‘operationalisable’. For instance Silva, Kimura, and Sobreiro (2017) define SR as a simultaneous realization of losses that leads to contagion effects. In addition, Montagna, Torri, and Covi (2021) describe SR as a joint probability of bank’s default.

General definitions, as the one provided by the IMF (2009), are useful from a regulatory point of view. They allow identifying events that fall under the prudential regulatory framework. Furthermore, they encompass a large spectrum of mechanisms and possible developments. However, their inability of general definitions to lead the construction of a coherent measure of SR have pushed academics to develop more operational definitions. By doing so, the literature had to stray away

⁴In the case of Mishkin, the disruption is informational, and, as a consequence, disrupt the well-functioning of capital markets.

⁵Since a crisis is deemed systemic only if it ends up impacting the real economy.

from economic theories to econometric and probabilistic models. This shift fueled the gigantic existing literature on [SR](#) measurement. We present below in detail the most commonly used measure in the academic literature. Given the extent of the current literature, we will restrain ourselves to a not-comprehensive set of measure, and try, for the sake of avoiding redundancy, to present only briefly the measures applied in the corpus of this dissertation. We present a taxonomy based on the specific type of risk being assessed by the measure. We separate measure focusing on Losses, Connectedness & Contagion, Default, and, finally, Liquidity.

Systemic Crises are setting themselves apart by the extent of losses they cause. It seems then logical that most of the measures proposed by the academic literature focus on that specific characteristic. Acharya et al. (2017) derive a measure from the [Expected Shortfall \(ES\)](#). The measure allows to construct a marginal [ES](#), hence allocating the tail risk of the system to each of its institutions. The measure can be further developed into the [Systemic Expected Shortfall \(SES\)](#) that represents the (expected) contribution of a bank to a Systemic Crisis. Brownlees and Engle (2017) and Acharya, Engle, and Richardson (2012) build-up on this work to propose [SRISK](#), that incorporates the leverage and size of financial institutions. Adrian and Brunnermeier (2016) proposed one of, if not, the most used measure in the literature based on an improvement of the [Value-at-Risk \(VaR\)](#). [Conditional Value-at-Risk \(CoVaR\)](#) is essentially the [VaR](#) of an institution relative to the fact that the financial system is already at its [VaR](#). The measure benefits from its simplicity of computation, as well as its possible variation⁶. In the same vein, Engle and Manganelli (2004) propose the [Conditional AutoRegressive Value-at-Risk \(CAViAR\)](#). The measure is an autoregressive estimation of the [VaR](#) (or [ES](#)) of an institution. A multivariate extension of the model was proposed by White, Kim, and Manganelli (2015). Similarly, Allen, Bali, and Tang (2012) propose a measure of aggregate [SR](#), named [CATFIN](#), based on the arithmetic average of multiple tail risk measures⁷.

As noted by Oh and Patton (2018), the measures focusing on loss, presented

⁶For instance, the condition can be reversed for computing the [VaR](#) of the system while a specific firm is already at its [VaR](#), hence constructing a measure of systemic importance of the firm.

⁷Namely, [VaRs](#) are computed using the General Pareto Distribution, the Skewed Generalized Error Distribution and a non-parametric method.

above, lack crucial information about contagion/spillover effects. To address that limitation, another strand of literature focused on the connectedness component of the financial system. Connectedness in the literature can be considered from three distinct point of view. First, it relates to the statistical (Granger) causality existing among financial institutions. Billio et al. (2012) are the pioneers that introduced this particular method in the literature. Thanks to Granger-causality regressions, they estimate an adjacency matrix of the financial system, which, in turn, allows them to compute network-based measures. Hué, Lucotte, and Tokpavi (2019) propose an extension of this work, by proposing a measure based on how much the adjacency reacts when removing an institution from the system considered. Gong et al. (2019) provide an application of causal networks in the Chinese financial system. Secondly, it refers to the commonality present in financial markets. Kritzman et al. (2011) construct the Absorption Ratio, based on a [Principal Component Analysis \(PCA\)](#) applied on the returns of financial institutions. Blei and Ergashev (2014) offers a similar approach consisting in data aggregation and clustering techniques in order to derive a novel measure of [SR](#). Thirdly, it points to contagion and spillover effects. Diebold and Yilmaz (2009, 2014) develop a spillover measure, based on the decomposition of the variance-covariance matrix of financial returns. Balla, Ergen, and Migueis (2014) focus on the asymptotic dependence of the left tail of returns, for pairs of financial institutions, and derive a indicator of dependence rate in the system, the [Asymptotic Dependence Rate \(ADR\)](#).

The literature tends to become confusing, at times, due to the use of similar words to point out different concepts. For instance, the concept of contagion used above refers to dependencies in stock returns. However, the most common use of contagion relates to the failure cascades. Numerous measure of default are also proposed by the literature. Vassalou and Xing (2004) were the first to propose a measure of default risk derived from equity returns, the Distance-to-default. The measure is actually stemming from the model of Merton (1974). An extension of the model, the Distance-to-capital, designed for a better regulatory use of the measure, was proposed later by Chan-Lau and Sy (2007). Huang, Zhou, and Zhou (2009, 2012) propose to measure [SR](#) by the hypothetical cost of an insurance against the financial distress of financial institutions. Their measure, the [Distress Insurance Premium \(DIP\)](#), allows to observe the general level of [SR](#) as well as allocating individual

contributions to firms. The [International Monetary Fund \(IMF\)](#) also proposed its share of measures regarding the estimation of grouped default probability. The [Systemic Contingent Claims Analysis \(SCCA\)](#) of [Jobst and Gray \(2013\)](#) assesses the solvency risk of financial institutions, based on market-implied data. In a similar strand, [Segoviano \(2006\)](#) and [Segoviano and Goodhart \(2009\)](#) propose to derive the [Banking System Multivariate Density \(BSMD\)](#), stemming from the [Consistent Information Multivariate Density Optimizing Methodology \(CIMDO\)](#). Their approach allows developing joint probability measure of financial distress in the banking system. [Giesecke and Kim \(2011b\)](#) explore a similar type of measure, focused on the conditional probability of multiple failures.

[SR](#) is also closely intertwined with liquidity. However, yet another distinction is to be made. Oversight authorities tend to use the term ‘liquidity’ to refer as balance-sheet based measures, where the academic literature often refers to the market liquidity. For the first, the measure will be described in more details in the following section on the regulatory aspects of [SR](#). As for the academic literature, the amount of work proposed on systemic (market) liquidity is surprisingly sparse. Among the most famous, we find the [ILLIQ](#) measure of [Amihud \(2002\)](#). The measure consists in a straightforward ratio of absolute returns against the trading volume in U.S. Dollars. Advanced extension of the measure has been proposed by the [Volatility-Lab](#) of New York University, and will be detailed in the corpus of this dissertation. [Roll \(1984\)](#) proposed the [Roll Implicit Spread \(RIS\)](#), which consists in a simple measure that assesses the amount of autocorrelation in price’s variations. [Hasbrouck \(2009\)](#) generalizes the model of [Roll \(1984\)](#) using Gibbs sampling. [Severo \(2012\)](#) develops a measure of liquidity risk, namely the [Systemic Liquidity Risk Indicator \(SLRI\)](#), that finds its roots in the arbitrage violations observed among various asset classes.

The shift from economic theories to econometric models had an underlying cost that lies in the lack of recent theoretical framework of [SR](#) to lead measurement. The variety of measures is sometimes baffling and, consequently, it is difficult to know which measure is ‘right’⁸. A theoretical foundation help legitimize a particular measure. Moreover, it highlights the underlying assumptions and limitations.

⁸There is no right measure per se. We simply put forward the complexity of choosing a measure to assess [SR](#). Are all the existing measures assessing [SR](#)? If yes, why are they different?

Regulatory implications

This section starts by presenting the existing prudential regulatory frameworks for financial institutions. We detail the measures, directives and concepts documented by various oversight entities for banks, insurance companies and other types of financial institutions. In a second time, the section exposes the gaps in the current regulation, hence highlighting the importance of thoroughly researching [SR](#).

Current prudential framework

The initial prudential framework regards the banking activity. The proposal of the first Basel Agreements made by the [Basel Committee on Banking Supervision \(BCBS\)](#) (Basel I, 1988) and the following improved version, Basel II (2004) and Basel III (2009)⁹, constitutes the main prudential framework for banks nowadays. The framework provides both the method to identify [Global Systemically Important Banks \(G-SIB\)](#) and the regulatory tools at disposition. The identification of [G-SIB](#) ([BCBS, 2013, 2014](#)) starts with an initial sample of 75 of the largest banks¹⁰ in the world. Each bank is given scores over 12 indicators that are equally weighted in order to obtain a final score. The final score divides remaining banks into ‘buckets’ that decides their [Higher Liquidity Absorbency \(HLA\)](#) requirements (see Table 1). Moreover, such banks are also subject to a leverage ratio and liquidity ratios: the [Liquidity Coverage Ratio \(LCR\)](#) and the [Net Stable Funding Ratio \(NSFR\)](#).

$$Leverage = \frac{CET1}{TE} \geq 30\% \quad (1)$$

Where $CT1$ corresponds to Capital Tier 1, and TE is the total exposure of the institution.

$$LCR = \frac{HQLA}{TNLO_{30}} \geq 100\% \quad (2)$$

With $HQLA$ being High Quality Liquid Assets and $TNLO_{30}$ is the Total Net Liquidity Outflows over 30 days. Finally,

$$NSFR = \frac{ASF}{RSF} \geq 100\% \quad (3)$$

⁹Currently, Basel IV have been agreed upon in 2017 and should be implemented in January 2023.

¹⁰The banks are ranked given their leverage ratio (see Equation 1) detailed in Basel III.

Where ASF is the Available amount of Stable Funding and RSF is the Required amount of Stable Funding.

Furthermore, in order to mitigate the risk of bank runs, or the risk of a freeze of the interbank market, as it did occur during the Subprime crisis, prudential regulators have proposed various safety mechanisms. First, the infamous [Lender of Last Resort \(LOLR\)](#) was created to enable banks to cope with temporary illiquidity without having to rely on the interbank market. Additionally, the European Parliament issued the Directive 94/91/EC putting in place the *deposit insurance* in member states.

Table 1: **Higher Loss Absorbency Requirements.**

Table representing the corresponding HLA given a score based on various factors: Size, Interconnectedness, Financial Infrastructure, Complexity and Cross-jurisdictional activity. Each range of scores leads to a corresponding HLA ‘bucket’. Source: BCBS (2014) p.4.

Bucket	Score range	HLA requirement
5	530–629	+3.5% CET1
4	430–529	+2.5% CET1
3	330–429	+2.0% CET1
2	230–329	+1.5% CET1
1	130–229	+1.0% CET1

Nevertheless, banks are not the only financial institutions to be systemic. In 2010, the [Financial Stability Board \(FSB\)](#) mandated the [International Association of Insurance Supervisors \(IAIS\)](#) to develop a methodology to identify [Global Systemically Important Insurers \(G-SII\)](#)¹¹. The resulting framework for insurance companies (Solvency II), similarly to Basel II¹², is structured around three pillars: Minimum capital requirements, Supervisory review and Market discipline¹³. The identification process usually selects the 50 largest insurers¹⁴ for which scores are computed. A specific threshold decides whether the firms is of systemic importance. The main differences with the banking prudential framework resides in the use of internal models, which are accepted by the IAIS while Basel only approves the use of the [Asymptotic Single Risk Factor \(ASRF\)](#) model (Eling, Schmeiser, & Schimt,

¹¹IAIS, 2016.

¹²The second agreement of Basel were transposed into European Law under the [Capital Requirement Directive \(CRD\)](#).

¹³Eling, Schmeiser, and Schimt, 2007.

¹⁴The size of insurance companies, here, relates to the total assets and premiums ratio.

2007; Benoit et al., 2017). Additionally, there is discrepancies between the weight accorded to the indicators in the identification process (see Figure 1).

Even though no prudential framework yet exists, numerous studies have begun to include asset management firms in their SR assessment (Boyson, Stahel, & Stulz, 2010; Billio et al., 2012; Kress, McCoy, & Schwarcz, 2018; Hué, Lucotte, & Tokpavi, 2019). Shortly after the 2007-09 crisis, systemic vulnerabilities of the asset management sector were exposed in OFR (2013)¹⁵. The report identify numerous potential risks: ‘reaching for yield’ behavior or Exchange Traded Fund (ETF) related ‘redemption runs’. Moreover, the OFR confirms the systemic importance of asset management firms: ‘*the failure of a large asset management firm could be a source of risk, depending on its size, complexity, and the interaction among its various investment management strategies and activities*’ (OFR, 2013, p.18, para.6). Although, asset management firms are not yet prudentially regulated, the Investment Services Directive (ISD) and Markets in Financial Instrument Directive (MiFiD) provide a regulatory framework for their activity in Europe. Furthermore, recent research are arguing in favor of the creation of prudential oversight for such firms. For instance, Roncalli and Weisang (2015) expose numerous reasons why the method for identifying Other Systemically Important Institutions (O-SII)¹⁶ should also differs from the ones identifying G-SIB and G-SII. The European Banking Authority (EBA) propose an assessment methodology of O-SII in a report (EBA, 2014).

Current gaps

The existing prudential regulatory framework has a large scope of action, from liquidity requirements to stress testing passing by resolution procedures¹⁷. Although the current prudential framework has proved its usefulness, especially during the current crisis, some aspects can be further developed. Schwarcz (2019) argues that the fact that macroprudential regulation remains entity-based constitutes a serious limitation. Indeed, most of the current regulation aims to mitigate the impact of Systemically Important Financial Institution (SIFI) failure on the financial system. Even though they relate to financial instability, the default of SIFIs are only a part of the possible triggers of SR. For instance, financial markets are less regulated when

¹⁵The report was commissioned by the Financial Stability Oversight Council (FSOC) to the Office of Financial Research (OFR).

¹⁶In this particular case, O-SII refers to Systemically Important Asset Management Firms.

¹⁷Schwarcz (2008) proposes a comprehensive introduction to SR regulation.

Figure 1: Scoring method for G-SIB and G-SII

Differences in the scoring process for G-SIB (a) and G-SII (b). The tables display the weight associated with each categories of indicators. The table (a) is retrieved from the report of the BCBS (BCBS, 2014, p.2). Table (b) is retrieved from a report from the IAIS (IAIS, 2016, p.14).

Indicators and their weights			Table 1
Category	Indicator	Line item	Indicator weight
Size	Total exposures ¹	2o	1/5 = 20%
Interconnectedness	Intra-financial system assets	3f	1/15 = 6.6̄%
	Intra-financial system liabilities	4g	1/15 = 6.6̄%
	Securities outstanding	5i	1/15 = 6.6̄%
Substitutability/financial institution infrastructure	Payment activity	6n	1/15 = 6.6̄%
	Assets under custody	7a	1/15 = 6.6̄%
	Underwritten transactions in debt and equity markets	8c	1/15 = 6.6̄%
Complexity	Notional amount of OTC derivatives	9c	1/15 = 6.6̄%
	Trading and AFS securities	10f	1/15 = 6.6̄%
	Level 3 assets	11a	1/15 = 6.6̄%
Cross-jurisdictional activity	Cross-jurisdictional claims	12c	1/10 = 10%
	Cross-jurisdictional liabilities	13d	1/10 = 10%

¹ Note that the total exposures indicator is as defined in the leverage ratio worksheet of the December 2012 Basel III monitoring exercise. This is different from the leverage ratio exposure measure adopted by the BCBS in January 2014.

(a) G-SIB

Category	Subcategory	Indicator	Weight
Size		Total Assets	2.5%
		Total Revenues	2.5%
Global activity		Revenues derived outside of home country	2.5%
		Number of Countries	2.5%
Interconnectedness	Counterparty exposure	Intra-financial assets	6.7%
		Intra-financial liabilities	6.7%
		Reinsurance	6.7%*
		Derivatives	6.7%
	Macroeconomic exposure	Derivatives Trading (CDS or similar derivatives instrument protection sold)	7.5%*
		Financial guarantees	7.5%*
		Minimum guarantees on variable products	7.5%
Asset liquidation		Non-policy holder liabilities and noninsurance revenues	7.5%
		Short term funding	7.5%
		Level 3 assets	6.7%
		Turnover	6.7%
		Liability liquidity	7.5%
Substitutability		Premiums for specific business lines	5%

*Denotes the application of an absolute reference value

(b) G-SII

it comes to **SR**. Although, it is known that panics on financial markets are usually related to financial crises and systemic crises, they are considered as consequences rather than causes of **SE**.

Furthermore, Schwarcz (2019) identifies main triggers and transmission mechanisms that would need to be better regulated. The triggers of **SR** are numerous. The issue of complexity, and the subsequent opacity, poses one of the greater challenges of the 21st century. The degree of complexity of the financial markets rose to such an extent that existing exposures become difficult to identify. Furthermore, agency costs¹⁸ and behavioral limitations¹⁹ are serious threats to the stability of **SIFI**. Additionally, the rigidity of the regulatory framework compared to the rapid evolution of the system regulated poses a number of issues. Without constant monitoring, which would imply a great complexity to put in place, it is difficult for a regulatory framework to remain coherent for a long time.

The regulatory framework also have to take into account the various transmission mechanisms. The financial system becomes more and more interconnected, and the diversity of interconnections increases accordingly. Interconnection can occur over financial obligations and common risk exposure. Hence, the size of a **SIFI** have a direct relationship with the amount of connections it has. In some cases, a shock might be transmitted through central compensation chambers that act like a central node in a network²⁰, or through derivatives markets. The spillover from one market to another plays an important role in a **SE**, hence needs also to fall onto the prudential oversight.

‘Macropudnetial regulation is also subject, of course, to our limited understanding of systemic risk, including its triggers and transmission mechanisms’ (Schwarcz, 2019, p.23, para.2). There is and always will be, especially regarding **SR**, a need for a deeper understanding on how **SE** unfolds. **SR** keeps evolving and changing alongside our financial markets and economy’s structures. Although it may seems like an

¹⁸Agency costs are stemming from the misalignment of objectives between managers and owners. Managers are often compensated under short-term objectives that are in opposition to the long-term interests of the company.

¹⁹Behavioral limitations include, among other concepts, herding behavior and cognitive biases.

²⁰Acemoglu, Ozdaglar, and Tahbaz-Saheli, 2015.

impossible task, theoretical insights could lead the macroprudential regulation to a viable solution for SR.

Research Question

The amount of the existing literature on measuring SR is sprawling. This fact can be explained by the urge of the oversight entities to obtain a proper and robust measure of financial instability towards the unwinding of the Subprime crisis. The crisis had uncovered the fundamental lack of understanding in how financial instability emerges from endogenous mechanisms of the economy ²¹. In response to that need, academics flooded journals with new measures, definitions and approaches of SR. Despite the extent of the current literature, there is no consensus on what is SR and how to measure it²². Each oversight entity has its own definition and assessment methodology. This dissertation first endeavors to address this issue.

How to measure coherently Systemic Risk?

The answer to this initial question is twofold. First, SR is a dynamical concept. In other words, it will, by construction, change with time. SR was initially a bank-focused concept, due to the fact that banks were the largest financial institutions at the time. However, the financial system evolved; the functions of banks changed; new financial institutions emerged; and financial innovations appeared. Taking these facts in consideration, it is not surprising that no consensus on SR was ever reached. The second, intrinsically linked to the first, is that no theoretical framework taking into account the fact that SR will evolve with time has been created. In order to address this gap, we propose a theoretical framework answer the following question:

Chapter I. How to define Systemic Risk?

²¹Minsky (1986) discusses the fact that the current (at his time) prevalent theory, the neoclassical view, could not be used for policy purposes due to its inability to describe endogenously the creation of recessions, and economic downturns.

²²The defining problem and assessment problem are two sides of the coin. It is simply impossible to propose a coherent measure of a phenomenon if that very phenomenon is not properly defined.

Our theoretical framework parallels the work of Artzner et al. (1999) and Biagini et al. (2020). Our work consists in a Bottom-Up approach that starts by redefining all subsequent concepts of SR and builds its way up to the process of a SE, optimal time of regulatory intervention and the definition of SR. From that initial work, we now aim to validate the theoretical framework proposed. Two main questions arise. First,

Chapter II. Is Systemic Risk a combination of different risks?

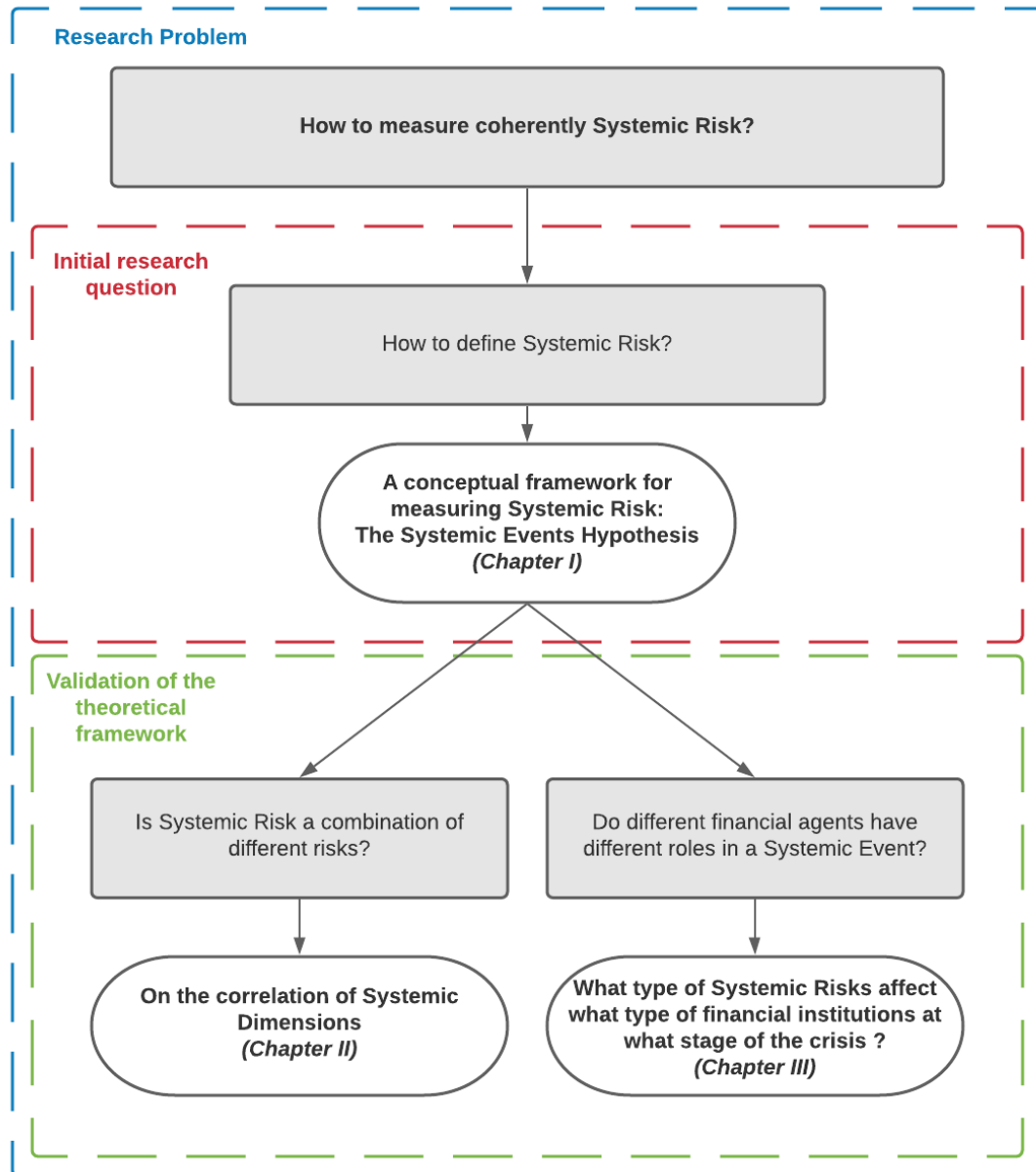
The chronology of a SE proposed in our framework postulates that SR is a succession of occurrence of different risks. We address that question in the second chapter of this dissertation. The second question is,

Chapter III. Do different financial agents have different roles in a Systemic Event?

Stemming from the theoretical framework and the previous one, this last question consists in examining the differences in SR incurred by different types of financial institutions. By knowing the differences, we can then relate the results to the initial theoretical framework in order to assign a role of a type of financial institution in the unraveling of a Systemic Crisis. Figure 2 summarizes the structure of the thesis work and shows explicitly the articulation of the chapters.

Figure 2: **Structure of the dissertation.**

Schematic representation of the structure of this dissertation. Blue squares represent the research questions, while green items are the dissertation's chapters answering the research questions, correspondingly.



Contents of the dissertation

This section introduces the contents of this dissertation. It presents, successively, each chapter by describing the initial rationale of the underlying study, the research question, methods used, as well as presenting the results.

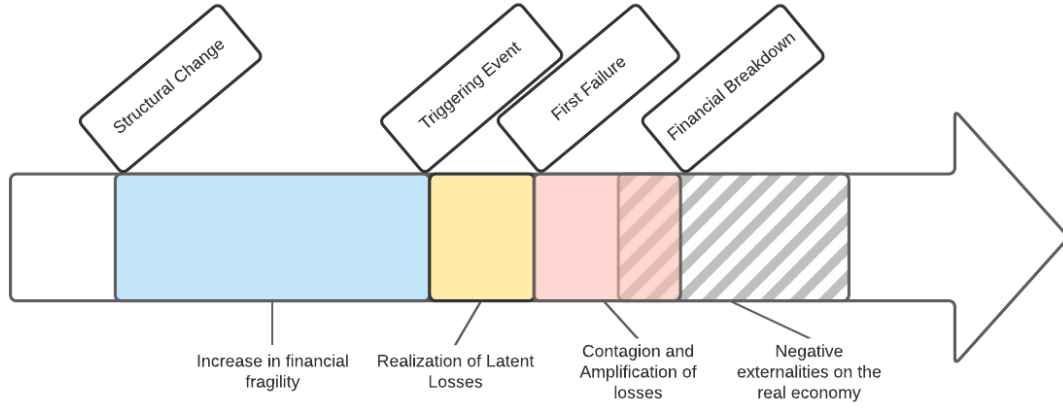
Chapter I

The first chapter poses the question on how to properly measure **SR**. Indeed, there exists a significantly large literature on numerous measures of **SR**, yet no consensus has been reached on what measure is the proper one. We argue that the lack of agreement comes from the concomitant lack of theoretical framework on how to approach a **SE**. This chapter define all concepts relevant to understand **SR**.

We start by defining the concept of risk, and additionally provide definitions for financial fragility, financial shocks, financial crises and, eventually, **SR**. We define **SR** as: ‘the probability of occurrence of a systemic event’. This definition relates to the work of Zigrand (2014). It however significantly differs in the way we define a systemic event. In order to leave no space for confusion, we propose the **Systemic Event Hypothesis (SEH)**. The **SEH** is an assumption on how **SEs** birth. It details the chronology that any **SE** follows. The process starts with a structural displacement (Kindleberger, 1978; Minsky, 1991), which creates a new profit opportunity. Financial firms, looking for higher returns, will engage, unknowingly, in a correlated investment that will lead to a common exposure to the same risk factor. The risk associated with the profit opportunity is defined as a latent risk. At this stage, commonality in firms performance will probably arise, and grow. At some point, what Minsky used to call the ‘not-so-unusual’ event will occur. Financial firms will experience losses related to the latent risk and will thus push the financial system in a state of instability. Various mechanisms (e.g. contagion, amplification through feedback loops) will worsen the initial shock and will disrupt the financial system to such an extent that it will negatively impact the real economy. Reinhart and Rogoff (2009) and Atkinson, Luttrell, and Rosenblum (2013) describe specifically the kind of negative externalities such crisis can create. The Figure 3 proposes a graphical representation of the **SEH**.

Figure 3: **Schematic view of the Systemic Events Hypothesis.**

Schematic representation of the chronology of a systemic event as hypothesized in the SEH. The framed texts represent events, while frameless texts are phenomena occurring over a period.



Given the SEH is valid, there exists specific times when a given regulator should take action. Structural regulators²³ should focus on forecasting potential apparitions of common exposures, stemming from a structural change and to enforce rules/ratio in order to improve the resiliency of the financial system. Monetary authorities, as the European Central Bank (ECB) or Federal Reserve Bank (Fed), should limit the earlier build up of financial fragility by ensuring price stability, as well as serving as LOLR in case of extreme realization of latent risk that would put in danger an institution essential in the financial system survival²⁴. Lastly, market authorities as the Securities and Exchange Commission (SEC) or European Securities and Market Authority (ESMA) in Europe, should intervene at the triggering event in order to enforce market stability. Contagion across markets as well as fire sales phenomena are usually at the core of the amplification of losses, thus central in a crisis' development.

In order to provide empirical evidences of the SEH, we propose to have a focus on the crisis of 2007-09. We select various SR measures in order to capture all dimensions of a SE. The commonality in asset returns is assessed through a PCA à la Kritzman et al. (2011). For the exposure to systemic losses, we use the CAViAR of

²³In our sense, structural regulators are oversight entities that will change, with their regulatory actions, the very structure of the financial system. For instance, we consider BCBS, EBA, IAIS or even European Systemic Risk Board (ESRB) to be structural regulators.

²⁴Such institutions are currently known as Too Big To Fail (TBTF).

Engle and Manganelli (2004) and the CoVaR of Adrian and Brunnermeier (2016). To proxy contagion effects we chose the Average Chi (ACHI) of Balla, Ergen, and Migueis (2014), and, for illiquidity proxies, we have settled on the RIS of Roll (1984) and, the now infamous, ILLIQ of Amihud (2002). We choose changes in the real GDP of the U.S. and the unemployment rate in order to proxy the negative externalities of the financial crisis on the real economy. The measures are applied on a sample of 53 of the largest U.S. financial institutions., including insurance companies, banks as well as investment firms. Our data spawn from 2006 to 2011, and is of daily frequency. We find an uncanny empirical segmentation of the subprime crisis relative to what the SEH depicts. A rise in asset commonality occurs the earliest, followed by systemic losses. Eventually, contagion and illiquidity appear and real economy variables worsen. The observed chronology appears to fit the SEH quite well.

Chapter II

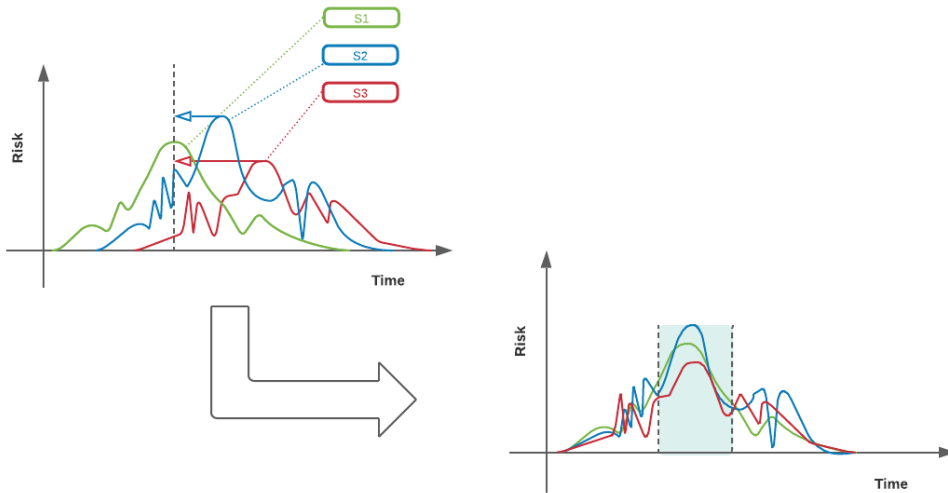
The SEH poses a lot of questions regarding its validity. Chapter II and Chapter III aim to answer a few. This Chapter will focus on the multidimensional aspect of SR. The rationale behind the study is to question whether SR really is a combination of different risks, thus whether the measures currently used in the literature are collinear, or actually bring new, useful, information about SR.

We start by postulating that SR actually is a combination of various risks. More precisely, we assume three Systemic Dimensions: Losses, Liquidity and Connectedness. Each dimensions is assumed to capture a specific type of SR that will appear in a systemic event. Given the existing literature, it appears that losses, illiquidity and connectedness are major components of SR. The purpose is then to assess SR through its dimensions. Since we know that financial markets are not perfect, it would appear surprising that any indicator, or measure, stemming from market-based data is perfectly assessing what it is supposed to assess. The underlying assumption of this part of the dissertation is that (systemic) risk measures are noisy signals. The noise component of each measure are uncorrelated among eachther, as

they are dimension-specific²⁵, however the signal, relative to **SR**, must be somehow correlated. During a **SE**, as **SR** increases, all Systemic Dimensions should increase accordingly, hence the proportion of noise-to-signal decreases. As noise is dominant in ‘stable’ times, we intend to observe empirically a lack of correlations between **SR** measures. Accordingly, as signal becomes predominant in crisis periods, the noise decreases and we expect to find evidences of correlation. The apparition of correlation in **SR** measures during a crisis would actually confirms the multidimensionality of **SR**²⁶. However, this initial analysis disregards the chronology of the **SE**, as exposed in the **SEH**. In order to further validate the **SEH**, we must not only put forward evidences of the multidimensionality of **SR** but also show significant evidences of a particular chronology in a **SE**. In order to do so, we propose a focus on the correlation of lagged Systemic Dimensions. The lagging procedure is described in Figure 4.

Figure 4: Lagging Systemic Dimensions.

*Schematic representation of the effect of lagging Systemic Dimensions. The transition, from the upper right to lower left charts, is made by lagging Systemic Dimensions (S_2 , S_3). The lag procedure allows to increase the precision of the estimation of crisis periods, thus showing evidence of a chronology in **SEs**.*



²⁵Here, dimension-specific refers to the Systemic Dimensions. A noise that is dimension-specific, corresponds to an increase in the Systemic Dimension, or risk measure that is not related to a corresponding increase in **SR**.

²⁶If we observe (1) the correlation of **SR** measures in crisis periods and (2) the absence of correlation during stable times, we would be able to confirm that **SR** is a combination of various risks, i.e. systemic dimensions.

We compute the systemic dimensions using well-known measures on two distinct samples. The first consists in 75 of the largest U.S. financial firms, composed of banks, insurance companies as well as asset management firms, from 2000 to 2020. Our second sample, meant for robustness analysis, consists in 100 of the largest European firms, divided in banks, brokers, insurance companies and asset management firms. The European data stems from January 2005 to December 2017. Our Systemic Dimensions are proxied as follows. [CoVaR](#) of Adrian and Brunnermeier (2016) represents the systemic losses, the illiquidity proxy, [ILLIQ](#), of Amihud (2002) for systemic illiquidity and, lastly, the [Degree of Granger Causality \(DGC\)](#) stemming from Granger (1969) and Billio et al. (2012) for systemic connectedness. We study the temporal evolution of the correlation between Systemic Dimensions using a rolling-forward [PCA](#). A specific orthonormal rotation (quartimax) is applied on the correlation matrix. Our results are threefold. First, we find that the explained variance of the first component, somehow similarly to Kritzman et al. (2011), can act as a [SR](#) signal. More precisely, the increase in the explained variance of the first component is a sign for [SR](#) if the increase is due to a decrease in the explained variance of the two other principal components. The measure still carries a significant amount of noise, which, we argue, is due to not taking into account the chronology of a [SE](#). Our second result answers that limitation. We show that, by lagging appropriately our Systemic Dimensions, we are able to reduce the amount of noise, hence allows the measure to capture more clearly crisis periods. Lastly, we show that the measure may also work for identifying [SR](#) in any type of system considered. We apply our procedure on separate parts of the financial sector. By doing so, we are able to observe which type of financial firms were the most systemically important during well-known crises (DotCom, Subprimes or the European Sovereign Debt Crisis). Results are similar on both samples, thus putting forward evidences of the robustness of our results. Furthermore, we compare the evolution of [SR](#) on both financial systems. Our results show, logically, that [SR](#) was transmitted from the American financial market to the European during the Subprimes crisis. Moreover, our approach allows to describe the differences in the levels of [SR](#). We show that the European financial system was more in distress than the American during the European Sovereign Debt crisis. These results prove the consistency and applicability of the method proposed in this chapter.

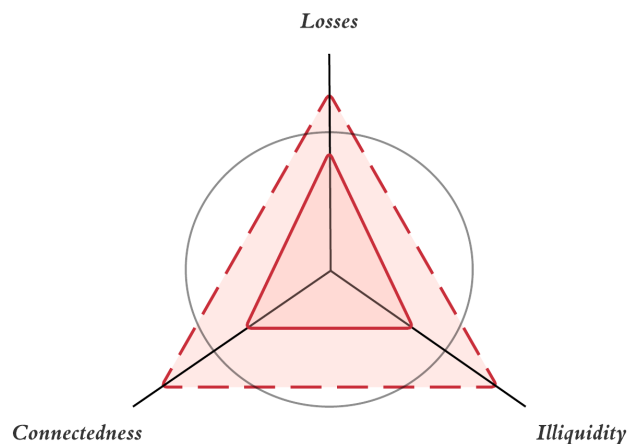
Chapter III

This Chapter aims to study the specific role of different types of financial agents in a SE. Indeed, the SEH proposed a chronology for SEs, and described extensively the mechanisms at play. It, however, disregards the specific role of each type of financial institutions. The underlying assumption of this research consists in the fact that different institutions function and interact in their own, specific way. Accordingly, each type of institutions must have a particular role to play in a systemic crisis.

We base our analysis on our previous findings, and assume that SR is composed of its three Systemic Dimensions: Losses, Liquidity and Connectedness. The Systemic Dimensions are computed on a sample of 417 European and U.S. financial firms, from 01-01-2001 to 21-01-2021. The financial firms are banks, insurance companies and asset management firms. The primary goal of the study is to uncover the specific SR carried by each types of firms. To that end, we introduce the concept of Systemic Risk Profile (SRP). An SRP is a graphical representation of the levels of Systemic Dimensions, for a given type of firm (see Figure 5). It represents the levels in ‘stable’ times as well as for crisis periods. By doing so, it allows to have a quick comprehensive view of the SR incurred by a type of firm.

Figure 5: Example of a Systemic Risk Profile.

A Systemic Risk Profile is a graphical heuristic to assess the Systemic Dimensions of a firm/type of firm/entity. In this article, we observe three Systemic Dimensions: Losses (up), Illiquidity (right) and Connectedness (left). The dark shaded line/are represents the levels of Systemic Dimensions in stable times. The dotted line show the Systemic Dimensions’ levels in time of crisis.



To that initial objective, is added three parallel goals. The first, is to examine the effect of size on the **SRP** of an institution. Indeed, stemming from the same logical process that allowed us to determine that different types of firm must have different types of risk, identical firms of different sizes may have different types of **SR** as well. To do so, we separate our initial sample in two sub-samples. The first contains the 10% highest market capitalized firms, while the second contains the 10% lowest. The second, is to uncover the effect of each crisis in our sample (DotCom, Subprimes, European Sovereign Debt and Covid) on the **SRP**. As said above, financial crises may come in different sorts and flavors. Their respective consequences on **SR** should then differ, and the **SRP** will provide a simple way to observe such consequences. The last, is to confirm (or refute) the presence of a chronology in Systemic Dimensions during a **SE**. The **SEH** hypothesizes that different types of **SR** exist (Systemic Dimensions), and, moreover, that each type will occur in a specific sequence.

Our results are numerous. Answering to our initial question, we show that **SRPs** differ depending on the type of institutions. Insurance companies tend to be largely exposed to systemic losses, while asset management firms are more interconnected and tend to be more exposed to illiquidity. Surprisingly, banks do not appear as the most systemically important type of institution in our sample. We observe that a significant size effect exists. Large firms will tend to carry more exposure to systemic losses, as well as being more interconnected. Smaller firms will tend to be more exposed to illiquidity. Lastly, we show that each financial crisis is different from the other, but a Systemic Crisis is characterized by a concomitant increase in its Systemic Dimensions. Moreover, we confirm that such Dimensions peaks successively during the **SE**, as the **SEH** hypothesizes. By combining our results, we show that large firms, especially insurance companies and asset management firms will tend to build up common exposure early in the crisis and will be the most impacted by the financial shock that follows. Small firms, specifically banks and insurers, will suffer the rise in illiquidity towards the end of the crisis.

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Chapter I

A conceptual framework for measuring Systemic Risk: The Systemic Events Hypothesis

I.1 Introduction

‘A systemic crisis is a paradigm crisis’ (Aglietta, 1993, p.196, para.4). The very concept of **Systemic Risk (SR)**, intimately related to the one of systemic crises, is still relatively new. It appeared with the failure of the German bank, Herstatt, in 1974. The stress caused on the currency market was large enough to display the inherent risks of a intricately linked system. The event provoked a wave of academic research on **SR** (Diamond & Dybvig, 1986, 1983; Aglietta, 1993, 1996; Bernanke & Gertler, 1989; Bryant, 1980). The fact that, most financial crises at the time, and the initial systemic crisis, were bank-related led naturally to a conception of **SR** centered on banking. Similarly, it is not surprising that first prudential regulations were also focused on controlling banking activity (Basel I) and reforming banking structure (Glass-Steagall Act, 1933; Dodd-Frank Act, 2010). As time passed by, the financial system evolved faster and grew more and more complex. New activities were developed (High Frequency Trading, Algorithmic Trading), countless financial innovations emerged (CDOs, etc.) and the regulatory oversight followed accordingly (Basel II and III, Insolvency). From a systemic point of view, we can affirm that the diachronic properties, that is to say the dynamics of the system’s structure, of the financial system changed radically in the early 2000s. The subprime crisis showed doubtlessly that the complexity of the financial system’s structure went above our comprehension. It appeared impossible to predict the numerous positive feedback effects who took place (IMF, 2009; Kapadia et al., 2012; Hautsch, Schaumburg, & Schienle, 2014), the contagion’s dynamics over financial institutions and markets (Jorion & Zhang, 2019; Kritzman et al., 2011; Acharya & Thakor, 2016; Azizpour, Giesecke, & Schwenkler, 2018), the illiquidity issues arising from fire sales and loss in trust (Bryant, 1980; Diamond & Dybvig, 1983; Shleifer & Vishny, 1992; Mishkin, 1996; Greenwood, Landier, & Thesmar, 2015; Bian et al., 2018), nor the consequences on the real economy (Reinhart & Rogoff, 2009). The variety of risks involved fueled a new surge in research on **SR**. An outstanding amount of papers on measure of **SR** were proposed (Billio et al., 2012; Adrian & Brunnermeier, 2016; Engle, 2016; Acharya, 2009; Cont, Moussa, & Santos, 2013). Each of the papers focuses on a specific dimension of the crisis and aims to find a reliable indicator of **SR**. The underlying assumption made when considering a single measure for a systemic event, is that the systemic event is unidimensional. The result of measur-

ing **SR** unidimensionally, is a noisy¹ measure which fits specifically to a type of crisis.

In this thesis, we argue that **SR** is multidimensional and should be assessed using different types of measures. This chapter aims to go further by redefining the basics of **SR**. Numerous academic definitions exist (Aglietta, 1993; De Bandt & Hartmann, 2000; Acharya, 2009) as well as from regulatory instances (IMF; ECB; etc.), however a consensus has yet to be reached. This issue is of first importance as definitions lead measurements. A theoretical framework seems essential to unify academics on a specific definition. Currently, we note the work of Chen, Iyengar, and Moallemi (2013), that presents an axiomatic framework for measuring **SR**. In our opinion their definition of **SR** is flawed, hence invalidating the rest of the framework. This chapter presents an attempt at defining **SR** empirically, and proposes a draft of measurement framework. We start with precisising the concept of risk, especially in finance. We continue by presenting the anatomy of a systemic event. Finally, we conclude with the measurement framework for **SR**, regulatory implications and the discussion of results.

Before starting off, we should also present a brief disclaimer in order to avoid future confusion. **SR** is by no means exclusive to finance. There exist a multitude of system that could be physical, biologic, environmental, etc. Even in economics alone, there is various systems that could be considered. In this article, we only present our conceptual view on the **SR** in finance. Hence, we will focus on how **SR** affects financial firms.

I.2 On the definition of risk

This section introduces the concept of risk. Firstly, we provide a discussion on the concept of risk and the definitions used so far. In a second time, we propose a definition of risk for our measurement framework. We also discuss the existing frameworks of risk measurements.

¹Here, noisy means that some increases in the indicators do not correspond to an actual increase in **SR**.

I.2.1 A conceptual discussion

‘Knowledge about risk is knowledge about the lack of knowledge’ (Hansson, 2018, section 2, para. 1). This sentence illustrates the complexity existing around risk and the interest given to it through the years. Intrinsically, the notion is linked to the unknown and how we dare to approach it. Because each area of research has different unknowns of interest, there exists as many definitions as domains. This constitutes the challenge of defining risk. How to provide a working definition fitting all different areas of research. Let us try to approach the reason why such a well-known concept is so difficult to corner. An easy place to start are dictionaries’ definitions. The Cambridge Dictionary defines risk as ‘*the possibility of something bad happening*’. The Stanford Encyclopedia of Philosophy gives out a more open description: ‘*related to a situation in which it is possible but not certain that an undesirable event will occur*’. Two main concepts emerge from these definitions. First, risk is related to an event which realization is uncertain. However, the details of what kind of uncertainty are not specified. Additionally, the conclusion is undesirable. Here, similarly, the concept of undesirable is tricky as it depends mainly on social constructs and subjective points of view. The issues related to the precision over the notions of undesirability and uncertainty are well exposed by Renn and Walker (2008). Actually, Renn and Walker (2008) add up a third concern about the rule of risk aggregation for the sake of comparability in the operational sense. Let us tackle first the issue of uncertainty. Pioneer work of Knight (1921) has specified the sense of uncertainty in the economic theory. The Knightian uncertainty is when an event cannot be fully formalized and no actual probability (or measure of the likeliness of realization) can be proposed. Consequently, the Knightian risk regards all events that can be defined and with which one can associate a likelihood of realization. This approach of risk directly leads to the use of probabilistic methods for risk assessment and disregards unknown unknowns (Luft & Ingham, 1955). Indeed, probability theory provides a powerful tool for analyzing the unknown. The development that followed the work of Bachelier (1900) and led to the existing option theory constitutes a perfect example. The question posed by the Knightian approach regards our ability to quantify the uncertainty surrounding a future event. What about the cases when it is not possible to assign a numerical value? Moreover, just because an event is difficult to formalize properly, should we overlook it? The gray area in Knightian approach lies in the way to deal with unknown unknowns.

Insurers for instance, have for long recognized that insuring all types of risk is not be possible, mostly because some risks are not easy to formalize and to quantify. Hence, the existence of non-insurable risks. Which leads to the second component of risk: undesirability. The question asked by Renn and Walker (2008): ‘*who determines what is undesirable?*’ is of first importance. The differences in definitions come from the fact that undesirability is conditional to your area of interest. In finance, a significant part of the literature have based their definition of risk on the probability of losing money. Even if the measures take different forms depending on the precise context (we would look at the variance in portfolio management, when you would look at the probability of death in life insurance for instance), all are associated with financial losses. An important point to note is the distinction of Luhmann (1990). The author differentiates between danger and risk. Danger being an external threat of the system considered while risk would emerge from within. The approach of Luhmann is interesting in the sense that he roots his approach on the fact that there is always a system considered. This point is of utmost importance indeed: every analysis of any event is implicitly based on a system. The system corresponds to the environment (both physical and conceptual) in which the event occurs. Risk assessment needs to initially consider a system before being able to identify what variable is of interest and how can one approach the event. The importance of the system considered on SR measurement is especially shown by Benoit (2017).

I.2.2 From discussing to defining

The discussion above on the definition of risk might seem trivial but it is an essential step to what follows. A concept’s definition frames its measurement. As it would seem preposterous to measure perfectly an imperfectly defined notion, the way one defines a notion leads one’s way to measure it. Up to now, most of the definitions focuses on the apparition of an undesirable event. However, no event simply emerges instantaneously and without causes. We argue in our approach, that no event is without cause, hence an event is the causality of an association of its causes. From here, we propose the following definition for risk:

Definition 1. Risk: *Possibility, that is measurable (or not), that an association of elements of a system leads to a realization of an undesirable event. The measurability of the event being a function of the complexity of the system considered.*

At this point, one might question the necessity of providing yet another relatively ordinary definition of risk. We provide an example as an answer. Let us consider the risk of an avalanche occurring in a given place. A previous definition would have stated that we should look at the probability of occurrence of avalanches. As the avalanche is an event that likely happened in the past, one could consider to empirically check the amount of occurrences in the past and derive an empirical probability (which is without doubts an inappropriate approach to this kind of problem, but let us consider it, for the sake of the example). Such a measure would fit the previous definition but not ours. Our definition would advise for looking at what causes the avalanche and hence look at the (joint) probability of the cause being reunited at the same time. Hence, our definition encompasses the coherent measures that were accepted by the previous definitions, while refusing the simplistic measures that they also allowed. This also constitutes an example of how a definition frames the measurement of a concept. Additionally to a definition, a proper measure of risk should respond to a given set of rules. This point echoes the third question of Renn and Walker (2008) on the comparison and aggregation of risks. Often, risk managers have to mitigate a risk or to optimize their decisions given a risk target. Hence, measuring risk in a way that you can aggregate it or mitigate it, is vital in risk management. In finance particularly, the initial work of Artzner et al. (1999), followed by Biagini et al. (2019) and Biagini et al. (2020), propose a set of axioms to follow when constructing a risk measure. Chen, Iyengar, and Moallemi (2013) offers an axiomatic framework for SR measurement. The axioms proposed by Artzner et al. (1999) are as follows:

Definition 2. Risk measure: *A measure of risk is a mapping from G to R .*

- Axiom T: Translation invariance. For all X belonging to G and all real numbers α , we have: $\rho(X + \alpha r) = \rho(X) - \alpha$.

- Axiom S: Subadditivity. For all X_1 , and X_2 belonging to G , we have: $\rho(X_1 + X_2) \leq \rho(X_1) + \rho(X_2)$.
- Axiom PH: Positive Homogeneity. For all $\lambda \geq 0$, and all X belonging to G , $\rho(\lambda X) = \lambda\rho(X)$.
- Axiom M: Monotonicity. For all X and Y belonging to G with $X \leq Y$, we have $\rho(Y) \leq \rho(X)$.
- Axiom R: Relevance. For all X belonging to G with $X \leq 0$ and $X \neq 0$, we have $\rho(X) \geq 0$

This research gives a proper framework for future constructions of risk measures. Even though the framework is not perfect (Dhaene et al., 2008), it serves as a great set of guidelines. Our approach tends to the same goal than Chen, Iyengar, and Moallemi (2013) as we aim for a set of rules of construction for (systemic) risk measures. More than refuting all the existing literature on risk measures, it builds up on it. The necessity of early risk measures lies in the fact that they allow a better understanding of the phenomenon considered. And as the measures get better, our understanding of the nature of the risk grows better.

I.3 Anatomy of a systemic event

This section presents our most important insights on what a systemic event is. We start by defining the concepts of financial instability, financial fragility, financial shock and crisis. In a second time, we detail the complete process of a systemic event. We provide our working definition of SR and conclude with the regulatory proposals in accordance with our view of a systemic event.

I.3.1 Financial instability, financial fragility and financial crisis

Let us apply the systemic approach (Walliser, 1977) to present our conception of the financial system. The financial system consists in agents (nodes) which interact among each other (links). It has rules as how agents may interact at any time t (synchronic properties) and a framework on how these rules may change over time (diachronic properties). A state of the financial system is defined as the set of characteristics that the system displays at time t . In this sense, the choice of the system considered is central. One could consider the international financial system, or observe national financial systems. The importance of the choice of the system for SR measurement is highlighted in the research of Benoit (2017). A simple model allows for an over-simplistic² two states conception: stable and unstable. In this framework, any phenomena can be described by a succession of interactions (or simultaneous interactions) between agents, taking into account the synchronic properties at the time. For instance, the subprime crisis was first a consequence of the housing bubble in the U.S. as well as large common exposures of banks to default risk through CDS. Every phenomena may have an impact on the diachronic properties of the system, hence on the future structure of the system. Following Walliser (1977), we define the structure of the system as the set of the types and amount of existing agents, the types and amount of links/interactions between them, the synchronic and diachronic properties. We hence define a structural change as a significant variation in any of these components. We will keep this framework in mind for the rest of the chapter and, more importantly, for the description of stages of a systemic event.

SR is well-known by both academics and regulators. It is usually defined as a “know-when-you-see-it” concept, which is a diplomatic way to say that it is not well defined. This inaccuracy stems from the imprecise definitions of subsequent notions. For instance, we often approach SR as related to the instability of a system (De Bandt, Drumetz, & Pfister, 2013). However, financial stability is not well defined itself. The financial system is doomed to crash every now and then, hence the difficulty of defining financial stability. It exists two distinct views on financial

²Conceptually, states are probably not clearly defined into crisis and stable. The concept of multiple states is probably a continuum of states. Hence the difficulty of settling on beginning and ending dates of crises.

instability. On one hand, academics that consider that we define negatively what financial stability is. That is to say, we define financial stability by what is not: financial instability. De Bandt, Drumetz, and Pfister (2013) presents the general characteristics of financial instability. On another hand, researchers that tried to define financial stability by what it is, a complex concept. Schinasi (2004)³ proposes the following definition:

Definition 3. Financial stability: *A financial system is in a range of stability whenever it is capable of facilitating (rather than impeding) the performance of an economy, and of dissipating financial imbalances that arise endogenously or as a result of significant adverse and unanticipated events. (Schinasi, 2004)*

In the view of Schinasi (2004), financial stability is a continuum. It implies that financial sectors are well-functioning⁴. More importantly, even though the financial system can be unstable (have an unstable state), stability is considered as a property. In other words, stability is a synchronous property of the financial system, which allows it to limit the development of large imbalances threatening the longevity of the stable state. Conceptually, one could consider that the financial system allows for two distinct states: stable and unstable. The diachronic properties of the system allows it to pass from one to another with probabilities that may vary with time. The whole purpose of SR measurement is to reach (or approximate correctly) these probabilities. Up to now, we have left undefined a few key concepts, such as financial fragility, financial crisis and systemic crisis. The concepts are closely intertwined but not equal. First of three, we know that financial fragility is:

Definition 4. Financial fragility: *Situations in which small shocks have a significant impact on the financial system. (Allen & Gale, 2007)*

³To see alternative definitions of financial (in)stability, see the survey at the end of Schinasi (2004).

⁴The well-function of financial markets implies the optimization of resources allocation; mobilization of savings; facilitation of wealth accumulation, development and growth; and smooth function of the payment system (Schinasi, 2004).

This definition is linked to the resilience of financial institutions. For instance, an institution can be individually resilient, and most of the most important ones are thanks to the current prudential oversight, and still be put into distress due to sectorial common exposure. The fact is that the network (system) must be resilient as well (Allen, Babus, & Carletti, 2010; Acemoglu, Ozdaglar, & Tahbaz-Saheli, 2015). Knowing that the financial system is composed of various agents, linked in numerous ways and have implicit diachronic and synchronic properties; we can now define a financial crisis as:

Definition 5. Financial crisis: *Event introducing the transition from stable to the unstable state of the financial system. Its risk is accordingly, the possibility that an association of elements of the financial system leads to a state of financial instability.*

One could argue that the real interest is then into finding the transition matrix for the financial system, that is to say the probabilities of going from one state to another or staying in the same state. In such case, an straight forward thinking could lead to using a Hidden Markov Model (HMM), allowing for two states. Such a method indeed give us the transition matrix. However, it seems difficult to expect such a model to differentiate “usual” financial crises and systemic crises. Finally, it does not tell us anything about the causes of the crisis, hence does not help for the regulatory response that is needed during the crisis and afterwards. The complexity of regulators’ task lies in the fact that financial crises come in all sorts and flavors. Allen, Babus, and Carletti (2009) provide an insightful survey on the work on financial crises through the past decades. Troubles stems from the nature of the cause, the consequences being always identically undesirable (Eichengreen & Portes, 1987; Mishkin, 1996; Reinhart & Rogoff, 2009). Thus, the actual challenge with SR measurement is to extract generic characteristics from historical systemic crises. The first step consists in agreeing on the systemicality of a crisis, that is to say which crises are systemic and which are not. An important point to note here is that we should also identify which crises could have been systemic and were, hopefully, managed in time. Without including such crises, we would produce an ‘*inverse survivorship bias*’, by taking into account just the cases we could not deal

with at the time and missing all the situations that we managed appropriately. Here lies a central piece of insight. A crisis *becomes* systemic. Another difficulty of SR measurement stems precisely from this fact. It is complex to determine whether a crisis will remain benign, or will spread out and worsen. Generally, we admit that a financial crisis has three possible resolutions (LaBrosse, Olivares-Caminal, & Singh, 2009; Laeven & Valencia, 2010). First, the positive feedback effects create a downward spiral of losses and financial market(s) crumbles. Second, prudential authorities and central banks intervene before it is too late and resolve the crisis. Lastly, the financial markets themselves absorb the crisis; even though this case means that the financial system was resilient in the first place and it would be inappropriate to say that the crisis was systemic. Hence, any study for systemic crises should focus in priority to the first two resolutions. In this article, we believe, and thus assume, that a systemic crisis consists in a specific succession of steps.

I.3.2 Chronology

Having stated the above, let us take a closer look to the anatomy of a systemic crisis. The underlying rationale of the following lies in the assumption that systemic crises consists in identifiable steps that remain, regardless of the precise specifics of each crises. Through academic literature and empirical observations, we have identified the following steps:

1. Displacement, opportunity of profit & latent risk.

As Abreu and Brunnermeier (2003) observed for bubbles, each agent will realize the situation they are in at different times, hence the beginning of a crisis or a major structural change aren't publicly known. Thus, the search of a precise date for a beginning of a crisis is moot. We base the beginning of our analysis on the Minsky anatomy of a financial crisis (Kindleberger, 1978; Minsky, 1991). His original insight was to assume that a financial crises start with a 'displacement'. In his view, the displacement consists of the apparition of a new opportunity of profit in at least one important sector of the economy. The "displacement" could actually be anything but his view focuses on financial innovations. We argue that this 'displacement' is actually a structural change (as defined earlier). Note that our conception gener-

alizes the one of Minsky, and allows for a broader spectrum of possible structural changes. This new opportunity of profit changes the very structure of the financial systems. In other words, it might alter the way financial agents interact or the way the financial system evolves. Aglietta (1996) also agreed that the roots of a crisis were in the financial system's structure. This first step, often overlooked by the existing literature, is essential, as it will determine the form of the following crisis. Hence, each different type of structural change might lead to a correspondingly different type of systemic crisis. Structural events are various and have been documented in the past: Collective change in investor's behavior (Guesnerie & Azariadis, 1982), Financial innovation (Minsky, 1991), New institution/agent, New regulation (Allen & Gale, 2007), etc. Most of such events could appear harmless, but the fact is that they modify the existing structure of the financial system hence, modifying its dynamics. For instance, in Minsky's analysis, if the displacement is large and pervasive enough, there will be an improvement of anticipation of profits in at least one important sector of the economy. This will accentuate potential losses, as we will see in the next section.

The existence of the structural change brings a new type of risk. Here, the rationale is actually taken from the Modern Portfolio Theory (MPT) where, if the anticipation of returns increases, the risk should increase as well (there is no free lunch in finance). Let us consider a financial firm as an example. We already know the various risks it is exposed to: market, liquidity, credit, operational, etc. We will call such risks, usual risks henceforward. For usual risks there is actually a doubt on *whether* the risky event will occur. Such risks are known and there exists a wide documentation on how to manage them. Contrary to the risk born from the displacement, where the uncertainty lies in *when* the risky event will occur. We will call such risk, latent risk from now onward. One might wonder why we are going through such a distinction. In our view, once a displacement takes place, the financial system is doomed to go through a crisis⁵. The structural change creates a new profit opportunity that will lead to the creation of latent risk. We cannot hedge perfectly an unknown risk. Hence, we will try to manage this risk without perfectly knowing how to measure it, given we are aware of it. This leads to the second step

⁵Whether it is a financial shock, financial crisis or a systemic crisis. The distinction will be made later on.

of a systemic event.

2. Rise in financial fragility

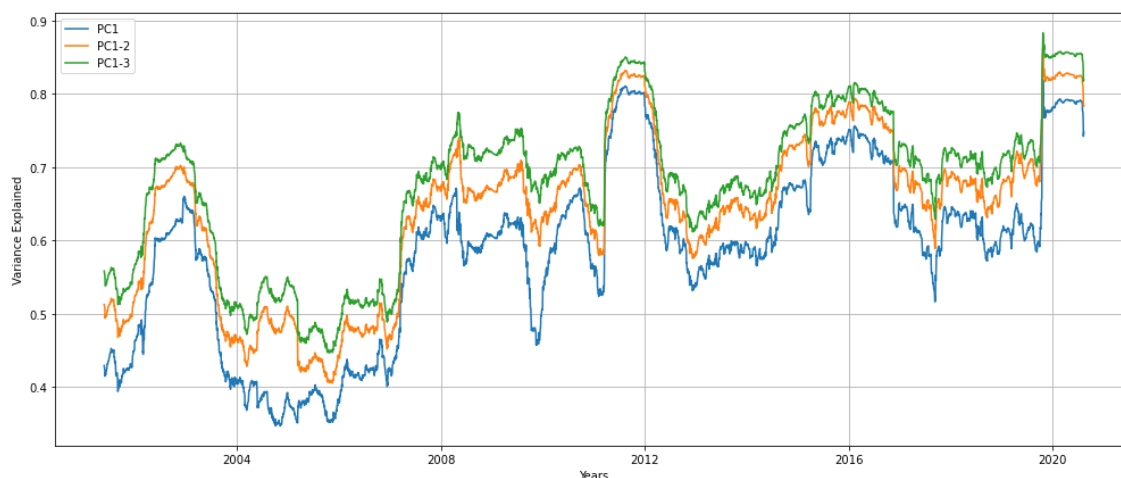
Financial firms do not go bankrupt without a strong event forcing them to do so. As put by Borio, James, and Shin (2014), ‘Financial crises are not like meteorite strikes from outer space. They resemble volcanic eruptions or earthquakes: they reflect the sudden and violent release of pressure that has built up gradually over time. [...] The build-up of such financial imbalances gives rise to endogenous boom-bust processes, or “financial cycles” ’ (Borio, James, and Shin (2016), p.3). Similarly, in our approach the triggering event of a systemic crisis only occurs due to a build-up of financial fragility. Financial fragility is inherently connected to the structure of the financial system (Cont, Moussa, & Santos, 2013; Acemoglu, Ozdaglar, & Tahbaz-Saheli, 2015; Caccioli, Barucca, & Kobayashi, 2018). Hence, when a new profit opportunity appears along with its latent risk, it serves as a foundation for financial fragility’s growth. The inability to assess properly latent risk makes engaging in the profit opportunity actually more risky than it looks. Depending on the nature of the initial displacement, the opportunity of profit can go to multiple markets⁶. This fact is highlighted by the international contagion effects occurring during and after financial crises (Guo, Chen, & Huang, 2011; Aloui, Safouane Ben Aissa, & Nguyen, 2011; Lee, 2012; Cipollini & Muzzioli, 2015). Our approach of financial fragility differs slightly from the one of Allen and Gale (2007), not in the definition but in its origin. Allen and Gale (2007) describe how financial fragility arise from the interactions between banks and financial institutions; as well as the central role of liquidity. In our approach, financial fragility stems from the growing common exposure to a given risk among the financial system. Note that both conceptions fit the definition given earlier (see Def. 4). We root our analysis, of this stage, on what Brunnermeier and Oehmke (2013) view as the run-up phase, and link to the literature on financial bubble’s creation. In our view, the opportunity of profit creates herding behavior on the market (Cai, 2020). Acharya and Yorulmazer (2008) shows that this herding behavior can be a strategy against negative effects of an information contagion. Numerous agents will react in a similar way, and will try to profit from the structural change. This translates operationally to a rise in cross-

⁶There is actually a need for studying pre-crisis building up on common exposure over multiple markets.

correlations of returns of financial firms. The Figure I.1 shows such an increase in the cross-correlation (or commonality) in returns before 2008.

Figure I.1: Commonality in stock returns.

The graph displays the explained variance of the first components for rolling-forward Principal Components Analysis (PCA) on the stock returns of 53 major U.S. financial institutions from 2001 to 2020. In green, the explained variance of Principal Components (PC) 1 to 3. In orange, the explained variance of PC 1 to 2, and in blue the explained variance of the first PC only.



In essence, the rise in financial fragility does not appear in a straight forward manner. That is to say, that, from an exterior point of view, it only seems as financial firms are making profit and the market appears bullish. However, the more financial firms engage in the opportunity of profit, the larger the impact will be when latent losses are realized. Consequently, in our view, the crises where multiple markets were affected, are the ones for which the opportunity of profit was exploited hence creating common exposure over multiple markets (Guo, Chen, & Huang, 2011; Aloui, Safouane Ben Aissa, & Nguyen, 2011; Lee, 2012; Cipollini & Muzzioli, 2015). Additionally, we know that derivatives markets can work as a channel of contagion (Aglietta, 1993, 1996; Weithers, 2007; Schwarcz, 2008). Hence, correlated hedging on the latent risk could as well constitute a build up of financial fragility via the derivative market. In a sense, this stage can be thought of the creation of common exposure to latent risk across the financial system (sometimes across markets) and the increase of individual exposure to macroeconomic event, or macro-risk (Weithers, 2007). The combination of these effects translate into the transition from Hedging to Speculative units; and Speculative to Ponzi units, presented by Minsky

(1991). As he described so accurately, the increase in financial fragility leads to an extreme reaction to a “not-so-unusual” event. Measuring the exposure to macroeconomic shocks and how a specific firm will react to what types of shocks is an arduous task. Most of the existing measures focuses on assessing the economic uncertainty and how it will impact countries/firms (Oxelheim & Wihlborg, 1995; Bali, Brown, & Caglayan, 2014; Briguglio, 2016).

3. Revealing event & realization of latent losses

Any hidden exposure will be uncovered at some point in time. In our framework, we consider that the high financial fragility is related to a common exposure to a particular event. Our insight comes from the work of Hellwig (1995, 1998), which studied how aggregate hidden exposures in the banking system can lead to extreme shocks in conjunction with macroeconomic shocks. The general build up of financial fragility, by definition, in the financial system inevitably leads to an extreme reaction to an otherwise normal event. We call such event, the revealing, triggering, event. The nature of the triggering event might be the most difficult to predict in fact; mainly because it relies on the nature of the structural change. Additionally, the revealing event can be endogenous or exogenous to the financial system. One could argue that financial firms have actually developed a higher sensitivity to macro events generally. Thus, leading to extreme reactions when the revealing event occurs. The primary effect of the macroeconomic event will be to make latent losses occur. It consists in the occurrence of common idiosyncratic shocks for firms, which had engaged in the profit opportunity. The existing literature on how to assess systemic loss exposure is substantially large. The subprime crisis brought a global academic interest in finding a proper **SR** measure. Among the most famous, we find the work of Billio et al. (2012), Adrian and Brunnermeier (2016), Brownlees and Engle (2017), Acharya et al. (2017). We argue that the measures mentioned above only capture a single dimension of **SR**. In addition, because of the difficulty to assess the extent of latent risk, we argue that the measures will also tend to underestimate the actual depth of losses. Danielsson et al. (2016) actually showed that our risk models also contain an inherent error, called model risk. We could, in a similar fashion, argue that the errors of the model observed empirically stem from the lack of knowledge on latent risk. Due to the gap between estimated losses and losses occurred, some financial firms will find themselves in a temporary period of distress. Which can lead

to the occurrence of other usual risk (as defined earlier). The combination of losses put the firm in an even more precarious state; and, if enough firms experience the same, pushes the financial system into a financial crisis. We have defined earlier the concept of financial crisis. However, it seems to be the time to present a precision. A financial crisis pushes the financial system from the stable state into the unstable; more accurately, it represents the transition. Given our definition, we cannot call this stage a financial crisis yet. We argue that the financial system only steps in the unstable state when there is a global disturbance on financial activity. Consequently, the occurrence of some idiosyncratic shocks does not disrupt global financial activity. We will define such events as financial shocks.

Definition 6. Financial shock: *Event causing one, or more, idiosyncratic losses for one, or more, financial firms. In the case where the losses are experienced by firms of a given sector/type, we will refer to the shock as systematic. The event may develop into a financial crisis, given the idiosyncratic shocks lead to a global occurrence of contagion and/or amplification of the losses.*

Such definition put forward the temporal aspect present in a systemic event. We observe first the triggering event (macroeconomic shock for instance), which turns into a financial shock, given that multiple financial firms suffer losses. Finally, the financial shock may turn into a financial crisis, when observing a contagion and/or amplification of losses.

4. Contagion and amplification

The financial world is one of (positive) feedback relationships. Any given system can be constituted of simple rules, and, yet, could display complex behavior (Walleriser, 1977). The existence of feedback effects create such complexity. There are the main reason why studying SR as a dynamic phenomenon is so difficult. The stage of contagion and amplification in a systemic event is one of feedback effects as well. For every loss incurred, the situation on financial market worsen, making the failure of some financial institutions more likely. For every marginal failure, the losses incurred increase, making the financial system's situation worse and worse. We often take the example of the banking system in order to illustrate the power

of feedback effect in a crisis (Freixas, Parigi, & Rochet, 2000; Degryse & Nguyen, 2007; Azizpour, Giesecke, & Schwenkler, 2018). As every bank is linked with the others via the interbanking market, every failure in the banking system translate to the occurrence of default risk. The more defaults occur, the more banks will be in distress, and/or will fail. Which will translates in additional default risk realization, etc. The propensity with which the banking market is exposed to feedback effects (contagion) explained the amount of empirical work on the matter (Allen & Gale, 2000; Acharya, 2009; Huang, Zhou, & Zhou, 2009; Giesecke & Kim, 2011a; Billio et al., 2012; Hautsch, Schaumburg, & Schienle, 2014).

In our chronology, the contagion/amplification stage marks the transition from a financial shock to a financial crisis. Due to the extent of the previous idiosyncratic financial shock(s), financial firms will try to recapitalize by selling liquid assets, and by trying to offload their positions related to the initial opportunity of profit. As we know, correlated selling behavior that is not accompanied by a corresponding rise in demand, will translate into a crash in the asset value. Hence, by trying to recapitalize and sell away their risky exposure, financial firms will actually worsen their situation, and market liquidity along with it. In some cases, a large common offloading of positions will although propagate the shock to other markets (Rajan, 2005; Roy & Roy, 2017). Moreover, positive feedback effects existing between contagion and illiquidity can easily speed up a financial system's crash. Boyson, Stahel, and Stulz (2010) show that the probability of contagion of Hedge Funds is linked to liquidity shocks. Numerous studies put forward the importance of liquidity in a systemic crisis (Aglietta, 1993; De Bandt & Hartmann, 2000; Amihud, 2002; Allen & Gale, 2007; Brunnermeier & Pedersen, 2009; Adrian & Boyarchenko, 2018). Shleifer and Vishny (1992), Stein (2012) and Greenwood, Landier, and Thesmar (2015) also describe the mechanisms of a fire sales event. It seems important to point out that other amplification mechanisms (besides liquidity events) exist; such as market freezes, payment system breakdown or coordination failures. More generally, one can find a comprehensive review of all documented contagion and amplification mechanisms in Benoit, Hurlin, and Perignon (2019).

At a given point, the amount of losses incurred previously by financial institutions summed up enough for a few to fail. The first failures are determinant in whether

other institutions will be ‘contaminated’⁷ or not. Cont, Moussa, and Santos (2013) show that the most systemic nodes are not necessarily the most interconnected, but the ones for which their creditors are (eigencentality). The general disruption in financial market already starts causing negative externalities on the real economy at this point. We can quote the crisis of Cyprus in 2013, where the banking system situation forced the freezing of deposit withdrawals for instance. The more financial institutions fail, the more the payment system is disrupted, which obviously causes problems for day-to-day operations of commercial firms. The failure of financial institutions also disrupts the financing mechanisms, which interrupts firms’ development and cancels investments’ opportunities. Furthermore, it impairs the functioning of financial markets, which poses essential issues on the price discovery process and immediate liquidity.

5. Consequences on the real economy

Inevitably, the succession of events described above lead to a severe disruption of financial markets. Based on the insights of Aglietta (1993), we denote three major types of disruptions: **1. Payments System.** Numerous counterparty default transfer risk onto central counterparties. Thanks to Acemoglu, Ozdaglar, and Tahbaz-Saheli (2015), we know that star networks⁸ are prone to failure if the central node fails. Hence, the transfer of counterparty risk from financial institutions to central counterparties does not reduce SR. It merely changes its nature. **2. Credit system.** Correlated failures in the banking system, possibly combined with freezing of the interbanking market, leads to credit providing disruption. Banks are more focused on trying to recapitalize and prove the reliability of their collateral, hence tend less to provide credit efficiently. Such episode of decrease in aggregated credit and increase in borrowing costs are denominated as *Credit Crunch*. **3. Stock Markets.** Chaos in the financial system also lead to higher informational asymmetry. Such fact stems from a higher market illiquidity, as developed above, which leads ‘true’ or fundamental values of stock to be mistaken with noise (Mishkin, 1992), with irrational expectations (Kindleberger, 1978; Minsky, 1991) or even under rational expectations (Blanchard & Watson, 1982). Irregularities on financial markets are

⁷Here, contaminated means, whether the firm i will fail due to the losses incurred by the failure of firm j .

⁸Networks where all connections goes towards a single node. Central counterparties naturally create such network (Jorion & Zhang, 2019).

the logical outcomes of previous stages of the systemic event. Hoggarth, Reis, and Saporta (2002) compute the cost of a banking crisis on the loss of GDP experienced by countries. Reinhart and Rogoff (2009) develop on the nature of a crisis' aftermath. Their research shows that, after severe financial crises, that can arguably be compared to systemic crises, housing and equity prices stumble down. Economic output and employment drop severely. Moreover, public debt tend to increase drastically. Importantly, they argue that the increase in government debt is more due to the decrease in tax revenue and general consumption more than the costs bailing out financial institutions. Atkinson, Luttrell, and Rosenblum (2013) reach the same conclusion as Reinhart and Rogoff (2009), and add the additional fiscal costs of saving banks from bankruptcy, as well as the indirect costs of 'national trauma'. Indeed, crises leads to waves of job loss in an economy, as well to tend to increase the duration of unemployment. Goodhart (2010) identifies five costs of a failure of a Systemically Important Financial Institution (SIFI). The direct (accounting and juridical) costs of bankruptcies; the potential breakdown of financial markets and the costs associated in the loss of resource allocation; loss of information leading to temporary (frictional) unemployment; losses incurred by all creditors of firms which crumbled down; loss of funding for commercial firms. All of these categories of negative externalities can translate in a straightforward manner into an actual shock for the real economy, ending in a shock on national outputs, international trade and countries' development.

I.3.3 A definition for systemic risk

We have now defined precisely all the underlying concepts of SR. Furthermore, we have proposed a detailed chronology of systemic events based on the extant literature. Knowing all of the above, we propose the following definition for SR.

Definition 7. Systemic Risk: *Risk associated with the occurrence of a systemic event.*

The definition links itself quite closely with the one given by Zigrand (2014)⁹,

⁹For the definition, see in Appendix I.A.1.

and, yet, strongly differs. The actual contribution of this chapter does not lie in the definition, but in its implications. We have defined the concept of systemic events, and all subsequent notions. Hence, the risk of occurrence of a systemic event roots in the possible consecutive occurrence of all stages mentioned above.

The resulting challenge is to determine the stage we are in, at any specific time, and to obtain the transitions' probabilities. It seems important to point out that, given our definition of risk and the complexity of systemic events, it is, by no means, obvious that **SR** can be properly measured. As most of the concepts involving human behavior, there is always a chance that, when understood by most of the system's participants, the dynamics of the system itself would change. This relates directly to the Lucas' critique (Lucas, 1976) onto the implications of changes in human's behavior on econometric models. **SR** also links directly to the risk inherent of a given system. By looking at the extent of the financial system's evolution, and the speed with which it occurred, giving a unique definition of **SR**¹⁰ seems foolish. The definition should be related to system's structure, which make the definition generic, allowing it to remain relevant as the system changes over time.

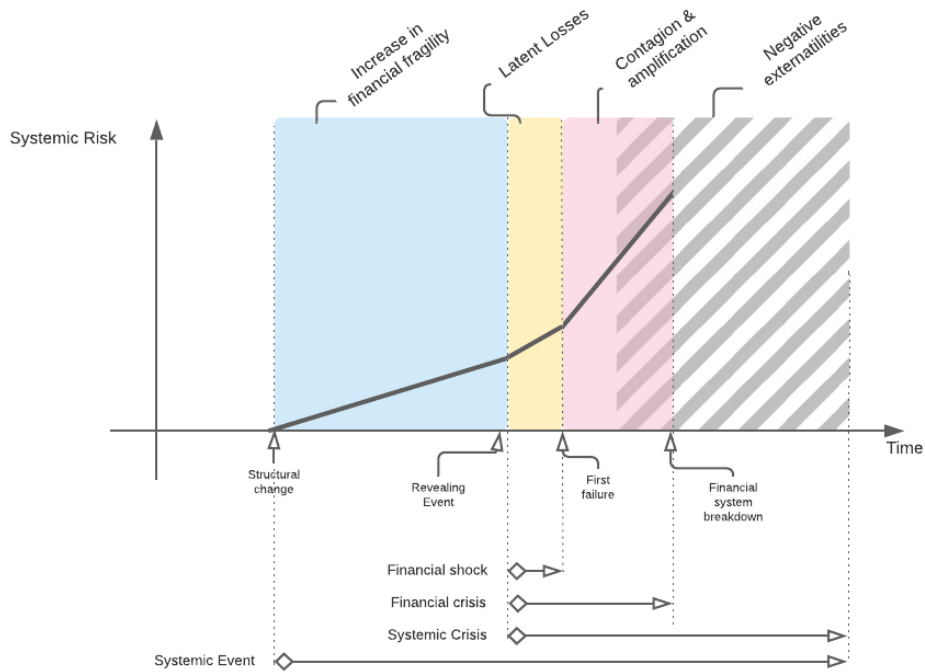
Figure I.2 summarizes all concepts previously mentioned and clarify our view on what a systemic event should look like. Even though, **SR** is naively represented by straight lines, it does not imply that the increase in **SR** must be linear.

¹⁰Here, unique definition means a definition that is not generalized. That is to say a definition based on specific values and/or events.

I.3. ANATOMY OF A SYSTEMIC EVENT

Figure I.2: **Process of a systemic event.**

Schematic view of the process of a systemic event. The process is composed of 4 events and 4 periods. In chronological order: Structural change (event), Increase in financial fragility (period), Revealing event (event), Latent losses occurrence (period), First major failure (event), Contagion and amplification (period), Negative externalities (period), Financial system breakdown (event).



I.3.4 Regulatory opportunities

In this section, we explore the opportunities that oversight authorities can exploit from our framework. In our view, the opportunities lie in the timing of a systemic event, hence the importance of knowing in which stage are we at each point in time. We classify prudential authorities under three groups: Structural, Monetary and Market regulators. We summarize their role and prudential-related instruments, and discuss their place in the chronology of a systemic event.

Structural Regulation

The structural regulators are the institutions that will impose restraints on financial institutions in order to limit their systemic potential. From which, we find in Europe the [European Systemic Risk Board \(ESRB\)](#), the [Basel Committee on Banking Supervision \(BCBS\)](#), the [Financial Stability Board \(FSB\)](#), the [European Banking Authority \(EBA\)](#), and many other abroad. The adjective structural comes from the fact that the directives created by such institutions will change the ways financial institutions can interact and/or function. It changes the ‘rules’ of the system, thus its structure. In the European Monetary Union, the set of macroprudential instruments is already quite restrictive and covers most of the risks considered above. It prevents the excessive fragility of the financial system using counter-cyclical buffers, requirements on Loan-to-Value and Loan-to-Income as well as a leverage ratio. Additionally, the [Liquidity Coverage Ratio \(LCR\)](#), the [Net Stable Funding Ratio \(NSFR\)](#) along with the Loan-to-Deposit ratio prevent financial institutions from suffering a liquidity crisis. It includes as well restrictions on the build-up of large common exposure and additional capital requirements for [SIFIs](#). The extent of the existing regulation is the result of decades of improvement of the prudential oversight framework. Banks have been regulated the earliest with Basel I (1988), followed by Basel II (2004) and Basel III (2010) agreements which came to complete the previous agreements. Insurers have also been identified for being systemic, and have been accordingly regulated (Solvency II in 2009). Up to now, the structural regulation has had no choice but to fill the gaps, which were exposed during financial crises, left by earliest reforms. It is inevitable for the system to go through structural changes, however regulators should expect the risks that will be created due to the change and

react accordingly. For instance, the regulatory arbitrage shown by Adrian (2014) consists in a structural failure that creates a possibility for a common reactions of large credit institutions to turn to shadow banking. This constitutes a significant rise in financial instability due to the opacity of this practice¹¹.

Given the above, we identify two important times for the structural regulators to be involved. The first is well-known. Structural oversight has the role to implement regulatory tools in order to increase the resilience of individual firms. In other words, it focuses on how to prevent the triggering event to have a significantly large impact on the financial system, hence limiting the chances of the shock to turn into a financial crisis. This particular aspect is well accounted for. Numerous ratio and buffers are engineered to make the financial system more resilient. The second aspect however is currently overlooked. Structural regulators have the responsibility to forecast what particular risk might be created from the initial structural displacement. The forecasting of potential impacts from a structural change is an arduous task. However, there exists methodologies to assess risks that happen in the past, or that may occur given a particular scenario (e.g. stress testing). This phase would imply two steps. First, one must identify what is the structural displacement and what might be the risk associated. And, in a second time, one would construct relevant scenario to test financial institutions' sensitivity to that particular risk. The use and construction of such tests is already recommended by the Dodd-Frank Act (2010), and the EBA. The use of stress tests for regulatory purposes is described in the work of Weber (2014)¹².

Monetary intervention

Monetary policy is also a central regulatory tool during a systemic crisis. Numerous studies shows the link between monetary policy and SR. Laséen, Pescatori, and Turunen (2017) shows that a surprise tightening of monetary policy does not necessarily reduce SR. Furthermore, an excessive attempt to stabilize output through monetary

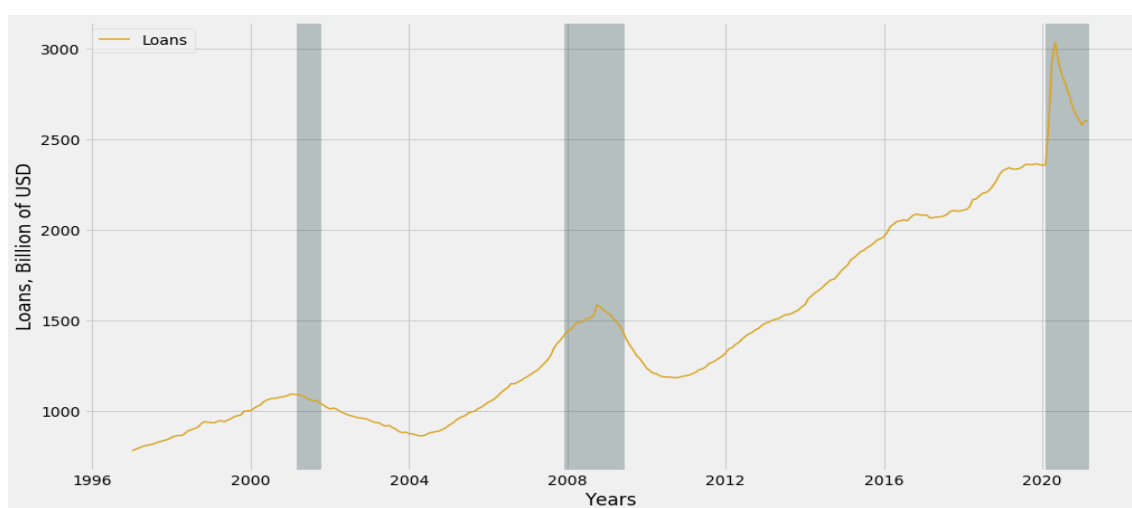
¹¹Lysandrou and Nesvetailova (2015) and Prates and Farhi (2015) provide elements of understanding for the impact of the shadow banking system on the financial system (in)stability in 2007-09.

¹²The use of stress tests is also a recommendation of Aglietta (2011) regarding the role of central banks in prudential regulation.

policy will tend to decrease risk premium while increasing leverage, hence increasing the vulnerability of the financial system¹³. Colletaz, Levieuge, and Popescu (2018) explains that the impact of monetary policy on SR is essentially appearing in the long run. Additionally, their work show that excessively loose monetary policy can lead to a build up of SR. The fact that loose monetary policy may lead to ‘SR taking’ is also highlighted by Kabundi and De Simone (2020).

In our framework, monetary policy has two major tasks. The first comes in during the building up of financial fragility. As Borio and Lowe (2002), and other, suggest, excessive leverage tend to precede periods of financial stress and/or financial crises (See Figure I.3). As the primary goal of Central Banks is to insure the stability of prices as well to control the inflation (as it is the case for the ECB), preventing excessive increase in leverage falls under their responsibilities. The literature on how monetary policy can control credit granting in the economy is substantial and the methods are now well-known. Central banks may increase the main refinancing operations rate in order to increase credit’s funding cost, hence indirectly limiting credit supply. Alternative solutions also exists, as varying the mandatory reserve ratio, or performing open market operations.

Figure I.3: **Loans issued by commercial banks in the U.S.** *Commercial and industrial loans of U.S. Commercial banks from 1996 to 2020. The loans are in billions of USD. Shaded areas are, respectively, the dotcom crisis, subprime crisis and covid crisis (ongoing). The dates of the crises are the one provided by the FRED. Source: Federal Reserve Bank of St Louis.*



¹³This part relates of the volatility paradox exposed in Brunnermeier and Sannikov (2014).

The second task is to deal with short-term liquidity issues (Rochet & Tirole, 1996). Central banks are known to have the capacity/role to act as a Lender of Last Resort (LOLR) given an essential¹⁴ institution might fail. The function of LOLR, especially during the subprime crisis, already reached a significant place in the existing literature (Bordo, 1990; Zaleski, 2011; Herr, Rudiger, & Wu, 2016). The role of LOLR is of major importance. Indeed, there might be times where the measures taken by structural regulators will fall short to the extent of losses suffered by financial institutions. In such case, it is vital, for the survival of the financial system, to save **TBTF** institutions in order to prevent a potential cascade of failure.

Market authorities

Market authorities as the **Securities and Exchange Commission (SEC)**, in the U.S., or the **European Securities and Market Authority (ESMA)** also have a role to play in a systemic event. As we have presented above (see Figure I.2), a systemic event will have to through a financial shock. Such shock will be observable in financial markets, and we know that disruptions on financial markets have a direct impact on financial firms. Thus, the first task of market authorities is to mitigate excessive volatility, sharp decrease in liquidity, which, in essence, consists in ensuring market stability. We already discussed above that a financial crash might affect significantly the values of collateral, as well as erasing market liquidity in case of fire sales. Moreover, there exists evidences of volatility contagion through markets (Hamao, Masulis, & Ng, 1990; Xiong & Han, 2015), and that such volatility spillovers have systemic implications (Yang, Zhou, & Cheng, 2020). Market authorities have various tools in order to enforce market stability, and research have shown their effectiveness. Subrahmanyam (1994) show that circuit breakers allows to reduce volatility in the particular asset price, but will however tend to reduce its liquidity along and to move volatility to a ‘satellite’¹⁵ market. Buss et al. (2014) compare other regulatory tools used to reduce/mitigate market volatility. Moreover, the Dodd-Frank Act (2010), also put in charge the SEC to monitor ratings agencies. Since the European

¹⁴Essential here means essential to the survival of the financial system. Such institutions are known to be **TBTF**.

¹⁵Satellite is used here as a meaning that a very similar asset is traded in this market. Hence, while investors will stop trading the asset on the first market due to the trading halt, they will switch to the ‘satellite’ market to continue trading.

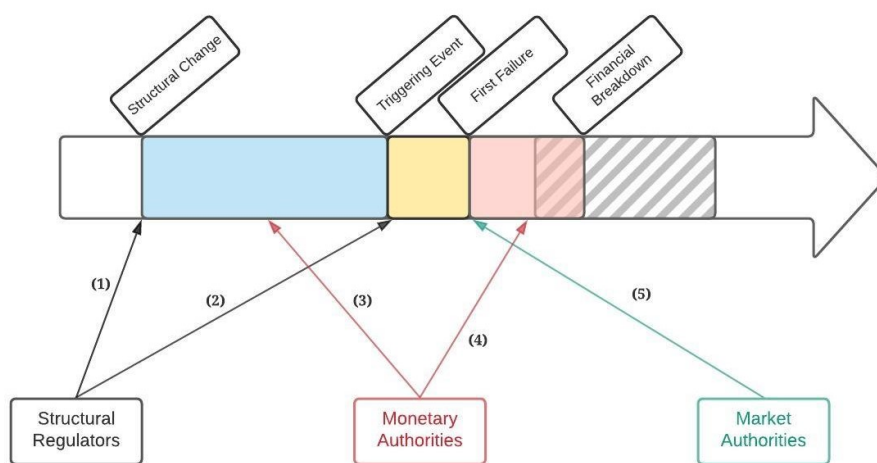
sovereign debt crisis, regulators noticed the systemic importance of rating agencies and assigned them regulatory oversight. In the European Union, the directive No 462/2013 of the European Parliament forbids financial institutions to mechanically rely on credit ratings.

Regulatory actions

In order to summarize, we provide below (see Figure I.4) a schematic representation of points of action for regulatory institutions in a systemic event. Chronologically, structural regulators' task is to first analyze any potential structural change and assess its systemic importance, while assuring the resilience of the financial system through prudential measures on financial institutions. Monetary authorities should then try to limit the build of large imbalances and the creation of excessive leverage. In case of the occurrence of the triggering event, market authorities should enforce market stability and prevent volatility spillovers across markets. Eventually, should TBTF institutions might find themselves in harm's way, monetary authorities will act as a safety net for the financial system's survival, assuming their role of LOLR.

Figure I.4: **Points of action for regulatory oversight**

Schematic view of where each regulatory institutions should intervene in a systemic event. (1): Risk assessment of the structural change and scenario analysis of the impact of the structural change. (2) Requirements and ratios on financial institutions (Basel I to III, Solvency). (3) Limitation of the excessive build up of leverage via monetary policy. (4) Lender of Last Resort for financial institutions in distress. (5) Prevention of market crash (circuit breakers, liquidity monitoring/provision, etc.)



It seems clear that only a coordination of all regulatory institutions will be able to cover the entire systemic event process. Kabundi and De Simone (2020) advocate for an improvement in the coordination of monetary and macroprudential policies. In the same vein, Schwarcz (2019) campaigns for the need for a global coordination of regulators. The major gap in current systemic oversight is the lack of coordination existing between these institutions. However, communicating insights and coordinating policies may just be the way to tame systemic events.

I.4 Systemic Risk measurement

This section will be twofold. We will first present the coherence propositions, based on the description of a systemic event above, for proper SR measurement. In a second time, we propose an empirical demonstration of the SEH. We apply various SR measures on two samples, European and American, in order to demonstrate the SEH empirically. Furthermore, the empirical study shows the importance of the coherence propositions, detailed below, for measuring consistently SR.

I.4.1 Coherence of Systemic Risk measures

Similarly to Artzner et al. (1999) and Chen, Iyengar, and Moallemi (2013), we propose conditions of coherence for measuring SR. Based on the empirical evidences on systemic crises, we believe that the following characteristics are intrinsic to SR, hence should be included somehow in its measures.

1. Temporality

This first aspect is a key feature of SR. Any measure of SR must be dynamic because the concept itself is. The main complexity in measuring SR lies in this fact. It changes with time. More importantly, the absolute value of the measure is generally not that important, the variations of the measure matters. Measures taking into account accounting data, for instance, will have a tendency to be late in describing SR. Any useful measure should be able to detect changes in SR levels at a reasonable frequency.

2. Multi-dimensionality

A systemic event is composed of different risks. Often, existing literature has proposed a measure, which was actually based on the risk of a single step in our framework. We argue that all these studies were partially right. We refer to these step-specific risks as *systemic dimensions*. Each stage presented above can be linked to a specific systemic dimensions. Each dimensions are, in stable times, uncorrelated (Chapter II). An additional complexity come from this characteristic, which is that each dimensions can have a different unit. Constructing a measurement becomes then a matter of associating measures having different units.

3. Chronological order

We know, that a systemic event is composed of successive stages. The order of the stages is naturally important. It implies two main facts for measurements.

(a) Nullity of systemic dimensions

As in Artzner et al. (1999), if the loading of a given risk measure is zero, then the risk is null accordingly. In our case, the logic is rather similar. Since all stages happen in a given order, if any stage does not occur, a systemic crisis will not appear either. The direct implication is that, if the probability associated with the occurrence of a systemic dimension is null, then **SR** is null as well.

(b) Convexity

The fact that an order exists in the process of a systemic event implies that **SR** must increase with each realized steps. Logically, there is a higher chance of being in a systemic crisis if there is contagion in financial markets than if we are just in the build up of financial fragility. Hence, **SR** increase both the probability of each steps; and with the occurrence of each additional step. We can then say that **SR** is a convex function of its systemic dimensions.

4. Feedback effects

One of the complexity involved with **SR** measurement lies in the existing feedback effects. The correlation between systemic dimensions in crisis times are

not actually linear. Some types of risk will feed other other to grow higher. For instance, there is known feedback effects between illiquidity and contagion. A firm that is already highly illiquid is prone to fail, furthermore, its bankruptcy will increase the illiquidity of firms owning its debts, hence increasing the probability of bankruptcy of these firms. It seems essential that a measure of *SR* must include the dynamics stemming from feedback effects.

I.4.2 Data & Methods

In this section, we propose to empirically validate the chronology presented above using well-known *SR* measures. We propose to perform the analysis on the Subprime crisis as it is a well-known systemic crisis, with widely accessible data. Our first sample consists in the daily returns of 53 of the largest financial firms¹⁶ in the U.S. from 01-01-2006 to 01-01-2011, over which, we compute measures designed to capture the effect of each stage of a systemic event. In order to show the robustness of the *SEH*, we apply the same methodology on a second sample. The latter consists in the daily returns of 50 of the largest financial firms in Europe. Our data starts the 01-01-2005 and ends the 30-12-2011. The summary statistics of both samples are presented in the Appendix I.A.2 (see Table I.1 and Table I.2).

Similarly to Kritzman et al. (2011) and Billio et al. (2012), we use a rolling-forward *PCA*, and compute the explained variance of the first principal component in order to proxy the level of commonality in stock returns. This indicator focuses on the rise in financial fragility. For the second stage of a systemic event, we use two widely accepted measures of systemic losses, the $\Delta CoVaR$ (Adrian & Brunnermeier, 2016) and the *CAViaR* (Engle & Manganelli, 2004; White, Kim, & Manganelli, 2015). For the contagion and amplification of losses, we use, respectively, the Average Chi of Balla, Ergen, and Migueis (2014) and illiquidity measures, *ILLIQ* (Amihud, 2002) and the Roll Implicit Spread, or *RIS*, of Roll (1984) and Hasbrouck (2009). Finally, we show the negative externalities of the crisis on the real economy, with the U.S. unemployment rate and U.S. Gross Domestic Product. We detail the computation of the measures below.

¹⁶Including banks, insurance companies and investment firms.

Commonality in Asset Returns

The proxy for the commonality in stock returns is straightforward. Billio et al. (2012) uses a rolling PCA on weekly returns to show an increase in the explained variance of the first component before the subprime crisis and Kritzman et al. (2011) use PCA to derive a turbulence index based on the Mahanobolis distance. In this chapter, we perform PCA on daily returns of the U.S. financial firms. Initially, we start by decomposing the covariance matrix of our stock returns.

$$H^T \Sigma H = \Lambda \quad (\text{I.1})$$

Where, Σ is the variance-covariance matrix, H are orthogonal matrices or size $m \times m$ of eigenvector, such that $H = (h_1, h_2, \dots, h_m)$, with h_1 being the first eigenvector. Λ is the diagonal matrix of eigenvalues, such that, $\text{diag}(\Lambda) = (\lambda_1, \lambda_2, \dots, \lambda_m)$. We extract principal components (U) by multiplying H to our initial matrix of returns (R),

$$U = H^T R \quad (\text{I.2})$$

From this, we compute the explained variance of the principal component as:

$$\pi_i = \frac{\lambda_i}{\sum_{j=1}^m \lambda_j} \quad (\text{I.3})$$

Where π_i is the explained variance of the i^{th} principal component.

Delta-Conditional Value-at-Risk

The work of Adrian and Brunnermeier (2016) is now famous in the literature on SR measurement. We compute the $\Delta CoVaR$ using quantile regressions¹⁷. The quantile

¹⁷There exists other ways to compute it. For instance, one could consider that returns are conditionally normally distributed. By assuming a bivariate normal distribution, one can construct a conditional value-at-risk that is based on the volatility of firms' returns and their correlation. Such model allows a simpler estimation procedure, but adds the difficulty of computing a coherent dynamic correlation. This method is used in the Chapter II.

regression allows the use of state variables, which lead the $CoVaR$ to be more linked to macroeconomic variables. Initially, we define the $CoVaR$ as,

$$Pr(R_i \leq CoVaR^{i|m}(q, p) | R_m = VaR_m(p)) = q \quad (I.4)$$

Where R_i, R_m are the vector of returns of firm j , and the market. $VaR_m(p)$ is the **Value-at-Risk (VaR)** of the market index at the p level of confidence. And $CoVaR^{i|m}(q, p)$ is the **VaR** of firm j at the q level of confidence, conditional to the market being at its **VaR** at the p level of confidence. $\Delta CoVaR$ is then defined as,

$$\Delta CoVaR^{i|m}(q, p) = CoVaR^{i|m}(q, p) - CoVaR^{i|m}(q, 50\%) \quad (I.5)$$

CAViaR

Based on the work of Engle and Manganelli (2004), the **Conditional AutoRegressive Value-at-Risk (CAViAR)** is an alternative to the $\Delta CoVaR$, for measuring the exposure to systemic losses. A multivariate application of the initial **CAViAR** was proposed by White, Kim, and Manganelli (2015), using a bivariate Vector AutoRegressive (VAR) model. Formally,

$$\begin{aligned} Q_1(q, t) &= R(t-1)\beta_1 + b_{11}Q_1(q, t-1) + b_{12}Q_2(q, t-1) \\ Q_2(q, t) &= R(t-1)\beta_2 + b_{22}Q_2(q, t-1) + b_{21}Q_1(q, t-1) \end{aligned} \quad (I.6)$$

$Q_i(q)$ is the quantile function for the returns of firm i , such that,

$$Q_i(q, t) = inf\{ R_i(t) \in \mathbb{R} : q \leq F(R_i(t)) \} \quad (I.7)$$

With, $F(R_i(t))$ being the distribution function of the returns of firm i , and q the probability level desired. $R(t-1)$ is a two columns-matrix of lagged returns for firms i and j . Correspondingly, β_1, β_2 are the vectors of parameters associated with the lagged returns. In the paper of White, Kim, and Manganelli (2015), the $CAViaR$ is directly derived from the Equation I.6. Contrary to other **SR** measures, the loss is considered as the quantile of the stock returns (which is the definition of **VaR**) and then, is estimated in a bivariate framework, in order to incorporate bilateral dependencies in the quantiles in firm's returns.

Asymptotic Tail Dependence

Balla, Ergen, and Migueis (2014) develop a measure based on the asymptotic tail dependence in the stock returns of large U.S. depositories. The article proposes two closely-related measures, founded on the Multivariate Extreme Value Theory, the Asymptotic Dependence Rate and the Average Chi. Our study uses the Average Chi on the lower tail of stock returns in order to assess system-wide common losses, thus providing a proxy for contagion effects in our sample. Initially, the χ_{ij} corresponds to the probability of the returns of firm i to fall below a given quantile, conditionally to the firm j experiencing itself such low returns. Mathematically,

$$\chi_{ij}(q) = Pr(R_i < Q_i(q) | R_j < Q_j(q)) \quad (\text{I.8})$$

$$\chi_{ij} = \lim_{q \rightarrow 0} \chi_{ij}(q) \quad (\text{I.9})$$

Where R_i, R_j are vector of returns for firm i and j . q is the target probability level. Finally, we define the Average Chi as,

$$Avg\chi = \frac{\sum_{i=1}^N \sum_{j=1}^N \chi_{ij}}{N(N-1)} \quad (\text{I.10})$$

With N being the number of firms in our sample. In essence, if $\chi = 0$, then the returns of firm i and j are said to be asymptotically independent. The larger χ_{ij} gets, the more probable it will be for firm i to experiencing extreme returns, given that firm j is already experiencing extreme returns.

ILLIQ

The measure of Amihud (2002) (ILLIQ) is one of the most widely used proxy for illiquidity. The reason for that lies in the simplicity of the measure and the fact that it relies on market-based data. ILLIQ essentially is a ratio between the absolute asset returns (R_i) at time t and the volume in dollar ($V\$$) at time t , such that,

$$ILLIQ(t) = \frac{|R_i(t)|}{V\$(t)} \quad (\text{I.11})$$

Following the recommendation from the Volatility-Lab of New York University (NYU), we apply a Multiplicative Error Model (MEM) on ILLIQ in order to extract its conditional mean (μ). The ILLIQ presented in Figure I.5 is actually its conditional mean. We apply an Asymmetric MEM that give higher importance of illiquidity when returns are negative. Formally,

$$ILLIQ(t) = \mu(t)\varepsilon(t) \tag{I.12}$$

$$\mu(t) = \omega + (\alpha + \mathbb{I}(t-1)\gamma)ILLIQ(t-1) + \beta\mu(t-1) \tag{I.13}$$

Where ε is Gaussian white noise, μ the conditional mean of ILLIQ, and \mathbb{I} is the indicator function, such that,

$$\mathbb{I}(t-1) = \begin{cases} 0, & \text{if } R_i(t-1) \geq 0 \\ 1, & \text{if } R_i(t-1) < 0 \end{cases} \tag{I.14}$$

Roll Implicit Spread

The RIS is a measure founded by Roll (1984). Roll (1984) propose a model that relies on two major assumptions. First, the asset considered is traded in an informationally efficient market. Second, the returns's probability distribution must be stationary. The second assumptions may be nuanced for long time horizons, but is however strict for short time intervals. The measure is then straightforward,

$$RIS = 2 * \sqrt{-cov} \tag{I.15}$$

Where cov is the first-order serial covariance of the changes of price of the firm. In other words,

$$cov = Cov(\Delta P(t), \Delta P(t-1)) \tag{I.16}$$

Where $P(t)$ is the stock price at time t , and

$$\Delta P(t) = P(t) - P(t-1) \tag{I.17}$$

In our case, the higher value of RIS will imply a higher illiquidity. This interpretation comes from the fact that the cov is inversely related to the effective bid-ask

spread (Roll, 1984).

I.4.3 Empirical Results

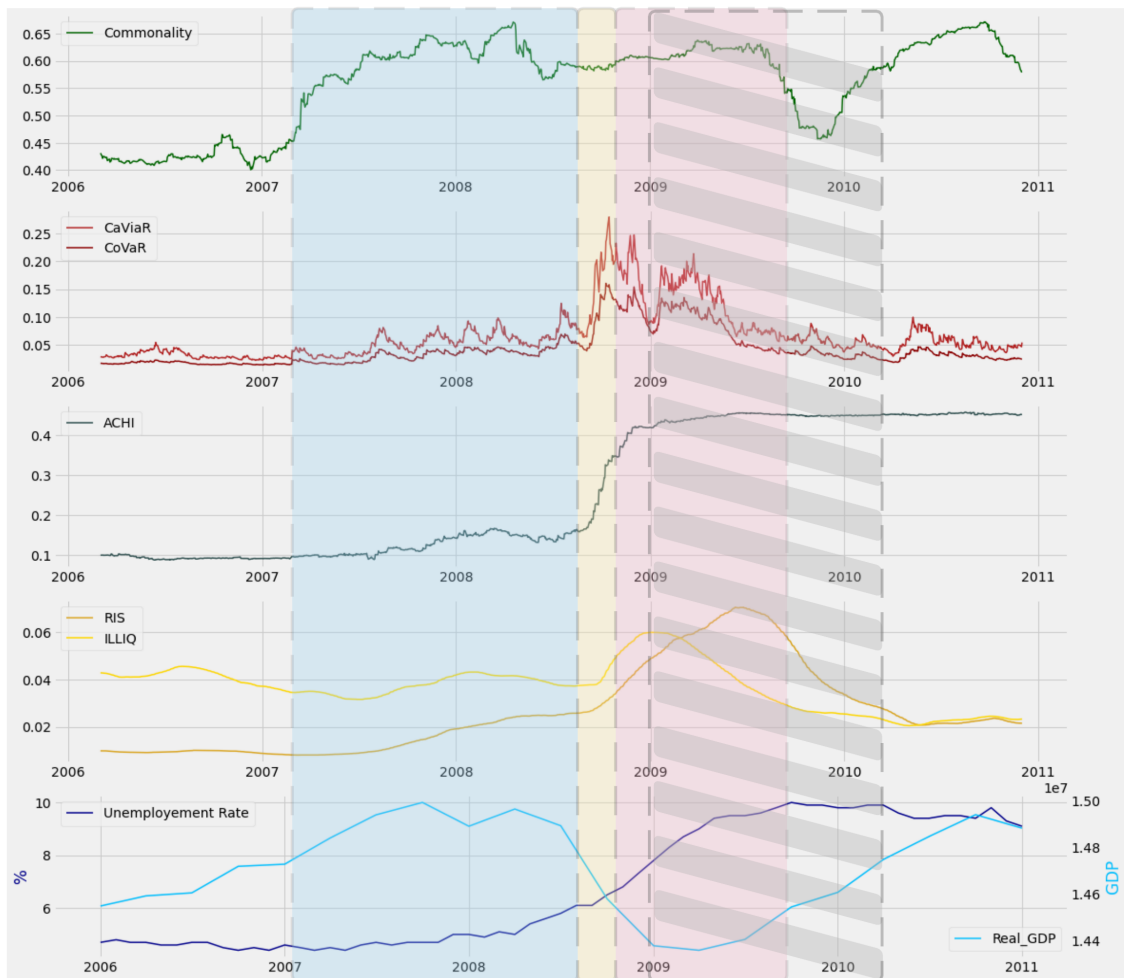
We compute the measures presented above on our sample of 53 of the largest U.S. financial firms, over the 2006-2011 period. Our results are summarized in Figure I.5. Our framework postulates the existence of four main periods in a systemic event: Financial Fragility increase, realization of Latent Losses, Contagion & Amplification of losses and the occurrence of negative externalities on the real economy. The choice of the measures was driven by the type of risk they assess. The commonality of asset returns is approximated by the explained variance of Kritzman et al. (2011); $\Delta CoVaR$ (Adrian & Brunnermeier, 2016) and $CAViaR$ (Engle & Manganelli, 2004) measure the extent of systemic losses; the average χ (Balla, Ergen, & Migueis, 2014) assess the contagion potential; ILLIQ (Amihud, 2002) and RIS (Roll, 1984) proxy the average illiquidity of financial firms; and the negative externalities are expressed in terms of unemployment rate and loss in real GDP.

The commonality in asset returns increases significantly (from 40% to 60%) in the beginning of 2007, while the other measures stay stable. From a logical point of view, the increase in financial fragility has to occur in advance. It comes from the fact that the exposure to the latent risk must grow enough to have a significant impact. The growth actually correspond to the growth in real GDP and house prices in the U.S.. The exponentially growing development of the U.S. housing market, fueled by the apparition of new financial instruments (e.g. CDOs) has led most of major banks, and insurance companies, to create a major common exposure to a potential housing market decline/crash.

When the housing market started to decline in 2007, and banks started to realize the extent of their current exposure, some got exposed to an unexpectedly high insolvency and bankrupted. The failure of Lehman Brothers gave was the gentle push that threw financial system into a state of instability. The financial shock¹⁸ starts at the end of 2008, right after the Bear Stearns avoided bankruptcy and got acquired by JP Morgan Chase, and shortly after the fall of Lehman Brothers.

¹⁸From the Definition 5, a financial shock marks the transition from the stable to unstable state.

Figure I.5: Chronology of Systemic Dimensions during the subprime crisis
 The chart displays *SR* measures (dimensions) from 2006 to 2011. We proposed to divide the graph according to the periods given above (see Figure I.2). Blue corresponds to the rise in financial fragility, yellow relates to the financial shock and realization of latent losses, red corresponds to the rise of contagion and amplification effects. Finally, the hatched area corresponds to the period of negative externalities. Commonality corresponds to the variance explained by the first factor of a *PCA* on asset' returns (Kritzman et al., 2011; Billio et al., 2012), *CAViaR* to the measure of White, Kim, and Manganelli (2015), *CoVaR* is the ΔCoVaR of Adrian and Brunnermeier (2016), *ACHI* is the Average Chi coefficient (lower tail) of Balla, Ergen, and Migueis (2014), *RIS* is the liquidity measures from Roll (1984), *ILLIQ* is the illiquidity measure from Amihud (2002). Finally, the last graphs displays the unemployment rate and the real GDP of the U.S. (Source: Federal Reserve Bank of St Louis).



However, the potential for contagion or the illiquidity have not peaked yet. The amplification of losses starts in the U.S. where multiple firms experience insolvency due to their toxic portfolio of CDOs, as the American Insurance Group (AIG) which

benefited a massive bail-out from the Federal Reserve. In October 2008, the crisis spreads to Europe and the international contagion starts and cause the interbank market freeze at the end of the month. Empirically, we observe that the increase in lower tail asymptotic dependencies happen actually in delay compared to the losses. Similarly, both illiquidity measures only summits in the beginning of the year 2009. Shortly after, the financial crisis turns into a major economic downturn, manifested by high unemployment rate and high decrease in real GDP. Furthermore, we observe a common decrease in systemic dimensions occurring through the middle/end of the Contagion & Amplification phase (except for the Average χ). Macroeconomic variables however, tend to be more sticky and take more time to adjust back to their previous respective levels.

In order to show robustness, we perform an identical analysis on the European market. The results, computed from our sample of 50 of the largest financial firms in Europe, show a similar process¹⁹. An increase in the commonality of returns occurs in advance of the crisis. The build-up of financial fragility is followed by a sharp rise in financial losses, followed by contagion and amplification effects. The economic variable worsen towards the end of the crisis, hence putting forward evidences of the presence of negative externalities caused by the crisis.

I.5 Conclusion

The chronology of systemic events should have been the primary goal of researchers interested in measuring SR. The definitions of SR being central regarding the construction of a coherent measurement, knowing the stages and nature of risks involved seems capital. The current literature lacks theoretical approaches of SR. This fact is highlighted by the evident variety of measures proposed so far (Allen, Bali, & Tang, 2012; Billio et al., 2012; Balla, Ergen, & Migueis, 2014; Adrian & Brunnermeier, 2016; Acharya et al., 2017; Brownlees & Engle, 2017). Academics have so far taken the assumption that SR can be boiled down to a single indicator. It is however an arduous task to find one estimator/factor capable to take into account the multiplicity of risks, mechanisms taking action in a systemic event. The numerous

¹⁹A figure summarizing our results for the European sample is provided in the Appendix I.A.3 (see Figure I.6).

feedback loops, latent exposures and other phenomena are already difficult to model by themselves.

We start from the fact that studies focusing on one specific aspect of **SR** are not in the wrong. Such work simply overlooks other dimensions of the problem. The Systemic Events Hypothesis (**SEH**) proposes an alternative view. There exists an actual succession of steps in a systemic event, and each steps can be assess using an appropriate measure. We propose a complete chronology of a systemic event that can be expressed in the following steps. First, a structural displacement gives rise a profit opportunity. Such opportunity is linked to a latent risk, difficult to assess. A significantly large amount of companies identify the profit opportunity and engage in an common, yet not coordinated, investment, leading inevitably to the building up of a large common exposure. An increasing state of financial fragility arises from this correlated exposure, and leads to the occurrence to the realization of the (latent) risk of the profit opportunity. The losses incurred simultaneously by financial firms push some to go bankrupt and makes the financial system falling into a crisis state. Individual, and common, losses are increasing due to contagion, amplification and feedback effects, eventually leading the financial system to face a potential breakdown. Regardless whether the crisis is resolved using government/authorities' intervention, the systemic event has caused such a disruption on the financial sphere that it impacts negatively the real economy.

We choose and compute well-known **SR** measures that correspond to a specific stage in our systemic event chronology. The measures are applied to a sample of 53 of the largest financial firms in the U.S. from 2006 to 2011. In order to show robustness, we applied these measures to a second, European, sample of 50 of the largest financial firms in Europe. Empirical evidences in our samples make a strong case for the **SEH** to be valid. We find that commonality in asset returns increases prior to the crisis, indicates a potential common driving factor. Losses occur in the breakout of the crisis, while contagion and illiquidity proxies peak, in delay, at the end of the crisis. The consequences of the subprime crisis are undeniable, and are shown as well in our results, in terms of loss of real GDP and increase in the U.S. unemployment rate. We discuss the optimal timing for different type of regulatory actions, and specify what type of actions should be used at what time in a systemic

event. Additionally, we provide definitions and related elements for concepts underlying **SR**.

While this study constitutes a preliminary look into **SEH**, which seems to fit the last systemic crisis in date, we call for more research on detailing the transitions from one stage to another, validation of the **SEH** using other measures/sample, or even the construction of a model capable to estimate the state of a crisis we are currently in. The following chapters of this dissertation are tackling some of these research proposals. Chapter **II** tackles the multidimensional nature of **SR**. It inspects more particularly the correlation existing between the Systemic Dimensions and the presence of a chronology in the realization of Systemic Dimensions during **SE**. Chapter **III** examines more in detail the role of each type of financial firms during a **SE**. Furthermore, it highlights again the chronology present in a systemic crisis.

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CHAPTER I. A conceptual framework for measuring Systemic Risk: The Systemic Events Hypothesis

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I.A Appendix

I.A.1 Definitions of Systemic Risk

Definition 1. Mishkin (1992): ‘The likelihood of a 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.’

Definition 2. Aglietta and Moutot (1993): ‘the possibility for an economy to experience a state where, the agents’ responses given the risk they face, far from leading to a better allocation of individual risks, leads to increase general insecurity.’²⁰

Definition 3. Rochet and Tirole (1996): ‘refers to the propagation of an agent’s economic distress to other agents linked to that agents through financial transactions.’

Definition 4. De Bandt and Hartmann (2000): ‘a systemic event that affects a considerable number of financial institutions or markets in a strong sense, thereby severely impairing the general well-functioning of the financial system. [...] At the heart of the concept is the notion of contagion, a particularly strong propagation of failures from one institution, market or system to another’

Definition 5. Group of Ten (2001): ‘the risk that an event will trigger a loss of economic value or confidence in, and attendant increases in uncertainty about, a substantial portion of the financial system that is serious enough to quite probably have significant adverse effects on the real economy.’

²⁰Traduction made by the author.

Definition 6. Kaufmann and Scott (2003): ‘refers to the risk or probability of breakdowns in an entire system, as opposed to breakdowns in individual parts or components, and is evidence by co-movements (correlation) among most or all the parts.’

Definition 7. Kupiec and Nickerson (2004): ‘the potential for a modest economic shock to induce substantial volatility in asset prices, significant reductions in corporate liquidity, potential bankruptcies and efficiency losses’

Definition 8. Hendricks, Kambhu, and Mosser (2007): ‘the risk of a phase transition from one equilibrium to another, much less optimal equilibrium, characterized by multiple self-reinforcing feedback mechanisms making it difficult to reverse.’

Definition 9. Schwarcz (2008): ‘the risk that (i) an economic shock such as market or institutional failure triggers (through a panic or otherwise) either (X) the failure of a chain of markets or institutions or (Y) a chain of significant losses to financial institutions, (ii) resulting in increases in the cost of capital or decreases in its availability, often evidenced by substantial financial market price volatility’

Definition 10. Acharya (2009): ‘Joint failure risk arising from the correlation of returns on asset-side of bank balance-sheets.’

Definition 11. IMF (2009): ‘the risk of disruption of financial services that is (i) caused by an impairment of all or parts of the financial system and (ii) has the potential to have serious negative consequences on the real economy.’

Definition 12. Billio et al. (2012): ‘Any set of circumstances that threatens the stability of, or public confidence in, the financial system’

Definition 13. Patro, Qi, and Sun (2013): ‘the likelihood of experiencing a systemic failure, a broad-based breakdown of the financial system that is triggered by a strong systemic event (e.g. financial institution failure), which severely and negatively impacts the financial markets and the economy in general’

Definition 14. Chen, Iyengar, and Moallemi (2013): ‘refers to the risk of collapse of an entire complex system, as a result of actions taken by the individual component entities or agents that comprise the system.’

Definition 15. Zigrand (2014): ‘the risk of an event - labeled a systemic event - occurring in a given system that at least temporarily, to an altered and damaged transitional “system” whose proper functioning is impeded. In the extreme, the structure of the system itself is damaged and the system can no longer function’

Definition 16. Silva, Kimura, and Sobreiro (2017): ‘the risk that several market participants are simultaneously affected by severe losses, which then spread to the entire economy through financial interconnections among economic agents’.

Definition 17. Montagna, Torri, and Covi (2021): ‘the probability to have a large number of banks going into distress simultaneously or, more formally, the probability that the number of banks’ default or other credit events in a certain period is higher than a given threshold’

I.A.2 Tables

Table I.1: **Summary Statistics - U.S. Sample.**

Summary statistics for each type of financial firms' daily returns, from 01-01-2006 to 30-12-2010. The sample consists in 53 American financial firms. The mean, standard deviation, max, min and median are expressed annually.

<i>Full Sample</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Bank	24	-0.082	0.636	0.626	-0.893	-0.0	-0.212	19.486	-0.070
Insurance	22	-0.026	0.495	0.705	-0.936	0.0	-0.372	18.521	-0.114
Asset Management	7	0.075	0.480	0.269	-0.261	0.0	0.052	6.984	-0.120
<i>During Subprimes</i>									
Bank	24	-0.561	0.885	0.626	-0.893	-0.003	-0.327	10.163	-0.053
Insurance	22	-0.450	0.696	0.705	-0.936	-0.002	-0.473	11.029	-0.108
Asset Management	7	-0.312	0.674	0.269	-0.261	-0.001	0.043	3.395	-0.127
<i>Out of Subprimes</i>									
Bank	24	0.417	0.446	0.463	-0.288	0.000	0.937	15.273	-0.126
Insurance	22	0.409	0.341	0.507	-0.481	0.001	0.571	11.680	-0.141
Asset Management	7	0.377	0.334	0.167	-0.145	0.001	0.444	4.866	-0.118

Table I.2: **Summary Statistics - European Sample.**

Summary statistics for each type of financial firms' daily returns, from 01-01-2005 to 30-12-2011. The sample consists in 50 European financial firms. The mean, standard deviation, max, min and median are expressed annually.

<i>Full Sample</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Bank	25	-0.068	0.482	0.550	-1.215	-0.0	-0.514	23.092	0.033
Insurance	14	0.029	0.366	0.233	-0.406	0.0	-0.183	12.151	0.007
Asset Management	11	0.021	0.394	0.328	-0.341	0.0	0.060	9.791	-0.000
<i>During Subprimes</i>									
Bank	25	-0.577	0.697	0.550	-1.215	-0.003	-0.422	12.391	0.032
Insurance	14	-0.415	0.539	0.233	-0.406	-0.002	-0.187	6.853	-0.012
Asset Management	11	-0.476	0.583	0.280	-0.341	-0.002	0.065	4.914	-0.021
<i>Out of Subprimes</i>									
Bank	25	0.229	0.381	0.220	-0.287	0.0	0.251	6.661	0.023
Insurance	14	0.253	0.285	0.198	-0.157	0.0	0.276	5.982	0.011
Asset Management	11	0.291	0.306	0.328	-0.192	0.0	0.388	7.570	0.010

CHAPTER I. A conceptual framework for measuring Systemic Risk: The Systemic Events Hypothesis

Table I.3: **Summary Statistics for the State Variables - U.S. sample**

Summary statistics for the state variables from 01-01-2006 to 30-12-2010. We have separated our summary statistics for the Subprimes period and stable periods. The state variables are used in the computation of the $\Delta CoVaR$. We use the TEDRATE (TED spread), DeltaTB3 (log returns of 3-months T-Bill), DJ_EXCESS (Dow Jones Industrial excess returns compared to S&P500), the FFR (the effective federal fund rate) and the Volatility index (VIXCLS). The mean, standard deviation, min, max and median of the log returns series are annualized.

<i>Full Sample</i>								
State Variable	mean	sd	max	min	median	skewness	kurtosis	auto-corr
VIXCLS	23.415	11.923	80.860	9.890	21.43	1.776	3.767	0.982
TEDRATE	0.741	0.664	4.580	0.090	0.49	2.029	5.696	0.977
DeltaTB3	-0.157	1.349	0.885	-1.447	0.00	-1.691	97.377	-0.095
DJ_EXCESS	0.008	0.026	0.013	-0.010	0.00	0.183	6.628	-0.142
FFR	2.451	2.234	5.410	0.050	2.01	0.163	-1.781	0.998
<i>During Subprimes</i>								
VIXCLS	30.583	14.670	80.860	14.210	24.270	1.372	0.917	0.975
TEDRATE	1.428	0.691	4.580	0.200	1.280	1.761	4.287	0.938
DeltaTB3	-0.288	2.083	0.885	-1.447	-0.002	-1.390	47.721	-0.104
DJ_EXCESS	0.020	0.035	0.013	-0.010	0.000	0.021	4.796	-0.190
FFR	2.644	1.757	5.410	0.080	2.185	0.071	-1.308	0.989
<i>Out of Subprimes</i>								
VIXCLS	19.664	7.918	45.890	9.890	18.045	0.915	0.372	0.973
TEDRATE	0.381	0.211	1.130	0.090	0.370	1.072	1.282	0.994
DeltaTB3	-0.079	0.707	0.398	-0.301	0.000	0.907	21.809	-0.055
DJ_EXCESS	0.003	0.021	0.008	-0.005	-0.000	0.438	2.773	-0.068
FFR	2.347	2.442	5.410	0.050	0.200	0.239	-1.920	0.997

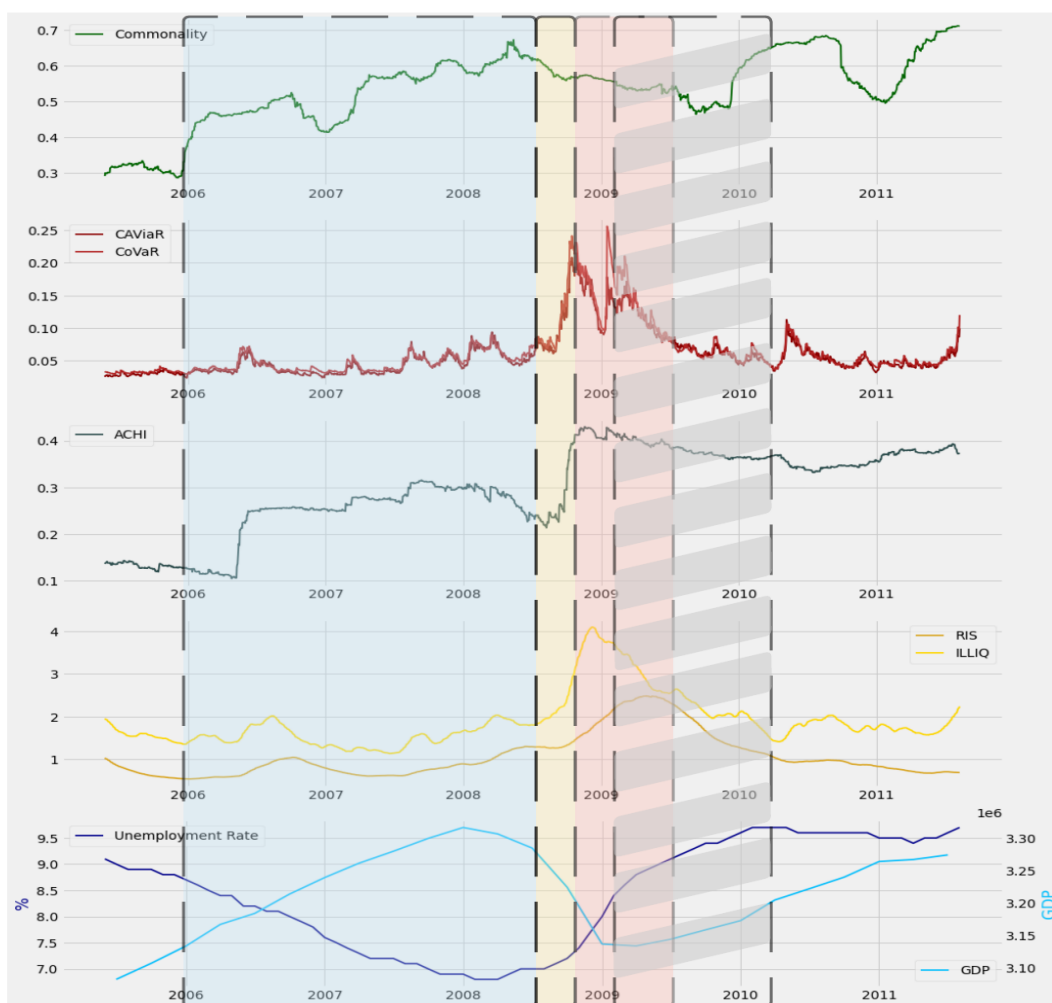
Table I.4: **Summary Statistics for the State Variables - European sample**
Summary statistics for the state variables from 01-01-2005 to 30-12-2011. We have separated our summary statistics for the Subprimes period and stable periods. The state variables are used in the computation of the $\Delta CoVaR$. We use MSCI_{EU} (log returns of the MSCI Europe), EUROSpread (spread between EURIBOR 3-months and French T-Bill 3-months), EONIA, Delta3M (log returns on French T-Bill 3-months), and the Volatility index (VIXCLS). The mean, standard deviation, min, max and median of the log returns series are annualized.

<i>Full Sample</i>								
State Variable	mean	sd	max	min	median	skewness	kurtosis	auto-corr
MSCI_{EU}	0.009	0.007	0.047	-0.044	0.000	-0.080	6.381	-0.010
VIXCLS	22.006	11.198	80.860	9.890	19.400	1.838	4.273	0.982
EUROSpread	0.005	0.004	0.031	-0.003	0.004	2.102	7.375	0.989
EONIA	0.021	0.014	0.046	0.003	0.021	0.159	-1.466	0.997
Delta3M	-0.078	0.043	1.243	-0.519	0.000	12.114	402.229	-0.087
<i>During Subprimes</i>								
MSCI_{EU}	-0.196	0.010	0.047	-0.044	-0.001	0.123	4.656	-0.033
VIXCLS	30.583	14.670	80.860	14.210	24.270	1.372	0.917	0.975
EUROSpread	0.009	0.005	0.031	0.001	0.008	1.860	4.914	0.986
EONIA	0.037	0.009	0.046	0.012	0.040	-1.849	2.175	0.983
Delta3M	-0.335	0.012	0.059	-0.139	-0.000	-4.013	44.082	0.068
<i>Out of Subprimes</i>								
MSCI_{EU}	0.087	0.006	0.036	-0.028	0.000	-0.109	3.257	0.000
VIXCLS	19.218	8.026	48.000	9.890	17.005	1.090	0.535	0.974
EUROSpread	0.004	0.003	0.015	-0.003	0.003	1.466	2.386	0.975
EONIA	0.016	0.011	0.041	0.003	0.011	0.491	-1.098	0.992
Delta3M	0.026	0.049	1.243	-0.519	0.000	10.820	313.997	-0.091

I.A.3 Figures

Figure I.6: **Chronology of Systemic Dimensions during the subprime crisis - European Sample**

The chart displays *SR* measures (dimensions) from 2005 to 2011, for our sample of 50 European financial firms. We proposed to divide the graph according to the periods given above (see Figure I.2). Blue corresponds to the rise in financial fragility, yellow relates to the financial shock and realization of latent losses, red corresponds to the rise of contagion and amplification effects. Finally, the hatched area corresponds to the period of negative externalities. Commonality corresponds to the variance explained by the first factor of a *PCA* on asset' returns (Kritzman et al., 2011; Billo et al., 2012), *CAViaR* to the measure of White, Kim, and Manganelli (2015), *CoVaR* is the Δ *CoVaR* of Adrian and Brunnermeier (2016), *ACHI* is the Average Chi coefficient (lower tail) of Balla, Ergen, and Migueis (2014), *RIS* is the liquidity measures from Roll (1984), *ILLIQ* is the illiquidity measure from Amihud (2002). Finally, the last graphs displays the average unemployment rate and the average real GDP for European Union members (Source: Federal Reserve Bank of St Louis).



Chapter II

On the correlation of Systemic Dimensions

II.1 Introduction

A financial crisis is a moment when all goes badly. This adage illustrates the most common view of a financial crisis. Numerous academics have tried to define and study these abnormal events, but never agreed on a specific definition. Hence, the sentence above is one that comes the closest to the truth. It is possible that a financial crisis is not defined by the amount lost, or the number of firms' failure but simply by the fact that 'all goes badly'. When looking at the history of financial crisis, it provides a relevant, although imprecise, description (Kindleberger, 1978; Atkinson, Luttrell, & Rosenblum, 2013). During a systemic crisis, which, most would agree, is worse than a financial crisis, it is even more accurate. A systemic crisis combines different risks occurring simultaneously. This article builds up on this insight and poses the question of the existing correlations between risk measures. Although there is an extensive literature on correlation risk¹, there is very few studies on how different risks are correlated. We postulate that, since **Systemic Risk (SR)** is a combination of different risks, a good proxy for **SR** measurement is the correlation between different risk indicators.

The first challenge of the article is to find and show that there exists different **SR** measures², and, thus defining how two measures can be different. The following challenge is straightforward. In the case where there exists more than two 'different' measures of **SR**, how can we find a measure of correlation for more than two variables? We base our initial thinking on the work proposed in Chapter I, which explains how **SR** is a combination of various, different, risks, called Systemic Dimensions. We propose to study specifically three of them: Losses, Connectedness and Illiquidity. The measures taken to proxy these Systemic Dimensions are the following. First, the ΔCoVaR that comes from the work of Adrian and Brunnermeier (2016) and proxies losses, the **DGC** (Billio et al., 2012) for connectedness, and **ILLIQ**, from Amihud (2002), for illiquidity. This chapter shows that the Systemic Dimensions are orthogonal in stable times and become correlated in crisis periods. The tests are performed on two distinct samples. The first spawns from June 2000

¹Correlation risk refers to the fact that financial returns of different firms are highly correlated, hence providing evidence of herding behavior and/or common exposure on a specific risk.

²There exists various types of **SR** measure. Here, 'different' refers to the specificity of a measure. Systemic Dimensions are, by definition, different types of **SR**.

to June 2020; and is based on the daily stock returns of 75 American firms (25 banks, 25 insurers, 25 investment firms). For robustness, we add a second sample based on European data. The second sample is composed of the daily stock returns of 100 European financial firms (25 banks, 25 brokers, 25 insurers and 25 investment firms). We use a [Principal Component Analysis \(PCA\)](#) as a correlation measure for our Systemic Dimensions. We applied the [PCA](#) over a rolling forward window, and find that the first component's inertia shows clearly the period of systemic crises in our sample. By showing that the correlation of different (systemic) risk measures is enough to find systemic crises in our sample, we argue that the very nature of [SR](#) lies in these correlations.

The contributions of this chapter are twofold. First, our study provides an innovative point of view on the nature of [SR](#). Up to now, most of the existing literature had the underlying assumption that [SR](#) was univariate, in such a way that a single indicator could reflect [SR](#). To answer that assumption, one can find numerous studies that provide a single measure to describe [SR](#). This chapter find its roots in the [Systemic Event Hypothesis \(SEH\)](#) and, hence, differs from this approach. We assume that there exists multiple types of [SR](#), and that the 'real' [SR](#) is measurable by the correlation between these different types of [SR](#)³. This is the first study, in our knowledge, to provide such an approach. Moreover, according to the [SEH](#), [SR](#) is also a succession of occurrence of Systemic Dimensions. Its measurement remains a challenge especially because of that temporal aspect. This chapter provides an initial answer to that aspect. We propose to apply a specific lag procedure on the Systemic Dimensions in order to capture this temporal effect⁴. Assuming that a [SE](#) is a succession of occurrence in Systemic Dimensions, the stages of increase and decrease in the underlying measures are offset from one another. By re-aligning the Systemic Dimensions before computing their correlation, we allow for a reduction in the noise of the measure. By doing so, we are the first to present such procedure and to put forward empirical evidences of a chronology in a [SE](#), on both the European and U.S. markets. Furthermore, we provide a comparison of the evolution of [SR](#) between the European and American financial systems. Our results shows the robustness and applicability of our approach.

³The different types of [SR](#) relate directly to the Systemic Dimensions, which are, by definition, different type of risks that are subsequent to [SR](#).

⁴For a graphical representation of the lag procedure, see [Figure 4](#).

The structure of this chapter is as follows. The next section exposes the existing literature. It first, presents the theory underlying [SR](#) and, especially, its relationship with banking models. In a second time, it covers the existing measures, and concludes with the concept of dependence. A following section presents the data in our sample along the descriptive statistics. It also provides the measures used to proxy the Systemic Dimensions and the use of a [PCA](#) for computing the correlation among the Systemic Dimensions. We will next expose our results for the American and European case, and, in a second time, present a focus on each type of firms considered in this research. The last section concludes the chapter.

II.2 Literature Review

This section expose the current literature on [SR](#). It first introduces the theoretical models that have pioneered the research on [SR](#). In a second time, the section presents famous measurements proposed by academics over the last two decades. Eventually, it concludes the section by a discussion on the measures of dependency and correlations in finance.

II.2.1 Theory of Systemic Risk

The study of [SR](#) directly stems from banking crises. One can easily argue that the globalization of finance was due to banking activity. Through the years, banking evolved and allowed businesses to invest, grow and spread. This fact is observable by the extent of banking regulation that took place over the years (Glass-Steagall Act (1993), Dodd-Frank Act (2010), Basel Accords (1988, 2004, 2010), etc.). The initial endeavors were to discover the natural properties of such phenomena. Among the most known papers, we note the work of Bryant (1980), Diamond and Dybvig (1986), and Kiyotaki and Moore (1997) on banking crises⁵. Such papers highlights the actual risk associated with banking activity and the solutions to regulate it. Kiyotaki and Moore (1997) particularly focused on the importance of credit cycles in a shock's transmission mechanism. They make an explicit link between banking activity and financial crises. Moreover, the risk of bank run was one of the major

⁵For a general overview on bank regulation, see Dewatripont and Tirole (1994).

issues tackled in the early researches, and the creation of deposit insurance directly stemmed from it. Although, the total efficiency of deposit insurance as a solution to bank runs remains arguable (Aglietta, 1993).

It is important to note that research on **SR** also started with the study of financial crises. The pioneer work of Kindleberger (1978), Minsky (1991) and Mishkin (1992) have laid a solid foundation for our understanding of the underlying process of financial crises. Kindleberger (1978) and Minsky (1991) share a common analysis on how financial crises build up. In their conception, a financial crisis is inherent to capitalism and develop regularly according to a given pattern: A change, called ‘displacement’, occurs and causes a shift in the behavior of financial agents. Afterwards, firms that were working regularly (hedge units) need to borrow in order to pay interest of their loans (speculative units). Firms that were already risky (speculative units) are forced to borrow continuously in order to survive (Ponzi units). This creation, and increase, in financial fragility leads to a point, where most of the financial system is composed of Ponzi units. A ‘not-so-unusual’⁶ event happens, pushing the first firms into bankruptcy. In Minsky (1991) and Kindleberger (1978)’s view, the crisis is created from irrational behavior⁷. On another hand, Mishkin believes that financial crises root from information asymmetry. Mishkin (1992) presents the different causes of a financial crisis and a chronology of how they entangle together. Information asymmetry creates adverse selection and moral hazard issues that worsen the crisis.

Due to the crises which spawned at the beginning of our millennium (Dot-Com bubble, Subprime crisis, European debt crisis, etc.), we have observed a rise in **SR** interest. Leading theoretical work such as, and among others, Acharya (2009), Freixas and Rochet (2010), Brunnermeier and Oehmke (2013) and Chen, Iyengar, and Moallemi (2013), have demonstrated the general interest in providing a theoretical framework for **SR**. As said by Brunnermeier and Oehmke (2013), in systemic assessment, theory should lead the operational measurement. The traditional view

⁶In Minsky’s view, the first failures of a crisis start because of a given macroeconomic event. It is called ‘not-so-unusual’ because, such event, would not have incur any failure in regular times. It is because of the large degree of financial fragility that the failures occur.

⁷See Blanchard and Watson (1982) for a study on how bubbles can develop under rational expectations.

of treating the banking sector as the only systemic institution slowly became less and less relevant. Recent theories include also insurers and hedge funds into their scope. The logic behind this adaptation of scope comes from the fact that the mechanisms linking all financial agents together constitute the roots of **SR**.

II.2.2 Measures of Systemic Risk

The subprime crisis created a relentless stream of research on how to measure **SR**. The impact of the crisis was so unexpectedly large, that it forced both academics and regulators to tackle the issue of measurement. We present in this section the most famous measures⁸. Existing measures can be separated in two main categories. The ones trying to give a global index of **SR**; and the ones proposing a firm-level contribution to **SR**. As explained in Borio (2003) and Bisias, Flood, and Lo (2012), both types of measure are complementary.

From one hand, measures providing a global index are essential for macroprudential supervision. Among these, the most famous are the following: The Composite Indicator of Systemic Stress (CISS), created by Hollo, Kremer, and Lo Duca (2012), focuses on how much of the financial system is at risk at any time point. The indicator is created from various financial stress indicators. It implies that **SR** is higher when many markets are at risk, taking into account various types of risk. In the same vein, Kritzman et al. (2011) propose a systemic indicator called the Absorption Ratio (AR) based on a **PCA** on financial returns. Hu, Pan, and Wang (2010) propose a measure of noise based on bond price. The rationale of the measure is that, in stable times, the Treasury market should be almost noiseless. Although, in crisis periods, the amount of capital in the bond's market is reduced, resulting in more noise. Their measure gives an indicator of liquidity crises and liquidity risk over time. All these measures allow for an analysis of how general **SR** evolves over time. They also permit regulators to evaluate the performance of their actions.

On another hand, we also need individual risk measures in order to identify which agent is causing the most risk in the financial market. This type of studies is, from far, the largest part of the existing literature on **SR**. Their objectives is to display

⁸For a more comprehensive view of the current literature, see Bisias, Flood, and Lo (2012) and Benoit et al. (2017) on **SR** measurement, and Smaga (2014) on the definition and concept of **SR**.

the risks, which can cause an institution to fail. We find first the measures linked to financial losses: the $\Delta CoVaR$ of Adrian and Brunnermeier (2016), Systemic Expected Shortfall (SES) of Acharya et al. (2017) and Co-risk created by Chan Lau et al. (2009). Such articles try to display the size of losses associated with an unusually risky period. Another stream of SR measures focuses on the connectedness of financial institutions. Freixas, Parigi, and Rochet (2000) represent the interbank system as a network and show the effect of one (or more) bank insolvency over the whole network⁹. Giesecke and Kim (2011b) propose a model timing banks' default. The model is made to display systemic linkages in an economy. Billio et al. (2012) show, through Granger causality regressions and PCA, the systemic importance of connectedness. The PCA shows the general level of correlation among financial returns, while Granger causalities identify the important linkages between financial firms.

II.2.3 Dependency measures

The measures presented above cover a wide range of variety in the measurement approach, or underlying definitions of SR. We set ourselves apart from these studies by assuming that SR is multidimensional. In other words, and in accordance with the SEH, SR is a combination of various different risks. Consequently, we provide in this chapter a new method in assess SR. The methods assume that (existing) SR measures assess different types of SR, and that the 'real' SR lies in their correlation. To that end, this section introduces the concept of correlation and dependency. Lehmann (1966) describes three distinct types of dependency:

1. *Quadrant Dependency*: $P(X \leq x, Y \leq y) \geq P(X \leq x)P(Y \leq y)$. In such case, there is dependency if the joint probability of an event is greater the product of the marginal probabilities.

2. *Regression Dependency*: $P(Y \leq y|X \leq x) \geq P(Y \leq y)$. Such dependency exists when, the probability of an event is greater when taking into account that the other event already occurred.

⁹For an update on the network models of SR, see Caccioli, Barucca, and Kobayashi (2018).

3. *Likelihood Ratio Dependence*: $f(x, y')f(x', y) \leq f(x, y)f(x', y')$, for $x' < x$ and $y' < y$, with $f(x, y)$ being the joint density of X and Y . The dependence here lies in the fact that probability of observing large (small) values of the couple (x, y) is greater than the one of observing disparate (one large associated with one small) values in the couple (x, y) .

We see that the appropriate approach will differ greatly depending on the chosen case. In this study, we present the correlations between our Systemic Dimensions. Hence, our approach would tend to fit the first definition of dependence above. Although, results in the chronological order of occurrence of Systemic Dimensions would advocate for using dependency measures associated with the second definition. We leave this gap for future research. Unfortunately, the current literature regarding correlation in financial risks is almost nonexistent. However, there exists a burgeoning one on correlation risk, that is to say the risk associated with the correlation between financial returns. Among most famous works, we find:

- *Copulas*: A copula is a concept coming from probability theory and, whose development is based on Sklar's theorem. Simply put, it corresponds to a joint cumulative distribution function of a random vector with uniform marginals. It is used to study the dependence between random variables. As an introduction, Embrechts (2009) provides solid and thorough explanations, as a must-read section that allows one to easily get a comprehensive view on copulas¹⁰. In finance, Malevergne and Sornette (2003) tests whether the existing dependencies between pairs of financial assets can be modeled convincingly by the Gaussian (and Student) Copula. Finally, Kole, Koedjik, and Verbeek (2007) show the importance of a copula's choice for modeling dependence.
- *GARCH models*: Generalized Auto-Regressive Conditional Heteroskedastic (GARCH) models are one of the most used tools to model dynamic variance and correlations. An initial method was the BEKK model¹¹ based on the work of Engle and Kroner (1995). Bollerslev (1990) constructed a model for modeling conditional correlation, called Constant Conditional Correlation (CCC). Engle (2002) built up on the work of Bollerslev (1990) in order to

¹⁰For a detailed description of the most important area of application, see the work of Genest, Gendron, and Bourdeau-Brien (2009).

¹¹The acronym BEKK is based on the names of the authors: Baba, Engle, Kraft and Kroner.

make a model which can model a Dynamic Conditional Correlation (DCC), that is to say, model time-varying conditional correlation.

- *PCA*: Additionally, the papers cited above that applied *PCA* directly to *SR* (Billio et al. 2012; Kritzman et al. 2011) have been using it for measuring commonality among financial assets. Avellaneda and Serur (2020) used a Hierarchical *PCA* to expose clusters of assets based on their principal components. Fenn et al. (2011) show the time varying behavior of correlations and principal components for financial returns. Shapira, Kenet, and Ben-Jacob (2009) study the correlations among stocks taking into account the market's index.

Over the methods presented above, this chapter uses the *PCA* for measuring the correlation in Systemic Dimensions. This choice have multiple justifications. First of all, the *PCA* is a method of dimensionality reduction, hence provides a single measure¹² for the correlation between our Systemic Dimensions. Moreover, the procedure is computationally cheap, and can be easily adapted to specific needs. Finally, we can perform a rolling-forward procedure in order to obtain a dynamic indicator of *SR*.

II.3 Data & Methodology

This present the data used for constructing the *SR* measures. In a second time, we detail the mathematical formulation of each measure. Finally, we present the methodology of the *PCA* used as a correlation indicator among our Systemic Dimensions.

II.3.1 Data & Summary Statistics

This research uses two distinct sets of data. The first is composed of American firms. More specifically, it includes the daily returns of 75 of the largest banks, insurance/reinsurance companies and asset management firms in the U.S., from June

¹²In this chapter, the *PCA* is used as a correlation measure. More precisely, it is performed over our measures (Systemic Dimensions) in order to extract the inertia of the first principal component. The underlying logic behind that choice is that the main (common) component of any set of measures built to assess *SR* should be *SR*.

2000 to June 2020. The firms were first selected on Osiris database, by looking at their market capitalization. We have extracted daily prices and market capitalization¹³ from Eikon database. In addition, we extracted daily prices, daily volumes and market capitalization for the underlying stock of the S&P100, which will be used for constructing a proxy for market liquidity. The summary statistics are provided in the Appendix II.A.3 (see Table II.1). Additionally, the financial system, as used in the $\Delta CoVaR$ of Adrian and Brunnermeier (2016), is simply an index constructed from the 75 financial firms in our sample, which are market capitalization weighted. Formally:

$$R_{system}(t) = \frac{1}{MV_{tot}} \sum_{i=1}^N R_i(t) MV_i \quad (\text{II.1})$$

In order to add robustness to our results, we perform the analysis over a second sample composed of the daily stock returns of 100 of the largest banks, insurance companies, brokerage companies and asset management firms. The data starts in January 2005 and ends in December 2017. The construction of the financial system via a market capitalization-weighted index is the same as for our American sample (see Equation II.1). The daily returns, volumes and capitalization of the Eurostoxx 50 were also retrieved for the computation of the market liquidity proxy. The data for the European sample was retrieved on Datastream. The summary statistics are presented in the Appendix II.A.3, Table I.2.

II.3.2 Systemic Risk measures

CoVaR

The Conditional Value-at-Risk (CoVaR) results from the work of Adrian and Brunnermeier (2016). Simply put, it represents the $q\%$ worst loss possible of a firm i , given that a firm j is already at its $p\%$ worst loss. Originally, the authors use quantile regressions, but we decided on using the bivariate Gaussian model in order to have daily observations for our $\Delta CoVaRs$. By definition, $CoVaR$ is a VaR of an institution j conditional to some event $\mathbb{C}(X_i)$ on firm i 's returns. Thus, we define $CoVaR^{j|i}(q)$ as,

$$Pr(X_j \leq CoVaR^{j|i}(q) | \mathbb{C}(X_i)) = q \quad (\text{II.2})$$

¹³The market capitalization are used in order to derive the financial system needed for the computation of the $\Delta CoVaR$.

The formulation of the *CoVaR* is useful when it comes to changing the condition terms, which generates multiple values and multiple interpretations of the measurement. In this chapter, we propose that the event $\mathbb{C}(X_i)$ consists in the fact that the i^{th} firm's returns are at their *VaR*, then,

$$CoVaR^{j|i}(q, p) \equiv Pr(X_j \leq CoVaR^{j|i}(q, p) | X_i = VaR_i(p)) = q \quad (\text{II.3})$$

In order to construct the $\Delta CoVaR$, we need to subtract the 50% level *CoVaR* to the $q\%$ level *CoVaR*. This specification describes differences in *CoVaRs* between when the conditioning event is that firm i is either distressed and when firm i is 'stable' or at its usual level. Formally,

$$\Delta CoVaR^{j|i}(q, p) = CoVaR^{j|i}(q, p) - CoVaR^{j|i}(q, 50\%) \quad (\text{II.4})$$

As presented in the appendices of Adrian and Brunnermeier (2016), we use the Gaussian model by assuming that the returns of firms i and j follow normal bivariate distribution. The mathematical development is made available in the Appendix II.A.1. We then obtain the following expression for *CoVaR*.

$$CoVaR^{j|i}(q, p, t) = N^{-1}(q)\sqrt{1 - \rho_t^2}\sigma_{j,t} + N^{-1}(p)\sigma_{j,t}\rho_t \quad (\text{II.5})$$

With ρ_t denoting the correlation between firms i and j . Like Adrian and Brunnermeier (2016), we focus our study of the *CoVaR* not on the relationships between two firms but rather on the analysis of one firm and the system. As for the *VaR* computation, we decided to implement time-varying correlations in our *CoVaR*. One obstacle, when trying to compute the *CoVaR*, as described above, is estimating the dynamic conditional correlation (DCC). In our computation, we follow the work of Engle (2002). We propose $R(t)$ as,

$$R(t) = \begin{pmatrix} R_i(t) \\ R_j(t) \end{pmatrix} \quad (\text{II.6})$$

With $R_i(t)$ and $R_j(t)$ being the returns of firms i and j . We assume that $R(t)$ follows a bivariate normal distribution with mean equal to zero and with the condi-

tional covariance matrix $H(t)$.

$$R(t) | \mathbb{F}(t) \sim N_{\mathbb{R}^2}(0, H(t)) \quad (\text{II.7})$$

Where:

$$H(t) = D(t) \Lambda(t) D(t) \quad (\text{II.8})$$

With $D(t)$ being a diagonal vector of conditional standard deviations $\sqrt{h_i(t)}$ and $\Lambda(t)$ being the conditional correlation matrix. Generally, the $h_i(t)$ term is the volatility extracted from a univariate GARCH model; in our case it comes from the EGARCH performed for the computation of $VaRs$. We specify,

$$\varepsilon(t) = D(t)^{-1} R(t) \quad (\text{II.9})$$

As all variances need to have positive values, $\Lambda(t)$ must be positive definite. A matrix is positive definite if it has non-negative eigenvalues. In order to respect that constraint, Engle gives the following proxy¹⁴ which is developed to be a matrix version of a GARCH model.

$$Q(t) = S(1 - \alpha - \beta) + \alpha(\varepsilon(t-1)\varepsilon(t-1)') + \beta Q(t-1) \quad (\text{II.10})$$

Where α and β are non-negative parameters and, so the process is mean-reverting, $\alpha + \beta < 1$. S is the unconditional correlation matrix of $R(t)$, obtained simply by computing the following.

$$S = \frac{\sigma_{R_i, R_j}}{\sigma_{R_i} \sigma_{R_j}} \quad (\text{II.11})$$

Where σ_{R_i, R_j} is the covariance of R_i and R_j . We find our final DCC,

$$\Lambda(t) = \text{diag}\{Q(t)\}^{-1} Q(t) \text{diag}\{Q(t)\}^{-1} \quad (\text{II.12})$$

As all the $CoVaRs$ that we compute are either on the i^{th} firm conditionally to the system; or the opposite, we only need to compute the time-varying correlations of each firm against the system. By allowing our measure to be time-varying, we can refine our analysis and study the behavior of the $\Delta CoVaR$ values through our whole sample.

¹⁴The development is available either in the original article of Engle (2002), or in the documentation for rmgarch models (Ghalanos, 2019).

Interconnectedness

We base our methodology on that of Billio et al. (2012) and develop Granger causality tests (Granger, 1969) to study the interconnectedness of firms in our sample. We perform linear Granger regressions on a rolling window of 200 days in order to get the evolution of the Granger adjacency matrix over the sample. Granger causality regressions are presented as in the original methodology of Granger (1969). The measure consists in performing two regressions, on two random variables and their lagged values. In other words, for the first regression, we regress the returns of the i^{th} firm against the lagged value of the j^{th} firm's returns and its own lagged value. The second regression is identical but inverts i and j in the regression. Formally,

$$\begin{aligned} R_i(t+1) &= \alpha_i R_i(t) + \beta_{ij} R_j(t) + e_i(t+1) \\ R_j(t+1) &= \alpha_j R_j(t) + \beta_{ji} R_i(t) + e_j(t+1) \end{aligned} \quad (\text{II.13})$$

Where $R_i(t)$ is the return for the i^{th} firm and $R_j(t)$ the return for the j^{th} firm, $e_j(t+1)$ and $e_i(t+1)$ are two uncorrelated white noises. The lagged value prevents the β to be biased by autocorrelation effects in the timeseries. We accept that the returns of firm i have caused firm j 's returns if $\beta_{ji} \neq 0$; conversely, if $\beta_{ij} \neq 0$ then it is firm j that causes the returns of firm i . We denote the fact that firm i 's returns cause firm j 's returns by the following.

$$\begin{aligned} (i \rightarrow j) & \text{ if } \beta_{ji} \neq 0 \\ (j \rightarrow i) & \text{ if } \beta_{ij} \neq 0 \end{aligned} \quad (\text{II.14})$$

All causality, as defined above, is computed to be significant at the 95% level of confidence. As stated by Billio et al. (2012), if both coefficients are significantly different from 0, there is a feedback relationship between the two asset returns. In a similar fashion of Billio et al. (2012), we develop connectedness indicators from causality regressions: IN, OUT and DGC.

- The 'IN' measure counts the number of firms whose returns caused the j^{th} firm's returns, in the Granger sense.

$$\text{IN} : (S \rightarrow j) = \frac{1}{N-1} \sum_{i \neq j} (i \rightarrow j)$$

- In contrast to the ‘IN’ measure, ‘OUT’ gives the number of Granger connections the j^{th} firm caused.

$$\text{OUT} : (j \rightarrow S) = \frac{1}{N-1} \sum_{i \neq j} (j \rightarrow i)$$

- The DGC or Degree of Granger Causality, is an index on how much causality relationships exist in a given system. Operationally, we sum up the IN and OUT measure and divide by the maximal possible amount of connections (74 given our sample). The resulting index gives an idea of how much the system is connected.

Market illiquidity

To gain an idea of how sectors’ returns interact with market illiquidity, we follow the methodology of Amihud (2002) in developing AILLIQ. We use AILLIQ as an indicator of market illiquidity. By regressing this proxy against financial returns of the firms in our sample, we assess their exposure to market illiquidity. To avoid endogeneity, we use the S&P 100, which contains only a few financial firms. The measure can be interpreted as the daily volume adjusted price variation or, alternatively, the response of the price against one dollar of trading volume. Although ILLIQ can also be considered a price impact measure, it remains an attractive illiquidity proxy due to its simplicity and the availability of its components. We begin by computing the ratio between the absolute value of daily returns on one firm’s returns and the daily euro trading volume for the same firm. When computing the mean of this ratio (i.e., by dividing by the number of trading days), we get the ILLIQ measure for the firm.

$$ILLIQ_i(y) = 1/D_i(y) \sum_{d=1}^{D_i(y)} |R_i(y, d)|/VOLE_i(y, d) \quad (\text{II.15})$$

With $R_i(y, d)$ being the return for firm i on day d and in year y . Similarly, $VOLE_i(y, d)$ represents the euro volume for firm i on day d and in year y . Also, $D_i(y)$ is the number of trading days for year y . Evidently, the ratio follows the definition of illiquidity as defined by Kyle (1985), which is to say the percentage of price change per unit of daily trading volume, here, in euro. Given our methodology, we need an indicator of market illiquidity rather than one of the illiquidity of each stock of the index. We therefore use the AILLIQ measure, as it is essentially the

mean of all the $ILLIQ_i$. Formally,

$$AILLIQ(y) = 1/N_i(y) \sum_{i=1}^{N_i(y)} ILLIQ_i(y) \quad (\text{II.16})$$

We construct a rolling-forward linear regression between the firm's returns and the AILLIQ indicator, taking a 200-day window. By doing so, we obtain a value of $\beta_i(t)$ for each firm i and each day t . Formally,

$$AILLIQ(t) = \alpha_i(t) + \beta_i(t)R_i(t) + e_i(t) \quad (\text{II.17})$$

By posing $\alpha = 1, 2, 3$ and M_α as the length of the sample in sector α , we construct the sector's average beta:

$$\beta_\alpha(t) = 1/M_\alpha \sum_{i=1}^{M_\alpha} \beta_i(t) \quad (\text{II.18})$$

In the work of Amihud (2002), such regressions were made with inverse dependent and independent variables. Nevertheless, the rationale remains identical: the measure assesses the relationship between market illiquidity and each sector's returns. Amihud (2002) did observe that the regressions give a positive β if illiquidity is expected. The measure is therefore able to show us when the illiquidity is not expected, hence, theoretically, when the risk associated with illiquidity is high. We consider the $\beta_\alpha(t)$ as a measure of SR for the following reasons. In a general sense, a market with high illiquidity is prone to greater variations in stock prices. Since excess asset returns will increase the variance, using ILLIQ's structure, it will increase the illiquidity measurement. It is then straightforward to link high volatility of an asset returns with its high illiquidity, *ceteris paribus*. In the context of SR management, we have to recognize that high market illiquidity has a substantial potential in amplifying a fire sale type of event. The measure allows for an additional specification that only a negative β will indicate significant SR, mostly because unpredicted illiquidity is more dangerous than expected illiquidity.

II.3.3 Principal Component Analysis

PCA is a statistical technique allowing to decompose the covariance matrix (Σ) of the $m \times n$ matrix (X), into a diagonal matrix of eigenvalues (Λ). Such as,

$$H^T \Sigma H = \Lambda \equiv \text{diag}(\lambda_1, \dots, \lambda_m) \quad (\text{II.19})$$

With $H = (h_1, \dots, h_m)$ being an orthogonal matrix of size $m \times m$, and h_i is an eigenvector corresponding to λ_i . Principal components are then computed as follows.

$$U = H^T X = (U_1, \dots, U_m) \quad (\text{II.20})$$

In more details, the first component consists in $U_1 = h_1 X$, with variance λ_1 . In a similar fashion, the second $U_2 = h_2 X$, with variance λ_2 . Necessarily, all components must be orthogonal, hence $Cov(U_i, U_j) = 0$ for all $i \neq j$. In our case, the PCA serves as an alternative measure for correlation. This article aims to study the correlation structure of SR measures through time. By applying PCA of our SR measures on a rolling forward window, we expose the changes in their common uncorrelated factors. Additionally, we use the quartimax rotation on our PCA. Generally, the unrotated PCA tries to maximize the variances of each factors and forces orthogonality on the principal components. Such variances of principal components should be strictly decreasing. A rotation can simplify the output in making it more understandable. Specifically, the quartimax method is an orthogonal rotation, which will result in a little amount of explaining factors. It does so by making large loading on a specific factor larger and conversely on small loadings, resulting in less large principal components.

Our results regard the evolution of the proportion of explained variance of the three first principal components. The rationale behind our approach is straightforward. Let us consider that each measure of SR is a noisy signal of the ‘real’ SR. In other words, the measure is assessing the actual risk during a crisis but also have increases during stable times due to the specificity of the measure. In essence, there exists an implied noise-to-signal ratio for each measure. In stable times, the ratio increases for each measures making them uncorrelated, because noises are uncorrelated among each other. However, during a crisis the ratio decreases as all the measures tend to indicate the increase in SR. Hence, the measures’ correlation in-

creases. In our case, we aim to study that evolution in correlation by applied a rolling-forward **PCA** on our Systemic Dimensions. By doing so, we interpret that an increase in **SR** is only relevant when multiple measure of **SR** increase at the same time.

II.4 Results & Discussion

First, we introduce results for the whole U.S. financial system. That is to say, we study the existing correlations between the three Systemic Dimensions (Losses, Connectedness and Liquidity). We add an analysis of an identical analysis, that is sector-specific, in order to observe potential differences in **SR** inside the financial sector. Eventually, we propose an improvement of systemic crises' period identification, based on lagging appropriately Systemic Dimensions before performing **PCA**. We see that the lagging procedure allows for an improvement of the identification, and provide a discussion on the reason why, below.

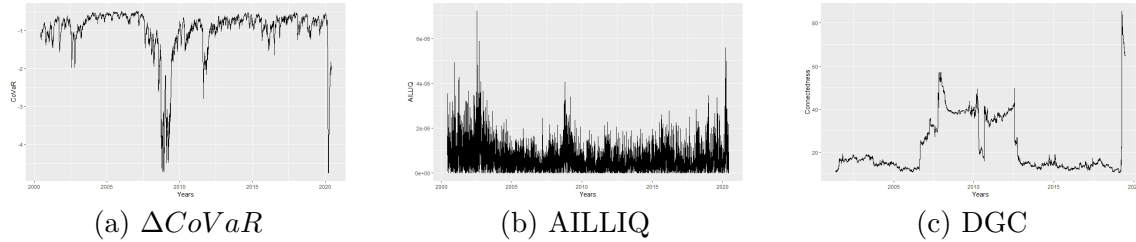
II.4.1 Othorgonality of Systemic Dimensions

We postulate the following: Measures of **SR** typically represent a noisy signal for the actual risk. Since they focus on different types of risk, the noise among each of them is uncorrelated. However, as they are **SR** measure, the signal is correlated. Logically, the stable periods, where **SR** is at the lowest, are characterized by a predominance of noise. Since noise is uncorrelated, the measure are uncorrelated accordingly. However, during crisis period, the proportion of noise to risk decreases. The signal for actual risk increases and, hence, so are the measures. The general rationale starts with Systemic Dimensions: Losses, Connectedness, Liquidity. Systemic Dimensions constitute the main risks involved in a systemic crisis. The assumption made in this study is that the orthogonality of the Systemic Dimensions is assured in stable period, and breaks in crisis times. Thus, this research aims to validate this assumption by, first, proving that Systemic Dimensions are orthogonal in stable periods, and that is possible to identify crisis periods by looking at the time-varying correlation of Systemic Dimensions. Intuitively, the **PCA** is used as a proxy for the correlation among the three dimensions. We expect the first component to increase in crisis

periods and it would become the driving factor of all risks.

Figure II.1: Systemic Dimensions - U.S. Sample

All average Systemic Dimensions of all firms in our sample from June 2000 to June 2020. Graph (a) displays the ΔCoVaR of Adrian and Brunnermeier (2016). Chart (b) the market illiquidity indicator (AILLIQ) of Amihud (2002). Graph (c) shows the average Degree of Granger Causality (DGC) present in our sample.



As Figure II.1 tells, all three Systemic Dimensions show significant spikes during crisis periods. We can identify residual stress from the dot-com bubble (2000-2002), the subprime crisis (2007-2009), the European debt crisis (2011-2012) and, more recently, the Covid situation (2020). A valid remark would be about the reason to use different measures if they all show clearly SR. The answer is twofold. It is first a question of meaning. We probably could find various indicators that show spikes during crisis period. Does it mean that they represent SR? The relationships we tend to postulate too quickly can often be spurious. A second reason is about noise. Even though each of the measures above serve as a decent indicator of SR, one could argue that they show noise; an increase in these indicators could mean something else than an increase in SR. An underlying reason of why we chose to determine three Systemic Dimensions comes from that last point. We argue that an increase in SR could only be ‘significant’ if there is a common increase in all three dimensions. Thus, by studying the time-varying correlation between the dimensions, we can get an accurate view of SR.

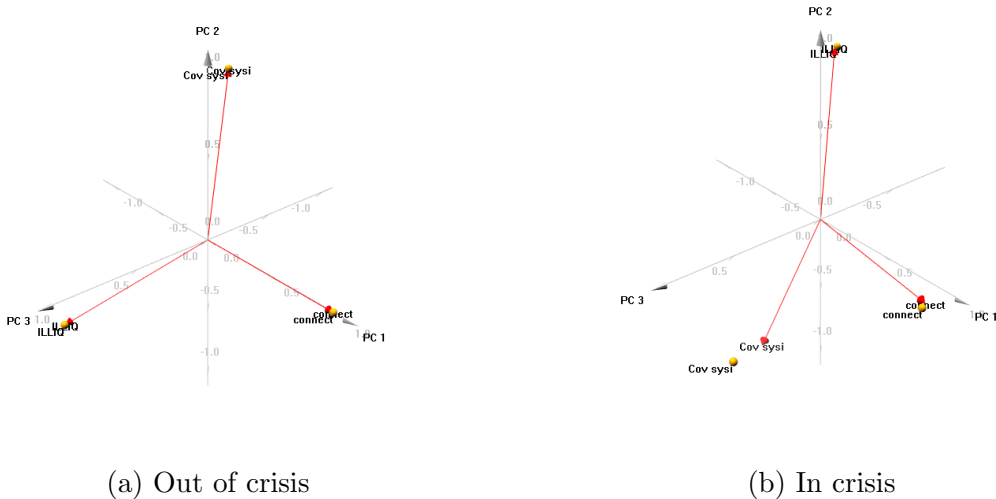
The orthogonality of the Systemic Dimensions shown in Figure II.2 constitutes a simple heuristic to understand the nature of SR. In times of financial stability¹⁵ all Systemic Dimensions are relatively close to being perfectly orthogonal, that is to say, uncorrelated. While, in crisis periods, they appear to be less orthogonal. The result is clearer for the connectedness and losses measures. The conclusion is straight forward, all dimensions are measuring different risks in stable times, which

¹⁵Here, financial stability is intended as outside of financial instability.

can increase/decrease ephemerally (i.e. noise). However, during crises, all risks occur simultaneously, which is directly translated statistically with the inertia of the first component. The results for our European sample are similar, thus bring additional robustness (see Figure II.11).

Figure II.2: Orthogonality of Systemic Dimensions - U.S. Sample

The chart shows the Systemic Dimensions on the first three principal components dimensions. The PCA is computed using an orthogonal rotation *quartimax*. ‘ILLIQ’ corresponds to the measure of Amihud (2002) that approximates the illiquidity dimension. ‘connect’ refers to the DGC of Billio et al. (2012) for systemic connectedness. ‘Cov sysi’ correspond to the $\Delta CoVaR$ of Adrian and Brunnermeier (2016) for systemic losses. All measure are performed on the sample of 75 U.S. financial firms. Chart (a) shows a nearly perfect orthogonality of all risk measures during the timespan excluding financial crises. Graph (b) shows the increase in Systemic Dimensions’ correlation occurring in financial crises periods.

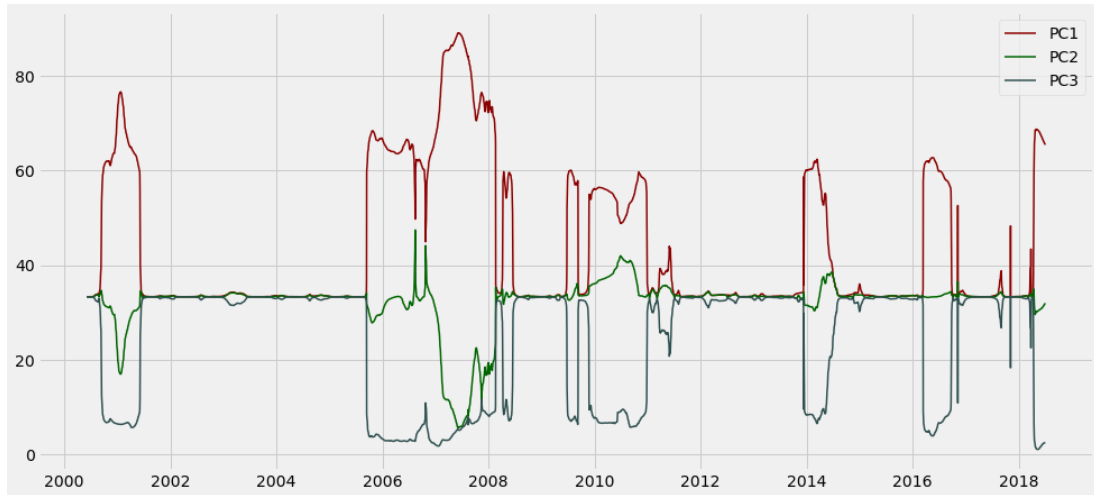


A weak point of our argumentation comes from the arbitrary choice for the stable and crises periods. In order to prove the robustness of the method, as well as its usefulness, we computed the PCA on a rolling forward window. The time-varying inertia of the first component is shown below (see Figure II.3). The variations of inertia of the first component allows to identify clearly the crises periods, with, as presented before, the residual stress for the dot-com bubble, the subprime crisis, the European debt crisis and the current coronavirus crisis (spike at the end of the graph). We can see that the realization of a systemic crisis actually happens when the increase in the explained variance of the first component occurs simultaneously with a decrease of the inertia of the other two components. In other words, a systemic crisis happens when all of the Systemic Dimensions stop to be orthogonal.

Moreover, the results computed over our European sample show similar dynamics of the inertia of principal components (see Appendix II.A.2, Figure II.9). More specifically, the SR arises when the increase of the first components is fueled by the decrease in the two other components.

Figure II.3: Inertia of the three first components - U.S. Sample

The chart shows the explained variance of the first three principal components arising from a rolling-forward PCA performed with the quartimax rotation. The procedure is performed on the U.S. sample of 75 financial firms over the 2001-2020 period. First principal component is in black, the second in red, and the third in green. An increase in the first component at the profit of the second and third means an increase in common correlation between Systemic Dimensions. The PCA is performed using a 300 days windows, the results shown are centered $([-150; +150])$



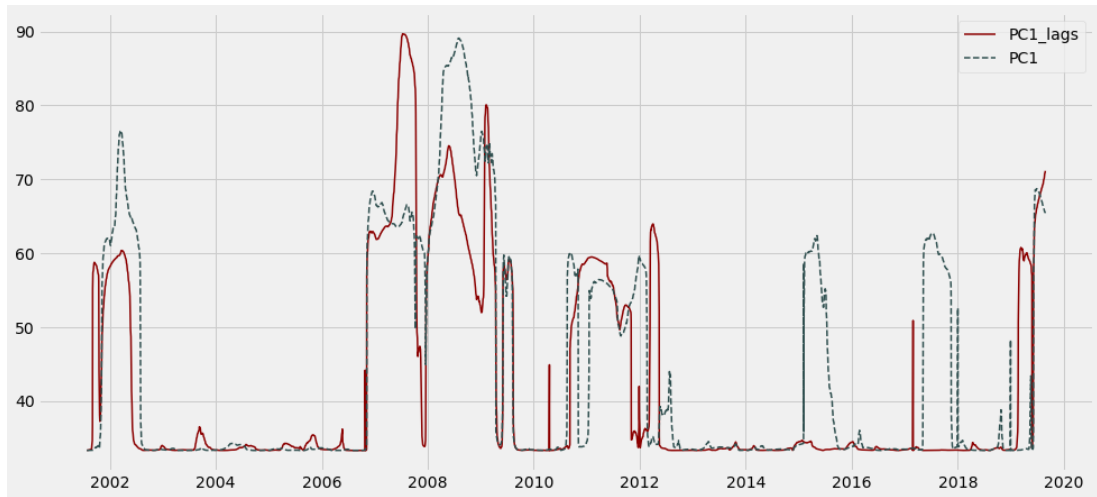
II.4.2 Lagged Systemic Dimensions

The measure is still yet to be optimal. We argued that noise was one of the reason why we needed a new measure. Yet, the inertia clearly show transitory spike between 2012 and 2020. There was not any notable financial crises in the American market over these period, and one could argue that the spike are actually noise, or, equivalently, a concomitant increase in Systemic Dimensions that was not evidence of a crisis. This particular issue comes from the temporal aspect of SR. We assumed above that all Systemic Dimensions were highly correlated *simultaneously* during crisis times. It turns out not to be precisely true. In Chapter I, described by the SEH, we displayed evidences of a particular succession of events in a systemic crisis. There is an order in which things get progressively worst. From this assumption, it

would seem reasonable to assume further that Systemic Dimensions evolve at different time, in a given order. Theoretically, the measurement would get better if we could find the appropriate lag. Practically, we lag our variables according to the supposed order, and the following results.

Figure II.4: Comparison of inertia of first components - U.S. Sample

This graph shows the explained variance of the first component for two rolling-forward PCA performed with the quartimax rotation. The first dashed series in black shows the original rolling-forward PCA of the Systemic Dimensions. The red series shows the rolling-forward PCA for which we have lagged the Systemic Dimensions. The DGC is naturally forward lagged (due to the rolling-forward procedure) of 150 days. We lagged the illiquidity indicator back for 90 days. The lagged series (in red) shows an improvement of crises identification by not incorporating the temporary increases between 2015 and 2020.



Based on the Chapter I, we propose the following process of a systemic event: first, the build of common exposure should happen early in the timeline, followed by losses and, finally, by the amplification via market illiquidity¹⁶. Since Granger causalities are performed on a rolling window, the measure is naturally delayed forward. We have tried iteratively different lags in order to find an appropriate fit for the illiquidity measure. As Figure 4 (p. 20) displays, we can get rid of the transitory spikes, by lagging our Systemic Dimensions.

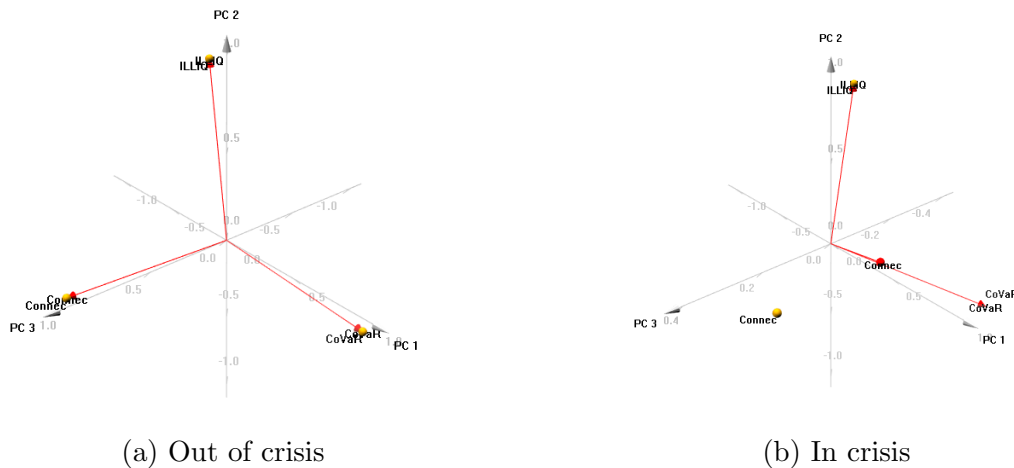
Such results put forward evidence of an order of occurrence in Systemic Dimensions. As the measure conforms to both theoretical idea of a systemic event and

¹⁶The amplification is usually accompanied by contagion. One could pose that Granger causalities constitute a proxy for contagion. We argue that Granger causalities display a potential for contagion due to a common exposure. Hence, it is a better proxy of buildup of financial fragility.

empirical periods of systemic crisis, we argue that it constitutes an initial proof that a systemic event is composed of various risks (major ones being denoted as Systemic Dimensions) which occur in a specific order. The results are also visible on the European market between 2005 and 2017. The orthogonality of Systemic Dimensions is also showed on Figure II.5.

Figure II.5: Orthogonality of Lagged Systemic Dimensions - U.S. Sample

The chart shows the lagged Systemic Dimensions on the first three principal components dimensions. The PCA is computed using an orthogonal rotation quartimax. ‘ILLIQ’ corresponds to the measure of Amihud (2002) that approximates the illiquidity dimension. ‘connect’ refers to the DGC of Billio et al. (2012) for systemic connectedness. ‘Cov sysi’ correspond to the $\Delta CoVaR$ of Adrian and Brunnermeier (2016) for systemic losses. All measure are performed on the sample of 75 U.S. financial firms. Chart (a) shows a nearly perfect orthogonality of all lagged risk measures during the timespan excluding financial crises. Graph (b) shows the increase in lagged Systemic Dimensions’ correlation occurring in financial crises periods.



The loss of orthogonality during the crisis is clearer for lagged risk measures. In our view, the importance of this result is central. Up to now, most of the existing literature on SR measurement, was implicitly assuming that only one dimension mattered¹⁷. Our result shows first, that different measures of SR are orthogonal in stable times. This means that they measure drastically different concepts, and only measure (together) SR in crisis periods. Hence, taking into account only one, blocks the analysis from capturing the full picture of SR. Secondly, there exists a chronological order in systemic crises. This second fact confirms the importance

¹⁷Each paper essentially chose a given dimension among the following: Losses, Liquidity, Connectedness, Contagion. And, assumed that this measurement proxies SR by itself.

of the first. Indeed, each dimension should be considered as they all participate in a systemic event. Our results show that, for both the U.S. and the European financial system, an increase in interconnectedness arises first. The rise in connectedness can be interpreted in two ways: First, it represents the potential for a wide spread shock, by saying that temporal cross-correlations proxy common exposures. Second, it represents the potential for contagion. In a second time the spike in financial losses occurs, captured by ΔCoVaR . Eventually, we observe the increase of exposure to market illiquidity. This sequence of events gives an initial idea of how a systemic events develop. This point in particular, will be further developed in the next chapter (Chapter III). Consequently, our results advocate for taking into account the multiplicity of Systemic Dimensions and their specific entanglement.

The regulatory implications are quite significant as well. Even though the SIFI assessment (BCBS, 2013) uses various types of indicators, the constraints posed on SIFIs are standardized. The results of this study combined by those attained in Chapter I preach that: Firstly, SR depends on various risks. Secondly, each type of financial firms has a specific profile of SR. Hence, prudential regulation should identify a specific SR profile¹⁸ per SIFI, which details where the SIFI locates in the systemic event unfolding. The changes are substantial in a way that the regulation should have to become more flexible in order to adapt to the profile of the SIFI. The main questions are the following: What firms participates in the increase of common exposure and how to restrict it? How to prevent financial losses to occur and how to prevent a contagion/amplification of these losses? Such questions have already been asked separately. Our results advise such questions to be considered conjointly.

II.4.3 Sectorial Systemic Dimensions correlation

When applying the PCA on the Systemic Dimensions only computed for a specific type of financial institution, we can see how much this particular sector was at risk. In a general sense, the method applied in this article to identify systemic crisis, is actually one for assessing the risk of a system considered. In this section, we thus propose to focus specifically on each type of financial firms to determine the

¹⁸We intend by SR profile, a detailed rapport of what risks are more relevant to this firm (or type of firm) in particular.

‘sectorial-systemic risk’.

Figure II.6: Sector-specific inertia - U.S. Sample

The graphs show the inertia of the first component arising from a rolling-forward *PCA* computed using the *quartimax* rotation over a 300 days window on the U.S. sample of 75 financial firms. An increase in the first component denotes an apparition/increase in sectorial Systemic Risk.

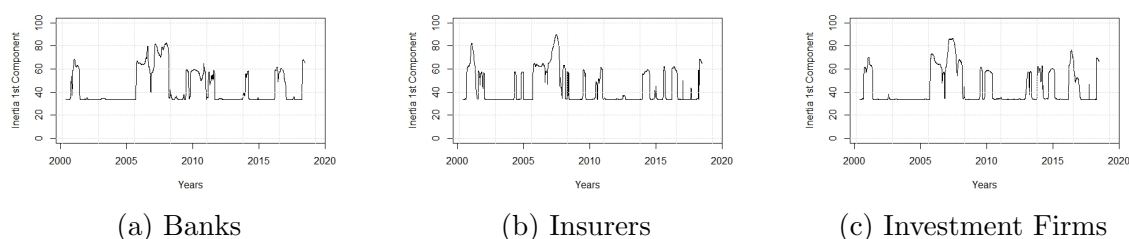
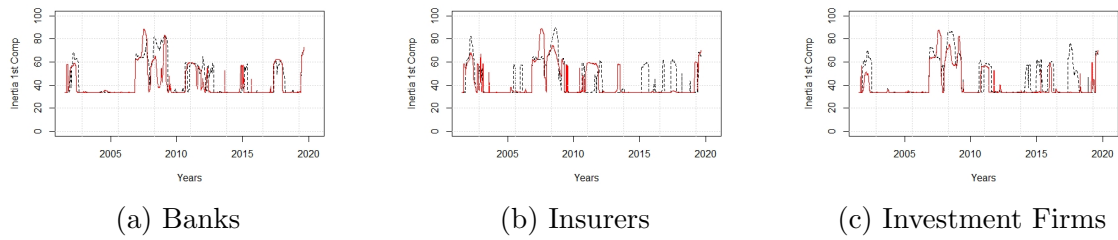


Figure II.6 emphasizes the evolution of inertia for the first components of the *PCA* for types of financial firms. The measure clearly shows spikes during the crises period in our U.S. sample, although remains more noisy than the global one (Figure II.3). This fact appears as logical. When considering a larger system, its inherent risk is determined by when most of its components are at risk¹⁹. For instance, times where only banks are at risk but insurers are not, will not be a high *SR* period globally. The noisy behavior of the measure then logically grows stronger as the system considered goes smaller. An important insight from this approach lies in identifying the period where a specific type of institution is actually risky. We can see for instance that all types of institutions were at risk during the subprime crisis, hinting the systemic aspect of the crisis. Let us then confirm that there exists a chronology in Systemic Dimensions. We apply the (identical) lags on the Systemic Dimensions and compare the accuracy of the method below (see Figure II.7).

¹⁹This is the underlying assumption for our approach.

Figure II.7: Comparison sector-specific inertia - U.S. Sample

The graphs show the comparison of inertia of the first components arising from a rolling-forward PCA computed on sectorial Systemic Dimensions with the quartimax rotation over a 300 days window, and the rolling-forward PCA computed on the lagged sectorial Systemic Dimensions, with the same calibration. The procedure is performed on the sample of 75 U.S. financial firms. The red line shows the explained variance for the first component of the lagged sectorial Systemic Dimensions, the dashed black line shows the explained variance of the first component for the sectorial Systemic Dimensions.



Without doubts, the lagging procedure allows for a reduction of the noise for all types of firms (even though slightly less for banks). Moreover, it shows more clearly the systemically risky periods in our samples. We argue that the results provide a solid initial evidence of a specific order of occurrence in Systemic Dimensions.

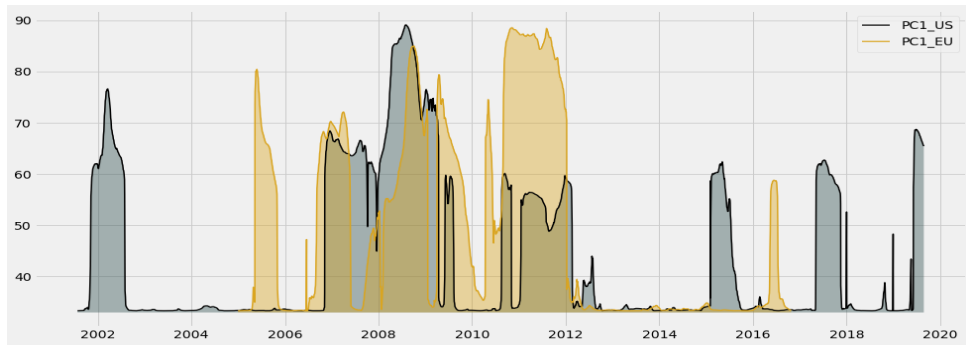
II.4.4 Comparing the European and American financial systems

This section presents the differences between the European and American cases. The first result that stands out is the common reduction in the noise of the measure for both the European and American markets. The transition from Figure II.8a to II.8b allows for a reduction in transitory spikes for both samples. This constitutes evidences that the lagging procedure (presented in Figure 4, p. 20) allows to improve the identification of crises periods. Thus, further validating the chronology of SEs.

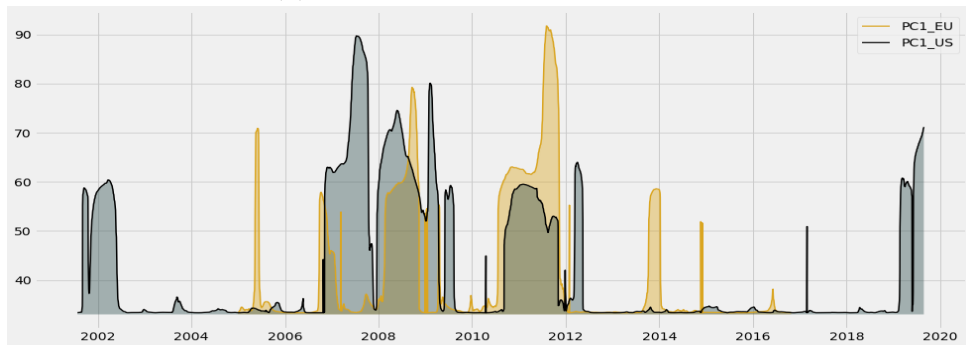
Moreover, the Figure II.8b presents notable features. It displays the delayed impact of the Subprimes crisis on the European market. Indeed, the explained variance of the first component for the U.S. sample spike in advance. Showing the loss of orthogonality in the U.S. Systemic Dimensions. The increase in the first component's inertia of the European sample only occurs in delay, after 2008. The result is coherent with historical event as the crisis started to unravel in the U.S.

first, before spreading out to the rest of the world. Furthermore, our measure allows to identify the extent of **SR** in a country. As Figure II.8 depicts, the **SR** was larger in the U.S. during the Subprimes crisis. However, the European sample show a higher level of **SR** during the European Sovereign Debt crisis. Again, the result is historically coherent. European countries have suffered more financial stress than the U.S. financial firms have during that particular time.

Figure II.8: Comparison of the 1st component's inertia - U.S. vs. Europe. The graph (a) display the inertia of the first component of a *PCA* computed on the Systemic Dimensions of our European sample compared to the one computed on our American sample. The graph (b) shows the inertia of the first components the lagged Systemic Dimensions of both sample. The Systemic Dimensions are the $\Delta CoVaR$, the exposure to market illiquidity and the *DGC*. The European sample starts in 2005 and ends in 2017, while the American sample starts in 2001 and ends in 2020. *PC1_EU* and *PC1_US* refer to, respectively, the inertia of the first component for the European and American samples.



(a) Inertia of the first components



(b) Inertia of the lagged first components

In essence, our approach²⁰ allows to study **SR** in any given system, whether it is a country, a sector or the whole financial system. The underlying assumption

²⁰We define our approach as the assessment of **SR** via the examination of the correlation of Systemic Dimensions over time.

is straightforward. The method assumes that the **SR** related to a given system, depends on the concomitant occurrence of various risks. In this view, the systemic importance of risks depends on their propensity to be accompanied by other risks. Furthermore, the procedure to follow is simple. The first step is to identify to Systemic Dimensions of the system. In order to assure the variety of risks, they should be orthogonal in stable periods. The next step is to assess the time-varying correlation between Systemic Dimensions. Using such procedure, we allow assessing the evolution of **SR** in Europe and the U.S. between 2001 and 2020 (see Figure II.8). This analysis provides additional evidences of a specific evolution of **SR** depending on the country/region examined.

II.5 Conclusion

SR measurement has been one of the most challenging field of research since the subprime crisis. The difficulties are numerous. As crises come in all sorts and flavors, it is complex to choose the variables that matter the most. Even though, a model fits existing crises, it is not obvious that such model will perform well on the next. As finance is mostly driven by human's behavior and investor's expectations, few, if none, of our available variables have stable distributions over time. Our study decided not to choose what indicator matters the most, by choosing to look at the correlation between the indicators.

We provide a correlation analysis on different **SR** measures computed on two samples: a European sample composed of a 100 financial firms, spawning from 2005 to 2018 and a American sample of 75 firms, starting in 2000 and ending in 2020. Because each measure corresponds to a specific type of risk and, as our results show, are usually orthogonal, we denote them as Systemic Dimensions. 'A moment when all goes bad' is a common thought on the nature of financial crises. Building up on this insight, we study whether it can be applied to **SR**. In such case, a systemic crisis consists in the occurrence of all its subsequent risks, hence when Systemic Dimensions lose orthogonality. We propose a rolling-forward **PCA** analysis on the Systemic Dimensions. We find that Systemic Dimensions are orthogonal outside of crises period and lose their orthogonality to become correlated during crisis periods. Moreover, we see that realized systemic crises are identified as moments when

the explained variance of first principal component increases due to the fall of the two others. This constitutes a solid evidence that **SR** occurs when multiple risks happen concomitantly, i.e. when all Systemic Dimensions become correlated. The results are similar for the European market. Additionally, we show that, by lagging some Systemic Dimensions in time, we allow for a clearer identification of systemic crisis periods. The result constitutes an evidence of a specific order in a systemic event. From our results, an increase in connectedness happens first. It is followed by a spike in financial losses. Finally, the exposure to market illiquidity rockets. We present the first research in our knowledge, to provide empirical evidence of a specific order in the occurrence of risks during a systemic event. This results opens research opportunities in **SR** measurement and predictions; as well as in prudential regulation. Furthermore, we compare the evolution of **SR** for the European and American financial system. Our method allows to describe the transmission of **SR** from the U.S. to Europe during the Subprimes crisis, and shows the differences in the level of **SR** during financial crises. In particular, we show that, logically, the European financial system was more at-risk than the American during the European Sovereign Debt crisis.

As time passes by, the financial world keeps getting more complex than ever. There is no certitude as if a proper **SR** model will ever exists. Mostly, due to the Lucas' critique (Lucas, 1976). Indeed, if a perfect model to predict **SR** existed, it is probable that financial agents will act in such a way that the model would become obsolete. However, models that are flexible, in the sense that they do not rely on precise indicators, have a chance to guide prudential regulation to financial resilience.

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II.A Appendix

II.A.1 Mathematical Developments

Gaussian model for the estimation of CoVaR

We assume that two random variables X_i and X_j follow a bivariate Gaussian distribution. We note:

$$(X_i(t), X_j(t)) \sim \Phi\left(0, \begin{pmatrix} \sigma_i^2(t) & \rho(t)\sigma_i(t)\sigma_j(t) \\ \rho(t)\sigma_j(t)\sigma_i(t) & \sigma_j^2(t) \end{pmatrix}\right) \quad (\text{II.21})$$

Since both firms i and j follow a bivariate normal distribution, we can write the conditional distribution for firm i as:

$$X_j(t) | X_i(t) \sim \Phi\left(\frac{X_i(t)\sigma_j(t)\rho(t)}{\sigma_i(t)}, (1 - \rho^2(t))\sigma_j^2(t)\right) \quad (\text{II.22})$$

We define the standardized value of our random variable X_j as Z_j :

$$Z_j(t) = \frac{X_j(t) - X_i(t)\sigma_j(t)\rho(t)/\sigma_i(t)}{\sqrt{1 - \rho^2(t)}\sigma_j(t)} \quad (\text{II.23})$$

And, as such :

$$Z_j(t) \sim \Phi(0, 1) \quad (\text{II.24})$$

We then come back to the definition of the Conditional Value-at-Risk:

$$Pr(X_j \leq CoVaR^{j|i}(q, p) | X_i = VaR_i(p)) = q \quad (\text{II.25})$$

Which we can rearrange by standardizing X_j into Z_j :

$$Pr\left(Z_j(t) < \frac{CoVaR^{j|i} - X_i(t)\sigma_j(t)\rho(t)/\sigma_i(t)}{\sqrt{1 - \rho^2(t)}\sigma_j(t)} | X_i(t) = VaR_i(p, t)\right) = q \quad (\text{II.26})$$

And, finally, we can develop this into its final form:

$$CoVaR^{j|i}(q, p, t) = \Phi^{-1}(q)\sigma_j(t)\sqrt{1 - \rho^2(t)} + \Phi^{-1}(p)\rho(t)\sigma_j(t) \quad (\text{II.27})$$

II.A.2 Figures

Figure II.9: Inertia of the three first components for the European sample

The chart shows the explained variance of the first three principal components arising from a rolling-forward *PCA* performed with the *quartimax* rotation on our European Sample of 25 Banks, 25 Insurers, 25 Investment Firms and 25 Brokers over the 2005 to 2018 period. First principal component is in black, the second in red, and the third in green. An increase in the first component at the profit of the second and third means an increase in common correlation between Systemic Dimensions. The *PCA* is performed using a 300 days windows, the results shown are centered $([-150; +150])$

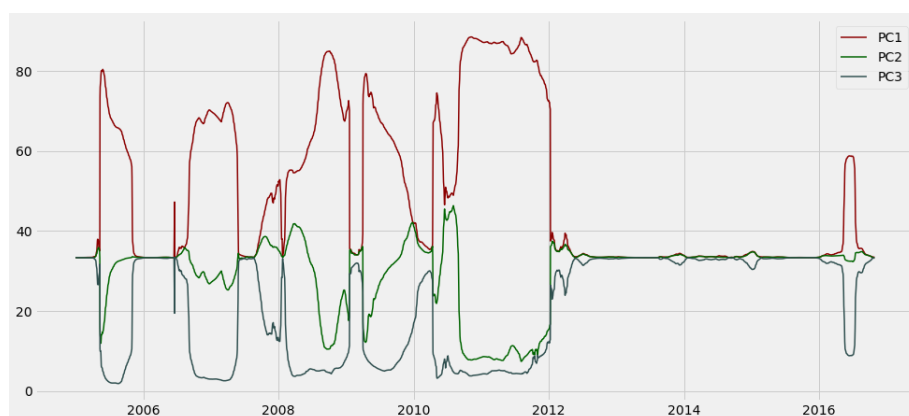


Figure II.10: Comparaison of inertia of first components for the European sample

This graph shows the explained variance of the first component for two rolling-forward *PCA* performed with the *quartimax* rotation on our European sample of 25 Banks, 25 Insurers, 25 Investment Firms and 25 Brokers over the 2005 to 2018 period. The first dashed series in black shows the original rolling-forward *PCA* of the Systemic Dimensions. The red series shows the rolling-forward *PCA* for which we have lagged the Systemic Dimensions. The *DGC* is naturally forward lagged (due to the rolling-forward procedure) of 150 days. We lagged the illiquidity indicator back for 90 days.

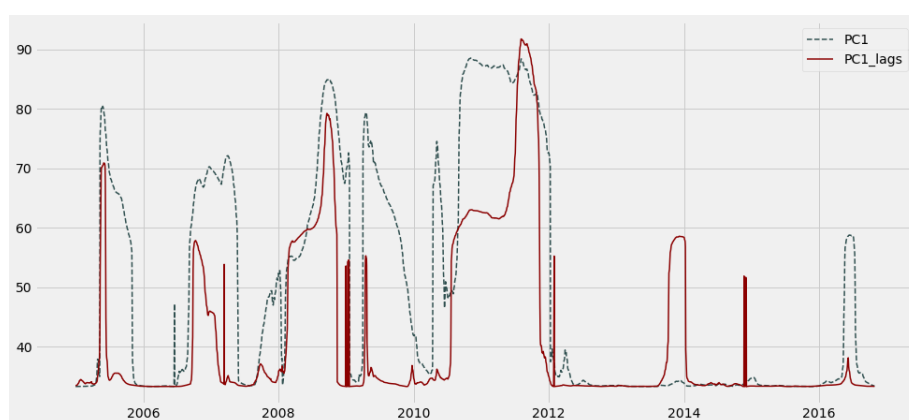
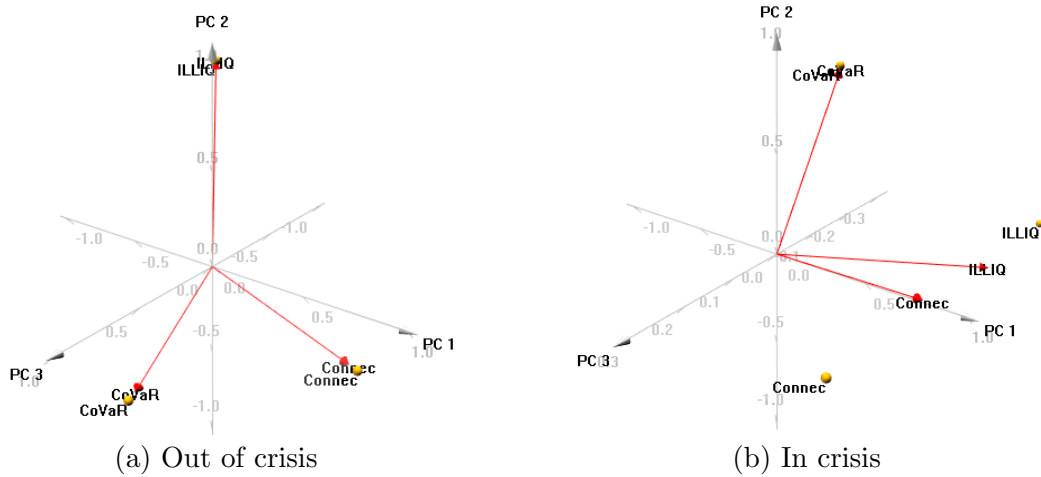


Figure II.11: Orthogonality of Systemic Dimensions - European Sample

The chart shows the Systemic Dimensions on the first three principal components dimension. The PCA is computed using an orthogonal rotation *quartimax*. 'ILLIQ' corresponds to the measure of Amihud (2002) that approximates the illiquidity dimensions. 'connect' refers to the *DGC* of Billio et al. (2012) for systemic connectedness. 'Cov sysi' correspond to the ΔCoVaR of Adrian and Brunnermeier (2016) for systemic losses. All measure are performed on the sample of 100 European financial firms. Chart (a) shows a nearly perfect orthogonality of all risk measures during the timespan excluding financial crises. Graph (b) shows the increase in Systemic Dimensions' correlation occurring in financial crises periods.



II.A.3 Tables

Table II.1: **Summary Statistics - U.S. Sample**

Summary statistics for daily returns of the 75 firms of our U.S. sample: June 2000 to June 2020. Of the 75 firms, 25 are banks, 25 insurers, and 25 investment firms. We include the annualized mean, annualized standard deviation, minimum, maximum, skewness, and kurtosis of the annualized daily returns.

<i>Full Sample</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Banks	25	0.003	0.381	0.725	-0.893	0.0	-0.116	59.689	-0.077
Insurance	25	0.038	0.351	1.982	-2.000	0.0	-0.375	94.063	-0.087
Asset Management	25	0.015	0.417	0.663	-1.024	0.0	-0.366	20.927	-0.045
<i>During Crises</i>									
Banks	25	-0.332	0.568	0.668	-0.893	-0.0	0.373	48.023	-0.084
Insurance	25	-0.259	0.494	0.705	-0.936	-0.0	-0.539	17.377	-0.094
Asset Management	25	-0.293	0.598	0.663	-0.687	-0.0	-0.378	14.887	-0.080
<i>Outside of Crises</i>									
Banks	25	0.173	0.279	0.725	-0.663	0.0	0.451	44.525	-0.075
Insurance	25	0.187	0.272	1.982	-2.000	0.0	0.455	84.495	-0.068
Asset Management	25	0.175	0.321	0.605	-1.024	0.0	-0.000	22.493	-0.011

Table II.2: **Summary Statistics - European Sample**

Summary statistics for daily returns of the 100 firms of our European sample: June 2000 to June 2020. The sample includes 25 banks, 25 brokers, 25 insurers, and 25 investment firms. We include the annualized mean, annualized standard deviation, minimum, maximum, skewness, and kurtosis of the annualized daily returns.

<i>Full Sample</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Banks	25	-0.024	0.441	0.413	-1.157	0.0	-0.445	21.202	0.043
Brokers	25	0.010	0.521	1.006	-0.939	0.0	0.454	27.681	-0.053
Insurance	25	0.079	0.341	0.788	-1.495	0.0	-0.882	48.047	0.002
Asset Management	25	0.063	0.414	0.517	-1.181	-0.0	-0.239	28.101	-0.008
<i>During Crises</i>									
Banks	25	-0.466	0.574	0.413	-0.877	-0.002	0.137	7.394	0.046
Brokers	25	-0.246	0.561	0.647	-0.698	-0.000	-0.411	17.037	-0.070
Insurance	25	-0.260	0.458	0.302	-1.495	-0.001	-0.500	16.851	-0.001
Asset Management	25	-0.357	0.480	0.511	-0.678	-0.001	-0.248	12.567	0.004
<i>Outside of Crises</i>									
Banks	25	0.247	0.373	0.363	-1.157	0.000	-0.446	18.256	0.032
Brokers	25	0.140	0.497	1.006	-0.939	0.000	0.884	25.037	-0.053
Insurance	25	0.247	0.279	0.788	-0.887	0.001	-0.120	17.523	0.004
Asset Management	25	0.316	0.378	0.517	-1.181	0.000	0.012	28.431	-0.033

Chapter III

Which Systemic Risks affect which financial institutions at what stage of the crisis?

III.1 Introduction

Banks have been prudentially regulated for a long time, and such regulations first became subject to international standards through the Basel I Accord in 1988. As described in Dewatripont and Tirole (1994), the banking sector was the first to be regulated in this way, not only because its core activity is systemic but because it looks after large sums of money for small and unskilled depositors. The very nature of the interbank market makes it vulnerable to systemic crises because failures can spread from bank to bank, leading to a loss of confidence and, ultimately, bank runs. Banks and insurers were the first to be subject to prudential supervision at the end of the millennium. However, after the 2007-2009 subprime mortgage crisis, other types of financial institution have also been seen as systemic. Since then, prudential regulators have pursued the increasingly delicate task of ensuring financial stability while allowing financial institutions to continue carrying out their core activities. This task has become more challenging as the number and size of institutional agents has increased over recent years. Interaction between the agents, which requires the use of different measures to capture distinct dimensions of **Systemic Risk (SR)**, makes the task especially complex. We already know the type of **SR** associated with banks: As they rely on the interbank market to provide short-term funding, they are exposed to the effects of contagion, which are demonstrated by cascading failures, and to interbank market freezing. Similarly, insurers are exposed to redemption runs. However, recent work supports the systemic importance of other institutional investors (Billio et al., 2012; Roncalli & Weisang, 2015; OFR, 2013; Kress, McCoy, & Schwarcz, 2018). As given in details in the Office of Financial Research report (OFR, 2013), for example, investment firms can engage in a behaviour commonly called “reaching for yield”. Due to their obligations to their clients, investment funds need to perform to a set standard. As they all search for alpha, they unknowingly engage in correlated investment strategies. The report thus suggests that banks and insurers are not the only firms to create **SR**. Indeed, the survey of Bisias, Flood, and Lo (2012) specifies that **SR** occurs endogenously in the financial system. The underlying implication, therefore, is that every type of financial firm has a role in the formation of **SR**.

Accordingly, we add to the existing literature by identifying **SR** based on the

type of financial firm and by studying differences in **SR** between large and small market capitalization firms in Europe and the United States. As **SR** is a multidimensional concept, we develop the comparison of interconnected risk between the financial sectors performed by Billio et al. (2012). We go beyond their original article by studying the interconnectedness of various financial institutions along with other type of **SR**. Furthermore, while Billio et al. (2012) study the case of the U.S., we extend our analysis by considering both the U.S. and European financial system, and by introducing the post-crisis period, as our data extends to 2021, while theirs stops in 2008. In a similar vein, Hué, Lucotte, and Tokpavi (2019) provide a development of the analysis of Billio et al. (2012), focussed on systemic banks. Similarly, we add to their work by considering multiple risk indicators, and for different financial institutions besides banking institutions. In doing so, our study allows a more complex and comprehensive understanding of the distribution of risk in the financial system. The results could be of particular interest to regulators as we demonstrate which risk occurs at what time for which kind of institution. Indeed, in order to formulate efficient regulations, regulators need to properly understand the nature of the **SR** carried by each agent. Current prudential regulation already takes into account multiple types of risk to identify systemically important financial institutions (SIFIs); however, the slight differences between the assessment methodologies used by regulators are not yet supported by academic work. Furthermore, this study demonstrates the need for different risk measures when assessing **SR**. This need implies that **SR** stems from multiple sources and therefore relies on interconnections in the financial system. We do not believe that the multidimensionality of **SR** has been sufficiently scrutinized in the literature, until now. In this article, we follow our initial intuition that each type of financial firm faces a unique form of risk, and that proper regulation should be developed accordingly. In doing so, we have formulated the following research questions:

1. Do different types of financial firm have different roles in a systemic crisis?
2. Within these types, does **SR** vary between large and small market capitalization firms?

Considering the varied nature of **SR**, we use a combination of three measures, namely: the $\Delta CoVaR$ of Adrian and Brunnermeier (2016), the Degree of Granger Causality (DGC) of Billio et al. (2012), and the ILLIQ of Amihud (2002). Each

CHAPTER III. Which Systemic Risks affect which financial institutions at what stage of the crisis?

measure describes a different, complementary element of **SR**. This combination of measures allows us to examine the **SRP** of each sector and its evolution over time. Our financial sectors are: banks, insurers, and asset managers. This breakdown of financial sectors follows the rationale given by Billio et al. (2012), in which the initial motivation is to take into account the links between the institutions. For example, insurers started to insure financial products that are extensively used by banks and investment funds. Similarly, securitization and credit link the banking sector to the rest of the financial system. In short, the complexity of the financial system itself reflects the nature and volume of the interactions between financial firms.

Our sample includes the daily returns of 417 European and U.S. financial firms, divided into three sectors and covering the period 2001 to 2021. Since the price of a stock reflects investors' expectations of a firm's future performance, using returns on stocks enables us to incorporate the most recent information. Moreover, market data allows daily observations, whereas accounting variables are, at best, available quarterly. The empirical results show significant differences in terms of the type and scale of **SR** of the sectors. Asset managers are the most interconnected and exposed to illiquidity, while insurers have the largest exposure to losses. Surprisingly, banks do not appear as the most systemic agent, regardless of the risk considered or the period. We show that large firms tend to be more interconnected and exposed to losses, while small firms have the highest level of illiquidity, especially small insurers. Finally, we observe that each type of **SR** (Systemic Dimensions henceforth) peaks successively: a rise in interconnectedness leads to a peak in loss exposure which ends in a spike of illiquidity. This leads us to believe that there is a determinate chronology in systemic crises, and, by using the results stated above, we can associate a type of institution to a specific step of a systemic crisis.

The rest of this article is structured as follows. Section 2 introduces the existing literature: theoretical models of **SR** and existing measures. Section 3 presents methodology and the specifications of the three measures used. Section 4 presents the characteristics of our sample and how the data were acquired. Section 5 details our findings and the regulatory implications of our results. Section 6 concludes and provides recommendations for future research.

III.2 Literature Review

This section provides a brief overview of the fundamental knowledge regarding SR. It begins by building on theoretical models of SR, from the early banking-focussed models to more recent approaches. We then present the different measures for SR, following the taxonomy provided by Bisias, Flood, and Lo (2012).

III.2.1 Theoretical models of Systemic Risk

SR has become a well-known concept. Intrinsically linked to the study of financial crises and bank runs, it was first documented by the pioneering work of Kindleberger (1978) in their detailed analysis of a financial crisis and bubbles and in Bryant (1980) and Diamond and Dybvig (1986), with their model on bank runs and deposit insurance. The results obtained in these studies constituted a drastic development in understanding how banks can generate risk in the financial system. One finding that is worth stressing that of Diamond and Dybvig (1986), which warns against the possible negative effects of central banks acting as the lender of last resort. This particular issue took on a new dimension after the crisis of 2007, when banks had to be bailed out to preserve financial stability following the failure of Lehman Brothers. Each of these studies created solid foundations for future research, and their findings have been used extensively by the literature that followed.

To draw a connection between the literature on banking risk and the literature on financial stability, we could not omit Mishkin (1992), Kindleberger (1978), and Minsky (1991). Although they agree on some factors that can give rise to SR, no consensus was reached on a comprehensive list of systemic factors. For Mishkin, certain factors are known to be a source of financial instability. Among these are an increase in interest rates, a crash in the stock market, increasing uncertainty, an unexpected drop in the aggregate price level, and, the most studied type of systemic event, bank runs. Kindleberger (1978) and Minsky (1991) agree that the procyclical behaviour of the credit supply increases SR. In fact, it is partly due to Minsky's model (1991) that regulators and academics began to study countercyclical policies..

Related to the study of bubbles and crises, Bernanke and Gertler (1989) created a neoclassical model showing that a shock in asset prices can initiate self-reinforcing

business fluctuations. Their model is reinforced by the findings of Freixas (2018), who shows that credit and equilibrium asset prices also have a self-reinforcing relationship. The relationship between asset prices and credit is also modeled by Kiyotaki and Moore (1997). They show how this relationship causes shocks to persist, amplify, and spread to other sectors. Both Bernanke and Gertler (1989) and Kiyotaki and Moore (1997) were among the first to show the importance of business and credit cycles to financial stability. Although these theories seem to support the use of countercyclical buffers put in place by Basel III, the work of Horvath and Wagner (2017) provides a limiting perspective. Horvath & Wagner's model shows that countercyclical policies are intrinsically linked to the interconnectedness of markets and that countercyclical buffers thus tend to strengthen the correlations in the banking system. Given a choice, regulators should instead focus on diminishing the interconnectedness of the banking sector, as this would have more beneficial effects than restricting business cycles. In line with these theories, Shleifer and Vishny (1992) show that banks' optimal debt levels vary according to their relationship with asset liquidity. Moreover, their model demonstrates that a bank's maximum leverage is not obtained endogenously but depends on other banks' levels of leverage. Consequently, given the similarity of assets within similar industries, a fire sale by a bank in distress might have a greater impact than expected. Additionally, Acharya and Thakor (2016) tell us that the probability of a bank's liquidation does not depend solely on its own leverage, but also on that of the overall banking system. The work of Adrian and Shin (2014) and Danielsson, Shin, and Zigrand (2004) shows that regulation based on Value-at-Risk is procyclical because VaR is itself procyclical, as banks have similar VaR models and similar investments. When markets go down, therefore, the VaR model for most bankers tells them to sell, thereby making the drop worse.

III.2.2 Types of measures of Systemic Risk

Alongside the development of theoretical models, academics have created new and innovative tools with which to measure SR. As stated by Benoit et al. (2017), this second strand of the literature is not rooted in any particular theory but rather aims to provide insight into how both academics and regulators can measure risk. The measurement of SR has already been the subject of much research. Most notably, the survey of Bisias, Flood, and Lo (2012) summarizes most of the measures created

up to now. It is also worth noting that the taxonomy for researchers developed by Bisias, Flood, and Lo (2012) provides a new perspective on how to classify all measures of SR.

Some measures have already been widely documented and analyzed, such as *CoVaR* (Adrian & Brunnermeier, 2016), SRISK (Acharya, Engle, & Richardson, 2012), co-risk (Chan Lau et al., 2009), variance decomposition (Kritzman et al., 2011), systemic expected shortfall (SES) (Acharya et al., 2017), and the distressed insurance premium (Huang, Zhou, & Zhou, 2009, 2012). One major advantage of these measures is that they use public data. We present well-known SR measures, organized by their specific type:

1. Cross-Sectional Measures: Most cross-sectional measures allow us to study the co-dependence of two or more financial institutions together. The major work in this area is undoubtedly the SES of Acharya et al. (2017), which is inherently dependent on the marginal expected shortfall (MES). MES is the measure of how much an institution contributes to the overall risk of a group of similar institutions. For instance, it can measure how much one bank contributes to the risk of the overall banking system. Engle, Jondeau, and Rockinger (2015) developed MES significantly by using a dynamic conditional beta (DCB) methodology provided by Engle (2016) and a univariate asymmetric GARCH model in order to construct the long-run marginal expected shortfall (LRMES) and, subsequently, SRISK. Engle, Jondeau, and Rockinger (2015) apply the measure to European data and find that some banks can be considered “too big to be saved,” which is to say that the cost to taxpayers of bailing out the bank would be too high. Other significant research includes conditional Value-at-Risk (Adrian & Brunnermeier, 2016) along with co-risk (Chan Lau et al., 2009). While *CoVaR* only requires financial returns, the co-risk measure requires Credit Default Swap (CDS) spread data, which can be more difficult to obtain. Another interesting feature of *CoVaR* is that the measure can show how much risk an institution has based on other institutions being at risk. Additionally, by using GARCH volatility modeling, *CoVaR* can become a forward-looking measure. The drawback of using such methods is that it relies on public returns data, which can be unreliable. At this juncture, we cannot omit the work of Hautsch, Schaumburg, and Schienle (2014), who developed a measure that appears

similar to *CoVaR*. The indicator defines the systemic impact of a firm i , as the effect of a change in firm i 's tail risk on the system's tail risk, given a particular network structure. This measure differs from that of Adrian and Brunnermeier (2016), as it focuses on the tail risk rather than a conditional probable loss. As well as monitoring the development of SR, the approach constructed in this chapter allows us to go beyond SR and classify firms as recipients, transmitters, or producers of SR. The work of Hautsch, Schaumburg, and Schienle (2014) links the literature on cross-sectional measures to research on financial networks.

2. Network and Connectedness Measures: As SR cannot be captured only by looking at macroeconomic features and firms' co-dependencies, the effects and connections of networks have been the subject of another major stream of SR-related research. Significant developments in the literature on networks have been made most notably by Acemoglu, Ozdaglar, and Tahbaz-Saheli (2015) on the structure of financial networks, Amini, Cont, and Minca (2016) on the resilience of networks, Allen, Babus, and Carletti (2010) on the use of the network theory in finance. A useful survey is Caccioli, Baruca, and Kobayashi (2018) on networks models of SR. Amongst the best-known measures of systemic linkages are the Granger causality networks developed by Billio et al. (2012) and further studied by Hué, Lucotte, and Tokpavi (2019).

3. Illiquidity Measures: The impact of liquidity on SR has been studied by, among others, Amihud (2002) with the ILLIQ measure and Khandani and Lo (2011) with their measures of equity market liquidity, which are based on a contrarian investment strategy and a price impact measure inspired by the model of Kyle (1985). Furthermore, the work of Getmanky, Lo, and Makarov (2004) uses the autocorrelation of hedge fund returns as a basis from which to extrapolate illiquidity exposure, thereby generating an alternative illiquidity measure. However, as hedge fund returns are reported with a fixed lag, it is impossible to use this measure for real-time monitoring.

Each of these studies focuses on a particular aspect of SR. We believe that SR is multidimensional and, hence, is composed of various risks. In order to analyze the 'actual' SR in the European financial system, we have employed three indicators. The three measures have been chosen accordingly to the three types of measurement explained above. By choosing different types of risk, we have developed an analysis

that takes three different perspectives on what SR really is.

III.3 Methodology

In this section, we present our proxy for the Systemic Dimensions. The three measurements are: $\Delta CoVaR$ (Adrian & Brunnermeier, 2016), Degree of Granger Causality (DGC) (Granger, 1969; Billio et al., 2012), and ILLIQ (Amihud, 2002). Of these, $\Delta CoVaR$ is used as a proxy for systemic losses; DGC as a proxy for the potential for contagion, and ILLIQ (Amihud, 2002) as a proxy for illiquidity¹.

III.3.1 CoVaR

We turn to the methodology of the delta-conditional Value-at-Risk ($\Delta CoVaR$), developed by Adrian and Brunnermeier (2016). We consider specifically the Exposure- $\Delta CoVaR$, which focusses on how much a firm is at risk when the system is stressed. By definition, the $CoVaR$ is the VaR of an institution conditional on some event $\mathbb{C}(R_i)$ on firm i 's returns (R_i):

$$CoVaR^{j|i}(q) \equiv Pr(R_j \leq CoVaR^{j|i}(q) | \mathbb{C}(R_i)) = q \quad (III.1)$$

The formulation of the $CoVaR$ is useful when it comes to changing the condition terms, which generates multiple values and multiple interpretations of the measurement. In this chapter, we consider the event $\mathbb{C}(R_i)$ to be the fact that the i^{th} firm's returns are at their VaR , and so

$$CoVaR^{j|i}(q, p) \equiv Pr(R_j \leq CoVaR^{j|i}(q, p) | R_i = VaR_i(p)) = q \quad (III.2)$$

Where the VaR is defined as

$$VaR_i(p) \equiv Pr(R_i \leq VaR_i(p)) = p \quad (III.3)$$

In order to construct the $\Delta CoVaR$, we need to subtract the 50% level $CoVaR$ from the $q\%$ level $CoVaR$. This specification describes the differences in $CoVaRs$

¹The computation of the measurements are based on the original code provided by Belluzzo (2021) which has been slightly modified for the purpose of this chapter.

between when the conditioning event is that firm i is distressed and when it is “stable” or at its usual level. Formally, this is

$$\Delta CoVaR^{j|i}(q, p) = CoVaR^{j|i}(q, p) - CoVaR^{j|i}(q, 50\%) \quad (\text{III.4})$$

In order to follow the methodology given by Adrian and Brunnermeier (2016), we estimate $\Delta CoVaR$ using quantile regressions at the q quantile². In contrast to the Gaussian model (see Adrian and Brunnermeier (2016)), quantile regressions allow the use of state variables which will condition the mean and volatility of the risk measure. Furthermore, different firms’ returns can have different loadings on each state variables hence correlations between the risk measures of different firms are not imposed by construction. The regressions are performed using lagged state variables ($\mathbb{M}(t - 1)$) according to the original methodology. Our state variables for the U.S. and European samples are given in detail in the next section. First,

$$R^{sys}(t) = \alpha_q^{sys} + \gamma_q^{sys}\mathbb{M}(t - 1) + \varepsilon_q^{sys}(t) \quad (\text{III.5})$$

$$R^{i|sys}(t) = \alpha_q^{i|sys} + \gamma_q^{i|sys}\mathbb{M}(t - 1) + \beta_q^{i|sys}R_q^{sys}(t) + \varepsilon_q^{i|sys}(t) \quad (\text{III.6})$$

Here, $R^{sys}(t)$ is the return of the market index at time t , $R^{i|sys}(t)$ is the conditional return of firm i with respect to the market index at time t , $\varepsilon_q^{i|sys}(t)$ and $\varepsilon_q^{sys}(t)$ are uncorrelated white noise, and $\alpha_q^{sys}, \alpha_q^{i|sys}, \gamma_q^{sys}, \gamma_q^{i|sys}, \beta_q^{i|sys}$ are the regression coefficients at the q quantile. We estimate equations (5) and (6) and use the estimated coefficients ($\hat{\alpha}_q^{sys}, \hat{\gamma}_q^{sys}, \hat{\alpha}_q^{i|sys}, \hat{\gamma}_q^{i|sys}, \hat{\beta}_q^{i|sys}$) in order to estimate our VaR_q^{sys} and $CoVaR^{i|sys}$ as given in detail below (see the complete demonstration in Adrian and Brunnermeier (2016) p. 1718).

$$VaR_q^{sys}(t) = \hat{\alpha}_q^{sys} + \hat{\gamma}_q^{sys}\mathbb{M}(t - 1) \quad (\text{III.7})$$

$$CoVaR^{i|sys}(t) = \hat{\alpha}_q^{i|sys} + \hat{\gamma}_q^{i|sys}\mathbb{M}(t - 1) + \hat{\beta}_q^{i|sys}VaR_q^{sys}(t) \quad (\text{III.8})$$

²In order to follow the comprehensive description of the quantile regression procedure and complete the development of the measure, we recommend the original work of Adrian and Brunnermeier (2016).

Hence

$$\Delta CoVaR^{i,sys}(t) = \hat{\beta}_q^{i,sys} (VaR_q^{sys}(t) - VaR_{50}^{sys}(t)) \quad (III.9)$$

III.3.2 Degree of Granger Causality

We base our methodology on that of Billio et al. (2012) and develop Granger causality tests (Granger, 1969) to study the interconnectedness of the firms in our sample. Granger causality tests are presented as in the original methodology of Granger (1969). This measurement performs two regressions by inverting the explained and explanatory variables and adding a lagged value of the explained variable. In other words, for the first regression, we regress the returns of the i^{th} firm against the lagged value of the j^{th} firm's returns and its own lagged values. The second regression is the same except that it inverts i and j in the regression. Formally, this is

$$\begin{aligned} R_i(t+1) &= \alpha_i R_i(t) + \beta_{ij} R_j(t) + \varepsilon_i(t+1) \\ R_j(t+1) &= \alpha_j R_j(t) + \beta_{ji} R_i(t) + \varepsilon_j(t+1) \end{aligned} \quad (III.10)$$

Here $R_i(t)$ is the return for the i^{th} firm and $R_j(t)$ the return for the j^{th} firm, while $\varepsilon_j(t+1)$ and $\varepsilon_i(t+1)$ are two uncorrelated white noises. We accept that the returns of firm i have caused firm j 's returns if $\beta_{ji} \neq 0$; conversely, if $\beta_{ij} \neq 0$ then it is firm j that causes the returns of firm i . We denote the fact that firm i 's returns cause firm j 's returns by the following:

$$\begin{aligned} (i \rightarrow j) & \text{ if } \beta_{ji} \neq 0 \\ (j \rightarrow i) & \text{ if } \beta_{ij} \neq 0 \end{aligned} \quad (III.11)$$

As stated by Billio et al. (2012), if both coefficients are significantly different from 0, there is a feedback relationship between the two asset returns. In order to show robustness, we perform Granger causality regressions with significance at the 1%, 5% and 10% level of confidence (displayed results are at the 5% level). Our Granger regressions at 1% allow for the same analysis, the only difference being in the absolute amount of connections realized³. Finally, similarly to Billio et al. (2012), we compute the degree of Granger causality (DGC), and check for intra-sectorial connectedness.

³We observe the same graphics as the ones displayed in Appendix B.4, the percentage of total realized connections are simply lower.

- The Degree of Granger Causality is the fraction of realized Granger connections⁴ given all possible connections. The DGC gives an idea of the global interconnectedness of the system. It is constructed as follows:

$$DGC = \frac{1}{N(N-1)} \sum_{i=1}^N \sum_{j \neq i} (j \rightarrow i)$$

We compute the DGC for each firm, showing their connectedness level, 100% meaning a total realization of all possible connections.

- The Intra-sectorial Connectedness is the percentage of connections realized between firms of the same sector with respect to all the connections realized by the sector.

$$\left(\sum_{\beta=\alpha} (S|\beta) \rightarrow (j|\alpha) \right) = \frac{1}{(M-1)N/M} \sum_{\beta=\alpha} \sum_{i \neq j} ((i|\beta) \rightarrow (j|\alpha))$$

III.3.3 ILLIQ

To compute a proxy for illiquidity, we follow the methodology of Amihud (2002) in developing ILLIQ. This measure can be interpreted as the daily volume adjusted price variation or, alternatively, the response of the price to an increase by one dollar in the volume of trading. Although ILLIQ can also be considered a price impact measure, it remains an attractive illiquidity proxy due to its simplicity and the availability of its components. We call ILLIQ_A the original measure of Amihud (2002) and ILLIQ the measure developed later on. The ILLIQ_A indicator for a single firm is defined as

$$ILLIQ_A_i(t) = \frac{|R_i(t)|}{VOLD_i(t)} \quad (III.12)$$

With $R_i(t)$ being the return for firm i at time t . Similarly, $VOLD_i(t)$ represents the euro volume for firm i at time t . Evidently, the ratio follows the definition of illiquidity as defined by Kyle (1985), which is to say the percentage of price change resulting from an increase in the daily trading volume by one unit, here, in U.S. dollars. The measure in itself remains quite simplistic and needs to be adjusted for the purposes of this study. In order to capture, sustainable changes in illiquidity

⁴At the 95% level of confidence.

and also to take into account the fact that illiquidity is more systemic when returns are negative, we follow the prescription of the Volatility Lab (V-Lab) of New York University, and compute an Asymmetric Multiplicative Error Model (MEM) for our illiquidity measure. The measure presented in the rest of this study is in fact, the conditional mean of $ILLIQ_A$ ($ILLIQ(t)$) which captures changes in the trend of illiquidity, and, thanks to the Asymmetric MEM, accounts for the fact that illiquidity is more systemic when returns are negative. That is, we assume that

$$ILLIQ_A(t) = ILLIQ(t)\varepsilon(t) \quad (III.13)$$

where $\varepsilon(t)$ follows a non-negative support distribution with mean one and variance σ_ε^2 . In such a case, $ILLIQ(t)$ is the conditional mean of $ILLIQ_A(t)$. The model further postulates that

$$ILLIQ(t) = \omega + (\alpha + \mathbb{I}(t-1)\gamma)ILLIQ_A(t-1) + \beta ILLIQ(t-1) \quad (III.14)$$

where $\mathbb{I}(t-1)$ is the indicator function. This allows giving a greater value to $ILLIQ$ when returns are negative, than when they are positive. That is,

$$\mathbb{I}(t-1) = \begin{cases} 0, & \text{if } R^i(t-1) \geq 0 \\ 1, & \text{if } R^i(t-1) < 0 \end{cases}$$

More precisely, the sign of γ decides whether negative shocks have greater weight than positive ones.

III.4 Data

This section presents the data used in our methodology as well as the data collection process. We decided to retrieve market data for three ‘sectors’ of the financial sector: Banks, Insurers, and Asset Managers⁵. Similarly to Billio et al. (2012) the rationale is to highlight the differences between different types of firms. We extract from Eikon the stock price, volume and market capitalization for 417 financial firms, composed

⁵The screening of the institutions in our sample, has been made using the The Refinitiv Business Classification (TRBC). Specifically, our Asset Managers include: Closed-End Funds, Mutual Funds, Collective Investment Funds Operators, Investment Management and Funds Operators, and Investment Management.

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of 65 Asset Managers 278 banks and 74 Insurers/Reinsurers; from 28 countries and from 01-01-2001 to 21-01-2021. We provide the details of the distribution of each type of firm by country in Appendix III.A.2, Table III.3.

In order to limit illiquidity in the timeseries, we have chosen firms that have been public since 01-01-2001 and have a market capitalization above 100M USD. We further remove illiquid series in the remaining sample. Our final sample includes most of the most important financial institutions, especially the ones figuring on the list of Systemically Important Financial Institutions (SIFI). In order to compute $\Delta CoVaR$, we also retrieve from the Federal Reserve Bank of St. Louis (FRED) the following state variables for the U.S.: TED spread (TEDRATE), VIX (VIX-CLS), changes in T-Bill 3 month's rate ($\Delta TB3$), the Effective Federal Fund rate (FFR) and the excess returns of the Dow Jones Industrial Average (DJ_EXCESS). As for the European firms, we retrieved from multiple sources (Eikon, Datastream, ECB, FRED): the VIX, the return of MSCI Europe (MSCI_EU), the 3-month EURIBOR rate (EURIBOR), the logarithmic returns of the 3-month French T-Bill rate (Delta3M), and the EONIA rate (EONIA). The equivalent of the TED spread in the U.S. for Europe, is the spread between the 3-months EURIBOR and the 3-months French T-Bills. The usual instrument used to construct the TED spread in Europe is the T-Bills from Germany. However, its historical data dates back only to 2005. In order to have an un-discontinued TED spread, we used the 3-month French T-Bills. All the summary statistics for the State Variables are provided in Appendix III.A.2, Table III.4. We provide the summary statistics for the financial returns of firms in our sample in the table below (see Table III.1).

Our choice for the crisis periods is displayed in Table III.2. The determination of when a crisis starts and ends is a difficult matter. Additionally, we take into account the fact that different countries might have been affected at different times even by the same crisis. As we are working with daily data, we need to settle on an actual day for when a crisis starts. For the Subprimes and the European Debt crisis, we based our choice on the timeline provided by the FRED⁶ and the work of Laeven and Valencia (2020). We explain the choice of our crisis periods as follows: The Dot-Com bubble spans from the beginning of our sample to the end of the corporate

⁶See the timeline at: <https://fraser.stlouisfed.org/timeline/financial-crisis>.

failures and after the stock market downturn ended in October 2002; The subprime crisis started soon before the failure of Bear Stearns in mid 2007 and lasted until the intervention of the Fed in early 2009; The European Debt Crisis began when major european institutions decided to come to the aid of Greece, and ended when the European Union came to the help of Ireland and Portugal at the end of 2011 and the beginning of 2012; lastly, the Covid crises started with in the first European lockdowns and were still not over before the end of our sample. Although the choice of the dates for the crises may seem a little arbitrary, we argue that our results are robust to changes in theses dates, and that the determination of these dates is not the primary focus of this study.

Table III.1: **Summary Statistics.**

Summary statistics for each type of financial firms' returns, from 01-01-2001 to 20-01-2021. The mean, standard deviation, max, min and median are expressed annually.

<i>Full Sample</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Asset Managers	75	0.082	0.352	3.625	-1.209	0.0	-0.269	37.346	-0.026
Banks	288	0.064	0.393	1.322	-2.266	0.0	-0.063	27.248	-0.095
Insurers	85	0.062	0.377	1.216	-1.495	0.0	-0.704	39.219	-0.054
<i>In Crises</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Asset Managers	75	-0.195	0.464	0.693	-0.893	-0.0	-0.540	17.252	-0.028
Banks	288	-0.158	0.513	1.179	-2.266	-0.0	-0.146	17.489	-0.108
Insurers	85	-0.197	0.509	1.208	-1.495	-0.0	-0.481	18.554	-0.067
<i>Out Crises</i>									
Sector	count	mean	sd	max	min	median	skewness	kurtosis	auto-corr
Asset Managers	75	0.236	0.286	3.625	-1.209	0.0	0.300	31.004	-0.029
Banks	288	0.186	0.322	1.322	-1.157	0.0	0.266	16.026	-0.080
Insurers	85	0.210	0.298	1.216	-1.077	0.0	-0.155	32.537	-0.041

Table III.2: **Crisis Dates**

Starting date and ending date for each crisis in our sample.

Crisis Name	Start Date	End Date
Tech Bubble	2001-01-01	2002-10-10
Subprime Mortgage	2007-06-20	2009-03-10
European Sovereign Debt	2010-04-23	2011-12-22
Covid	2020-01-01	2021-01-20

III.5 Results and Discussion

In this section, we compute and present the analysis of the measurements introduced in Section 3 using the data presented in Section 4. First, we present our three main results and discuss them. Then, we discuss the regulatory implications of our results.

III.5.1 Main results

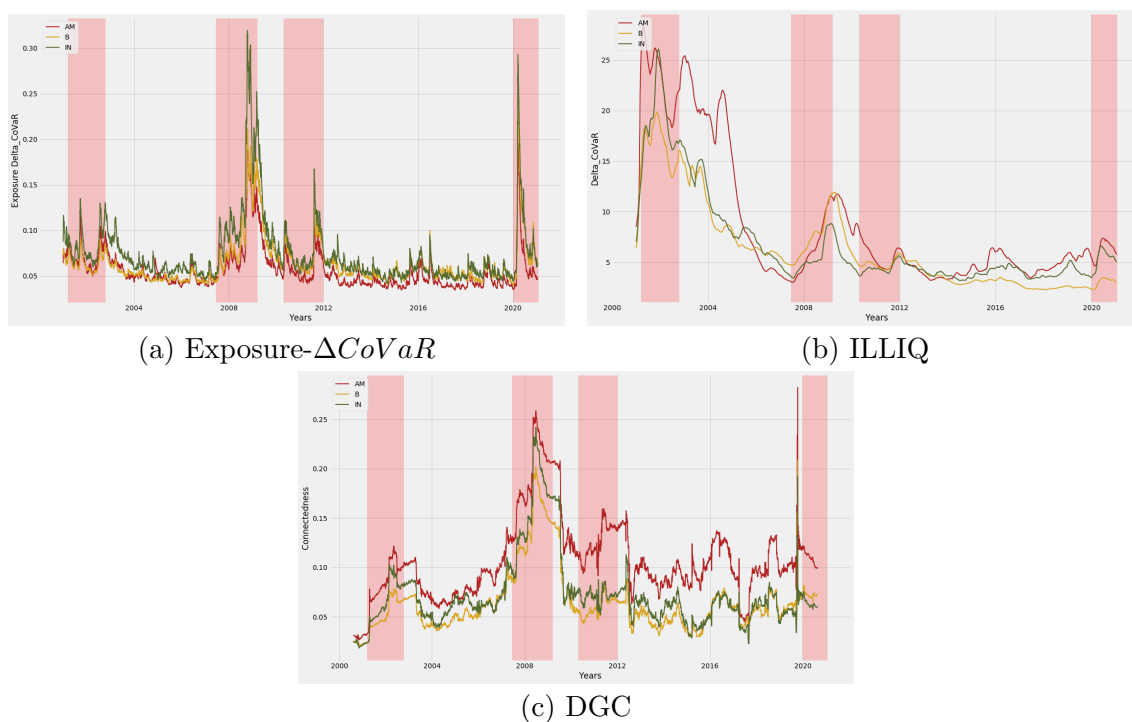
This section presents our findings and discusses their implications. First, we show that each type of firm has a specific combination of Systemic Dimensions. We then explain the size effect on the Systemic Dimensions for each type of firm. We study the differences between a sample of large firms (highest 10% market capitalization) and a sample of small firms (lowest 10% market capitalization). Finally, we propose a specific focus for each crisis considered in this study. The values used to plot the SRPs provided in this section are in Appendix A, Tables III.5, III.6, and III.7.

Systemic Risk by type of financial firms

We will present our results by first introducing the concept of a [Systemic Risk Profile \(SRP\)](#). A SRP summarizes the levels of the Systemic Dimensions for each type of financial firm, during stable and crisis periods. A SRP in our sense is a simple and concise visualization of the SR dimensions of a firm/type of firm. We plot on each dimension the value of the corresponding risk, yielding a triangle area representing the SR incurred by that firm/type of firm. In order to incorporate more information, we make a distinction on the same graph between SR during a stable period and that during crises. This allows observing quickly which risk increases the most in a crisis. A word of caution is necessary regarding comparing risks. As our Systemic Dimensions do not have the same units, the SRPs are not made in order to compare these risks. They allow comparing the same type of risk for different types of firm and during different periods. Our initial results are presented in the SRPs below. Figure III.1 shows the Systemic Dimensions for each type of financial institutions, from 2001 to 2021. As stated previously, Figure II.1 shows that all the Systemic Dimensions increase during a financial crisis.

Figure III.1: **Systemic Dimensions.**

All systemic risk measures from 01-01-2001 to 20-01-2021, for each type of financial firms. The red columns represent the crises periods. Asset Managers are in red, Banks in yellow and Insurers in grey.

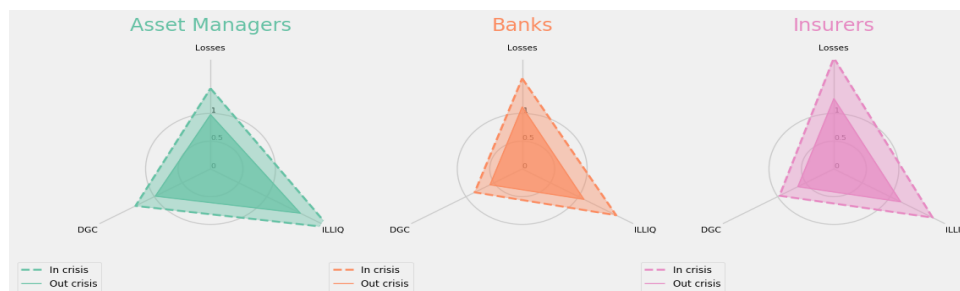


Moreover, Figure III.2 highlights some differences in the type of SR carried by each type of firm. Asset Managers are the most prone to illiquidity as well as the most connected agents. The significance of all differences mentioned above are displayed in Appendix A Table III.8. Insurers have the largest exposure to losses in the case of stressed financial market conditions. Surprisingly, banks turn out to be the least risky agents in our sample. This observation is to be nuanced by the fact that we are looking at average values overall. A detailed SRP of all crises is given later on and allows a more precise analysis of the risks faced by each sector.

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Figure III.2: Systemic Risk Profiles by type of financial institution.

Risks profiles for Asset Managers, Banks and Insurers. The dark triangle shows the Systemic Risk Profile during stable times while the dashed triangle shows Systemic Dimensions during crisis periods. The Systemic Dimensions are our risk measures: Exposure- $\Delta CoVaR$, ILLIQ, and Degree of Granger Causality (DGC).

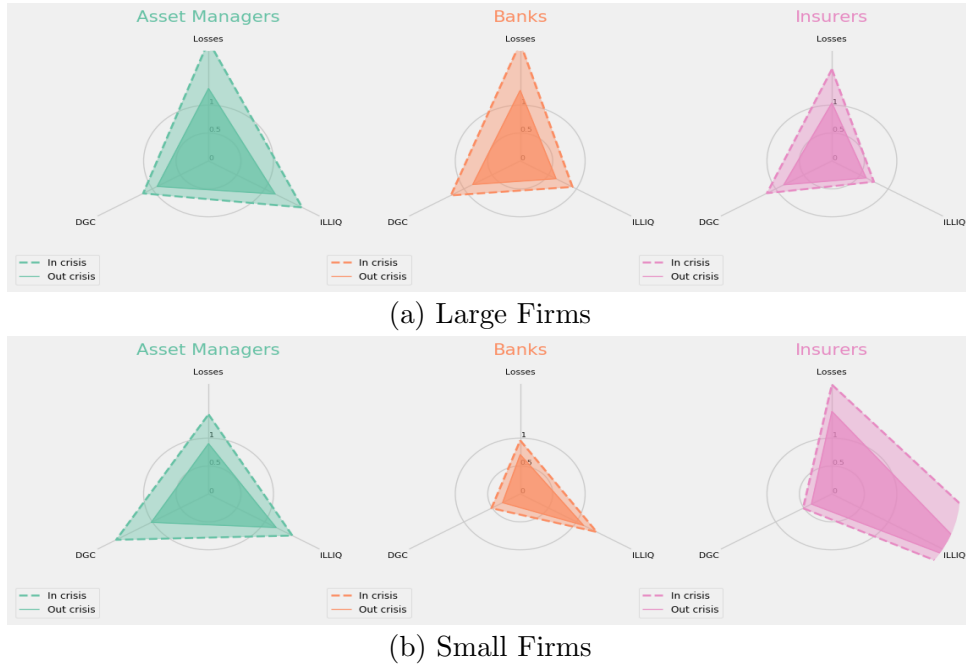


Systemic Risk by size of financial firm

The fact that we have more banks in our sample than insurers and asset managers also plays a big part. In order to ameliorate this limitation, we propose a view of Systemic Dimensions for large and small market capitalizations of each sector. The large sample consists of the 10% most highly capitalized firms while the small sample consists of the lowest 10%. While all the Systemic Dimensions tend to increase in times of crisis, these levels for small firms differ from those for large firms. We show that small firms have lower exposure to losses when the financial market is stressed, are less interconnected, but have larger illiquidity than large firms. We see as well that each type of risk peaks successively. Interconnexion peaks early, being followed by the maximum of loss exposure and finally, by a peak in illiquidity. Such a chronology makes sense in a crisis: First, agents tend to be more and more interconnected, which translates into a high potential for contagion. Secondly, a shock comes impacting most of the large corporations, starting a cascade of losses which is eventually aggravated by high illiquidity. In order to get a more detailed view of the distribution of SR between large and small firms, we have constructed the following SRPs (see Figure III.3). Figure III.4 summarizes the Systemic Dimensions for small and large firms over the whole period considered. We can also assess the extent of the differences existing between large and small firms.

Figure III.3: **Systemic Risk Profiles for large and small firms.**

Risks profiles for large and small market capitalization. The dark triangle shows the *SRP* during stable times while the dashed triangle shows Systemic Dimensions during crisis periods. The Systemic Dimensions are our risk measures: Exposure- $\Delta CoVaR$, ILLIQ, and Degree of Granger Causality (DGC).



From Figure III.3, we see clearly that the high illiquidity in the small sample is driven by insurers and also, to a lesser extent, by banks. On the other hand, the smallest loss exposure is for banks and asset managers. The differences mentioned above between small and large firms are statistically significant, as displayed in Appendix A Table III.9. Globally, we can observe that large firms tend to have a greater loss exposure and a greater level of interconnection, while small firms are more prone to high illiquidity. An interesting conclusion can be obtained by linking these results with the previously stated chronology of the peaks in the Systemic Dimensions (see the Figure III.5). Indeed, the results displayed in Figure III.1, show that different types of risk peak in a specific sequence, especially visible for the subprime crisis. Large firms are more prone to be impacted by large shocks and are more interconnected. Their contribution in a systemic event arrives the earliest, while small firms suffer a large spike in illiquidity late in a crisis. This observation suggests that small firms may be dependent on the large ones, which is not a strong assumption. Hence, when large firms build up large exposures to a correlated shock,

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as displayed by the DGC, and end up being greatly affected; small firms suffer the consequences. In this way, the role of small firms as a channel of contagion, due to the failures of large institutions, is an overlooked issue in the current prudential regulations.

Figure III.4: **Systemic Dimensions for large and small firms.**

All systemic risk measures from 01-01-2001 to 20-01-2021, for large and small firms. Large firms are the 10% biggest market cap in each sector, while small firms are the lowest 10%. The red columns represent the crises periods.

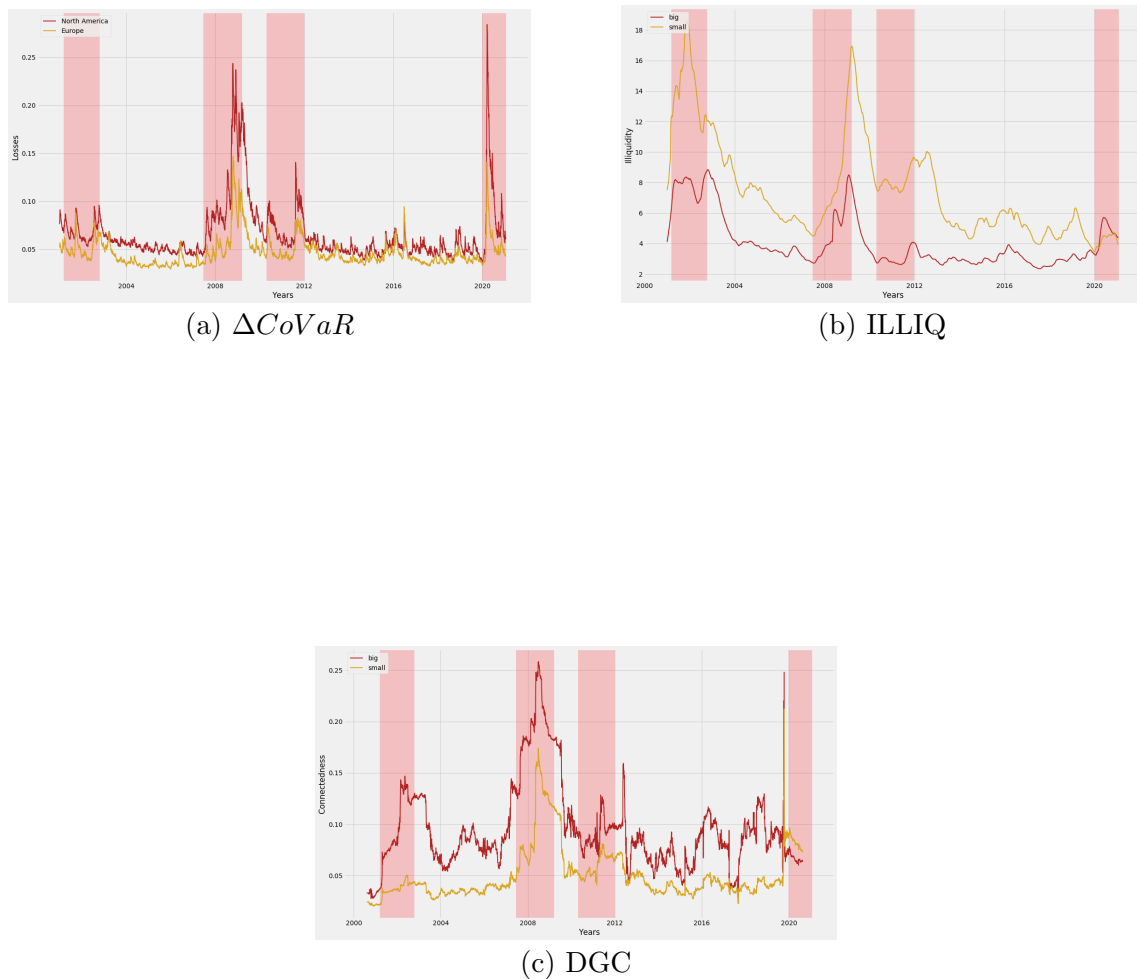
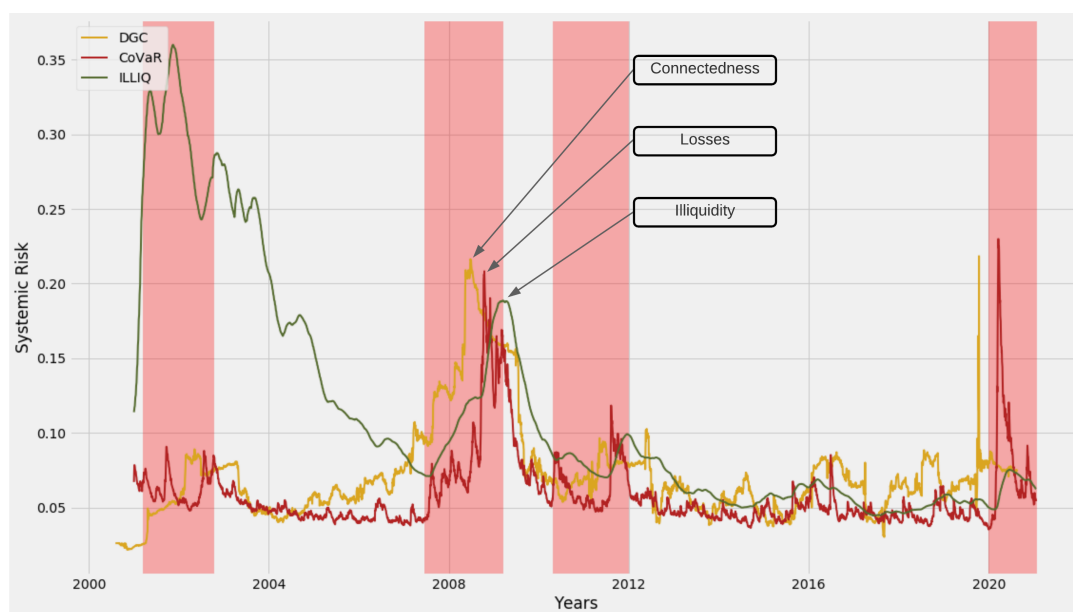


Figure III.5: **Chronology of a systemic crisis.**

Evolution of the three Systemic Dimensions (Losses, Illiquidity and Connectedness) from 2001 to 2021 for the complete sample of European and U.S. firms. The red shaded areas represents the crisis periods in our sample. In order, we have the Dot-Com, Subprimes, European Sovereign Debt and the Covid.



Systemic Risk by type of crisis

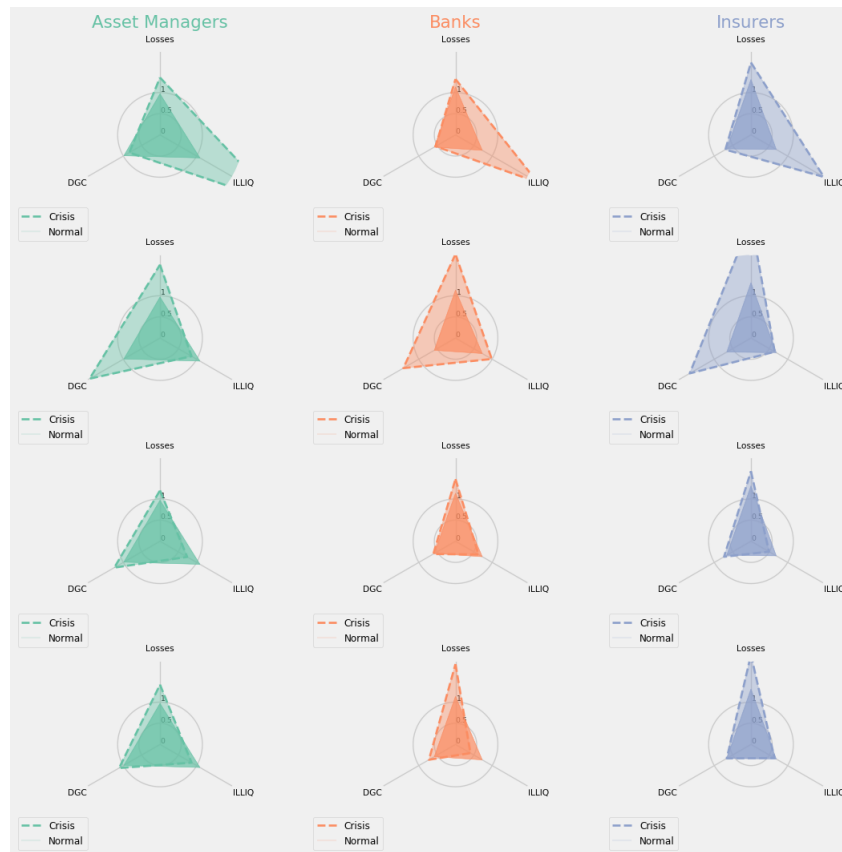
We now propose to take a look at the [SRPs](#) for each crisis considered in our sample. Earlier in this study, we described a systemic crisis as an event where all Systemic Dimensions increase. It is by no mean obvious that all crises considered in this study validate this affirmation. We propose to take a closer look at the [SRPs](#) displayed in [Figure III.6](#) as an heuristic for validating our insight. A first distinction to be made is that between realized systemic crises and potential systemic crises. We know that the subprime crisis dealt an heavy blow to the real economy. This is validated by the [SRPs](#). We can see that the Dot-Com bubble was a crisis of liquidity. The levels of illiquidity for all types of firm surpassed the ‘stable’ one. The subprime crisis, on the other hand, was a crisis of connectedness and extreme loss exposure. The small differences in illiquidity between stable and crisis periods can actually be explained by the fact that the spike in illiquidity occurred in the post crisis period. In the

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case of the subprime crisis, all of the Systemic Dimensions had a significantly strong tendency to increase (see Appendix A Table III.10), showing the multidimensional nature of SR.

Figure III.6: **Systemic Risk Profiles for each financial crisis.**

Risks profiles for Asset Managers, Banks and Insurers. The dark triangle shows the Systemic Risk Profile during stable times while the dashed triangle shows Systemic Dimensions during a crisis period. The Systemic Dimensions are our risk measures: Exposure- Δ CoVaR, ILLIQ, and Degree of Granger Causality (DGC). Each row compares the stable time SRP to the SRP during a specific crisis. The crises are ordered in the following way: Dot-Com, Subprime, European Sovereign Debt, Covid.



The latter two crises are also not proven systemic events. However, this conclusion for the Covid crisis cannot be ascertained as our sample stops before the end of the crisis. The SRPs show then low changes compared to stable periods. This fact has two reasonable explanations: First, the crisis was not of a systemic nature. Hence, only one systemic dimension realized itself. In this case, our approach allows separating systemic crises from other types of financial crises. Another, perhaps

more down-to-earth explanation, is that the efforts put in place by regulators and governments dammed any consequences of systemic importance. We know that in the case of the European Sovereign Debt crisis, the regulators and European interventions prevented a major breakdown. The lack of changes in the levels of Systemic Dimensions might have been the result of these actions.

III.5.2 Policy implications

The analysis provided in the previous section could help determine whether current regulations cover the prominent types of risk presented by each sector. The analysis in this section focuses on the regulators' assessment methodology for insurers and banks (BCBS, 2014; IAIS, 2016), to first ascertain whether the indicators used to identify systemic agents match our results and, second, to put in context the constraints faced by those identified as such.

The assessment method provided by IAIS (2016) develops systemic scores based on five factors: Size, global activity, interconnectedness, asset liquidation, and substitutability. Unlike the methodology for G-SIBs, the indicators are not equally weighted. The fact that the interconnectedness measures are weighted at approximately 50% confirms that large insurers are the most interconnected agents in the financial system. Furthermore, reinsurance is included in the methodology, supporting our insight that insurers' intrasectoral connectedness resides in their interaction with the reinsurance market. Our values of $\Delta CoVaR$ align with the asset liquidation indicators, which account for more than 35% of the systemic score. As such, the two 'heaviest' categories in the assessment methodology of the IAIS are also found to be the main Systemic Dimensions for the insurance sector in our research. The HLA requirements faced by G-SIIs force them to maintain equity of sufficient quality, which should nuance the value of $\Delta CoVaRs$ showed in this chapter. As the report of ESRB (2018) states: 'Most of the Solvency II provisions are not specifically designed to prevent or mitigate SR and only have an indirect macroprudential impact.' As such, Solvency II focuses strongly on the resilience of individual insurers through allocated capital charges (premium and reserve, lapse, and concentration risk capital charges). Although such charges are made to ensure the solvency of the individual insurers, an adverse asset price shock impacting the insurance sector could still lead to failure contagion via the reinsurance market. One observation we

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can make, therefore, in line with the report of ESRB (2018)⁷, is that regulation is needed to mitigate the possibility of contagion in the insurance market and, more generally, the financial system. The current supervision completely overlooks the fact that small insurers are heavily subject to illiquidity and, consequently, could become a primary channel of contagion in a systemic event.

The Basel framework also bases its assessment on 5 categories, which are comparable to the Solvency II regulations (the latter was, in fact, based on Basel II's three-pillar approach): Cross-jurisdictional activity, size, interconnectedness, substitutability, and complexity (BCBS, 2014). All are equally weighted. Although the methodology considers interconnectedness, it does not specifically consider interbank connectedness, which is one of the major risks presented by banks in our results. The liquidity ratio and capital buffers were implemented by Basel II in 2008, but the levels of Systemic Dimensions for banks do not appear to change radically after the subprime crisis. One new measure introduced by Basel III, partially to improve Basel II, is countercyclical buffers. This kind of regulatory tool directly affects banks' risk-taking behavior by adjusting its weight based on the lending cycle. The methodology does not include an asset liquidation component, but this does not mean that banks are not impacted by adverse events that force them to sell assets at fire-sale prices. A deposit run can cause banks to sell some of their assets at fire-sale prices in order to shoulder temporary illiquidity, especially during periods of general illiquidity. This issue is not fully covered by the assessment methodology because all European Union countries now have deposit insurance for up to EUR 100,000. As covered in numerous papers (Diamond & Dybvig, 1983, 1986; Cooper & Ross, 2002), the best way to mitigate and prevent bank runs is through a combination of deposit insurance and capital requirements. Similarly to the insurance sector, the current regulations overlook the high liquidity displayed by small banks. While large banks build up interconnectedness and have large exposure to financial shocks, they face prudential restrictions that might mitigate the impact of a shock. However, the financial shock might propagate quickly through the interbanking market to impact directly small and illiquid banks. In this view, liquidity ratios should be introduced to a larger sample of banks.

⁷This report presents possible regulatory tools to supervise insurers, among them the temporary halt of trading on an asset to prevent it from being subject to a fire sale and to mitigate the risk of contagion through multiple fire sales.

Nevertheless, one of the major risks that appears in every regulation report and academic paper remains the risk of a large adverse price movement. Indeed, an asset crash is a common source of SR for all types of sector. Since the core activities of all the sectors in this study are in the financial markets, any event that profoundly disrupts these financial markets are a natural source of risk. The importance of bubbles and asset price crashes for financial stability is indicated by the extensive literature on the subject, among which we must highlight the work of Claessens and Kose (2013) and Kindleberger (1978). Asset managers play in this particular point an essential role. Asset managers are the most interconnected sector globally, by building up common exposure and engaging in correlated investment strategies, they present a serious threat in their potential to create large swings in asset prices.

Our results highlight a current gap in the current prudential regulations. We know that each type of financial institution faces its own specific type of SR. This observation is already covered by the present regulations, as each institution faces its own prudential regulations. Current prudential oversight has allowed drastically improving the resiliency of individual, especially large, institutions. However, we also observe that financial firms have a different role in a systemic event depending on their size. The initial shock of a systemic event is more likely to come from large corporations, and spread and amplify through smaller firms. Hence, current prudential regulations should be adjusted, specifically regarding smaller firms' role in a systemic crisis. The current regulations focus on making large institutions more resilient to a given shock, and on preventing dire situations of temporary illiquidity. This approach tends to overlook smaller financial corporations, which will become yet another contagion channel, due to their high illiquidity, given that large corporations aren't robust enough.

III.6 Conclusion

Understanding the true nature of SR is an essential mission for today's regulators. Their task is complex as they should prevent any build-up of financial fragility while allowing financial firms to carry out their duty. Knowing what systemic dimension, or what type of risk, belongs to what kind of financial institutions would allow more

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efficient regulation. We propose that **SR** is composed of the following Systemic Dimensions: Losses, Illiquidity and Connectedness. We have computed the Systemic Dimensions of the American and European financial system and summarized our findings in **SRPs**. Our results are as follows: Firstly, different types of financial firms bear different types of **SR**. We found that asset managers are the most interconnected and prone to illiquidity, while insurers are the most exposed to large losses. Moreover, during a systemic crisis all Systemic Dimensions increase for all types of financial firm. Secondly, the levels of Systemic Dimensions vary depending on the size of the firms. We show that large firms are more prone to large losses and high connectedness, while small market capitalizations are significantly more illiquid. This has serious regulatory implications. The prudential scope of actions should widen to incorporate smaller financial institutions that play an important role in the contagion/amplification of losses in a systemic crisis. Finally, we find that the Systemic Dimensions reach their peaks successively. This highlights the fact that even though **SR** is composed of different types of risk (Systemic Dimensions), they do not occur at the same time. This result links itself to our two other findings above. We know that large insurers, banks and small asset managers accumulate a large common exposure in the early times of a crisis. At the same time, large asset managers and banks suffer the highest loss exposure during a crisis. Eventually, smaller firms experience a peak in illiquidity at the end of a crisis.

Our study builds on the work of Billio et al. (2012), Adrian and Brunnermeier (2016) and others endeavoring to provide regulators with a new synthetic view of **SR** using market data. We propose what is, as far as we know, the first analysis of **SR** based on various measurements using European and American data. Our study sheds a new light on the adjustment needed for prudential regulation and could be of interest for policymakers. Most of the existing literature has focused on finding one particular signal for **SR**. We have argued that, given the complexity of the financial system and interactions between financial firms, **SR** must be studied with different types of measures, on a larger sample than just SIFIs.

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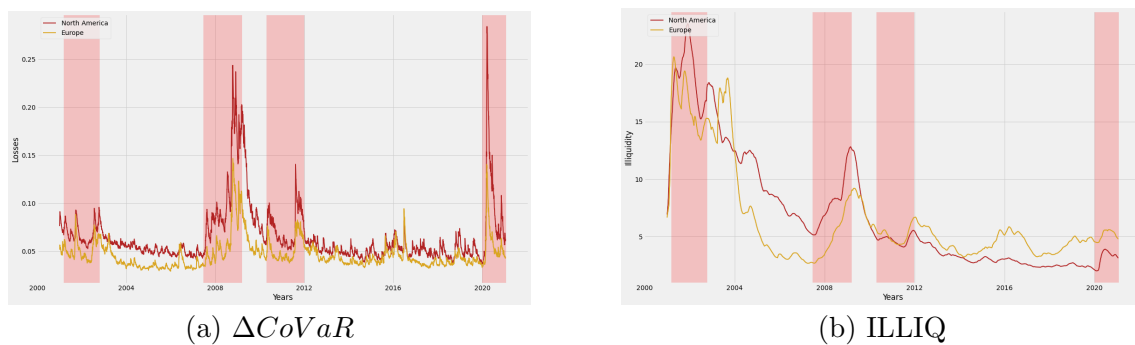
III.A Appendix

III.A.1 Comparison Europe vs. U.S.

This Appendix proposes a focus on the differences in the levels of **SR** between American and European firms. We provide elements of comparison between their Systemic Dimensions, as well their **SRP**. A first notable fact is that financial firms in the U.S. tend to be larger than European firms, on average. Stemming from that fact, it is possible that the differences presented below suffer from a size-bias. First of all, Figure III.7 display the evolution of Systemic Dimensions for European and U.S. firms over time. At a first glance, we can see that both firms, being already large institutions⁸, follow a similar trend and variations over time. However, we observe a tendency of European firms to be more interconnected overall, while suffering from higher illiquidity since the European Sovereign Debt crisis. American financial firms, on another hand, tend to have larger loss exposure during the 2000-2021 period.

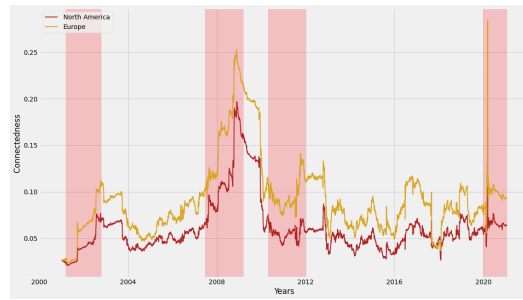
Figure III.7: Systemic Dimensions for European and American Firms

All systemic risk measures from 01-01-2001 to 20-01-2021, for European and American firms. The chart (a) display the values of the Exposure $\Delta CoVaR$. (b) shows the values of the Asymmetric ILLIQ indicator and the graph (c) shows the connectedness levels via the *DGC*. Red-shaded areas indicate the crisis periods in our sample. In chronological order: Dotcom, Subprimes, European Sovereign Debt and Covid.



⁸Our sample consists only of financial firms that have a market capitalization above 100 Million USD.

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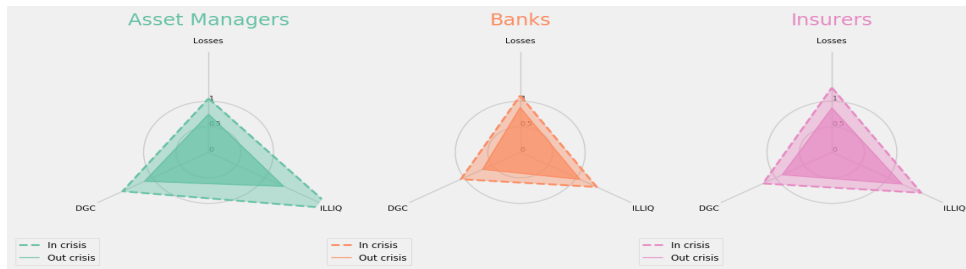


(c) DGC

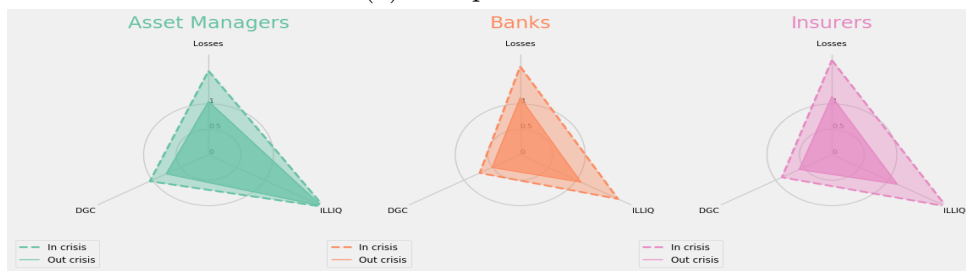
The SRPs (see Figure III.8) allow for validating the results put forward in Figure III.7 and provides additional details regarding each type of financial institutions. Table III.11 exposes the values displayed in the SRPs in Figure III.8.

Figure III.8: Systemic Risk Profiles for European and American firms.

Risks profiles for European and American firms. The dark triangle shows the SRP during stable times while the dashed triangle shows Systemic Dimensions during crisis periods. The Systemic Dimensions are our risk measures: Exposure- Δ CoVaR, ILLIQ, and DGC.



(a) European Firms



(b) American Firms

In particular, European firms are more interconnected than American firms, regardless of the type of firms, or the type of period considered (crisis or stable). Additionally, it appears that American banks and insurance companies experience bigger changes in illiquidity and loss during a crisis. Even though, their levels do not differ significantly from the European firms during stable periods, they display

a stronger sensitivity to crises. Furthermore, our results put into light the fact that American asset management company are actually the ones driving the high illiquidity of the U.S. financial system, exposed in our results above. The propensity of American firms can be explained, partially, by the size effect. Indeed, in average, the largest American firms will logically turn to be larger than the largest European firms, in term of market capitalization. Consequently, as the results presented in this chapter depict, larger financial firms tend naturally to be more exposed to systemic losses.

CHAPTER III. Which Systemic Risks affect which financial institutions at what stage of the crisis?

III.A.2 Tables

Table III.3: **Distribution of firms per country.**

Table summarizing the number of each type of financial institutions for each country in our sample. The Country Code column corresponds to the standard ISO Country Code.

Country Code	Sector	Count	Country Code	Sector	Count
AT	Banks	2	IE	Banks	1
	Insurers	2		Insurers	1
BE	Asset Managers	3	IT	Asset Managers	1
	Banks	1		Banks	7
	Insurers	1		Insurers	2
CH	Banks	7	JE	Asset Managers	2
	Insurers	1			
CZ	Banks	1	LI	Banks	1
DE	Asset Managers	2	LT	Banks	1
	Banks	3	MT	Asset Managers	1
	Insurers	4		Banks	2
		Insurers		1	
DK	Banks	8	NL	Asset Managers	2
	Insurers	2		Banks	1
ES	Asset Managers	1		Insurers	1
	Banks	3	NO	Asset Managers	1
	Insurers	1		Banks	10
FI	Asset Managers	1	PL	Banks	6
	Insurers	1	PT	Banks	1
FR	Asset Managers	3	RO	Asset Managers	5
	Banks	7		Banks	1
	Insurers	3	RU	Banks	1
GB	Asset Managers	16	SE	Asset Managers	1
	Banks	7		Banks	4
	Insurers	4	TR	Banks	10
GG	Asset Managers	3		Insurers	5
	GR	Banks	6	US	Asset Managers
HU	Banks	1	Banks		186
			Insurers		45

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Table III.4: **Summary Statistics for the State Variables.**

Summary statistics for the state variables from 01-01-2001 to 20-01-2021. We have separated our summary statistics for crisis periods and stable periods. As we have two groups of firms (European, American), we also have two set of state variables. For the U.S. we use the TEDRATE (TED spread), DeltaTB3 (log returns of 3-months T-Bill), DJ_EXCESS (Dow Jones Industrial excess returns compared to S&P500) and FFR (the effective federal fund rate). For Europe, we use MSCI_EU (log returns of the MSCI Europe), EUROSpread (spread between EURIBOR 3-months and French T-Bill 3-months), EONIA and Delta3M (log returns on French T-Bill 3-months). Both Europe and U.S. uses the Volatility index (VIXCLS). The mean, standard deviation, min, max and median of the log returns series are annualized.

Full Sample									
	Variables	mean	sd	max	min	median	skewness	kurtosis	auto-corr
	VIXCLS	19.798	9.086	82.690	9.140	17.23	2.215	7.395	0.980
U.S.	TEDRATE	0.004	0.004	0.046	0.001	0.003	4.088	23.634	0.983
	DeltaTB3	-0.116	1.313	0.885	-1.447	0.000	-0.907	44.484	-0.228
	DJ_EXCESS	0.002	0.024	0.013	-0.016	-0.000	-0.294	8.293	-0.028
	FFR	0.015	0.016	0.067	0.000	0.010	1.153	0.196	0.998
EU	MSCI_EU	0.021	0.006	0.047	-0.061	0.000	-0.390	8.999	0.009
	EUROSpread	0.003	0.003	0.031	-0.003	0.002	3.124	15.582	0.991
	EONIA	0.013	0.016	0.058	-0.005	0.004	0.652	-0.981	0.998
	Delta3M	0.110	0.074	1.243	-1.021	0.000	0.909	80.313	-0.222
In Crisis									
	Variables	mean	sd	max	min	median	skewness	kurtosis	auto-corr
	VIXCLS	27.395	10.898	82.690	12.100	24.155	1.912	4.454	0.965
U.S.	TEDRATE	0.006	0.007	0.046	0.001	0.003	2.176	6.096	0.979
	DeltaTB3	-0.506	1.590	0.885	-1.447	0.000	-1.267	51.500	-0.173
	DJ_EXCESS	0.004	0.032	0.013	-0.013	0.000	-0.217	4.492	-0.036
	FFR	0.015	0.016	0.055	0.000	0.015	0.893	-0.430	0.993
EU	MSCI_EU	-0.087	0.008	0.047	-0.061	-0.000	-0.279	5.816	0.018
	EUROSpread	0.005	0.004	0.031	-0.001	0.004	1.945	5.975	0.988
	EONIA	0.022	0.019	0.058	-0.005	0.029	-0.116	-1.594	0.997
	Delta3M	-0.284	0.033	0.229	-0.519	0.000	-3.559	58.905	-0.156
Out Crisis									
	Variables	mean	sd	max	min	median	skewness	kurtosis	auto-corr
	VIXCLS	16.529	5.608	45.890	9.140	14.870	1.704	3.457	0.969
U.S.	TEDRATE	0.003	0.001	0.011	0.001	0.003	1.578	4.015	0.984
	DeltaTB3	0.134	1.174	0.699	-0.903	0.000	-0.428	24.279	-0.273
	DJ_EXCESS	0.001	0.020	0.008	-0.016	-0.000	-0.383	10.615	-0.014
	FFR	0.015	0.016	0.067	0.000	0.010	1.266	0.487	0.996
EU	MSCI_EU	0.071	0.005	0.028	-0.040	0.000	-0.213	4.168	-0.016
	EUROSpread	0.002	0.002	0.014	-0.003	0.002	2.371	7.838	0.979
	EONIA	0.009	0.014	0.057	-0.005	0.001	0.913	-0.348	0.996
	Delta3M	0.340	0.086	1.243	-1.021	0.000	0.899	62.318	-0.226

Table III.5: **Values for Systemic Risk Profiles**

Values computed to plot the Systemic Risk Profile in Figure III.2. We separate the values of our indicators for stable times and crisis periods. $\text{Exp-}\Delta\text{CoVaR}$ measures the 1% worse return; DGC the percentage of total connectedness; and the higher ILLIQ is, the higher is illiquidity.

<i>In Crisis</i>			
Sector	Exp- Δ CoVaR	ILLIQ	DGC
Asset Managers	0.066	10.558	0.133
Banks	0.075	8.349	0.084
Insurers	0.093	8.778	0.097
<i>Out Crisis</i>			
Sector	Exp- Δ CoVaR	ILLIQ	DGC
Asset Managers	0.044	7.990	0.098
Banks	0.051	5.489	0.057
Insurers	0.058	5.942	0.064

Table III.6: **Values for Systemic Risk Profiles: Differences in size.**

Values computed to plot the Systemic Risk Profile in Figure III.3. We separate the values of our indicators for stable times and crisis periods as well as for large and small corporations. The large sample includes the 10% largest market capitalizations in each sector. The small sample consists in the lowest 10% market capitalizations in the sample. $Exp-\Delta CoVaR$ measures the 1% worse return; DGC the percentage of total connectedness; and the higher $ILLIQ$ is, the higher is illiquidity.

<i>In Crisis</i>				
	Sector	Exp- $\Delta CoVaR$	ILLIQ	DGC
Large	Asset Managers	0.101	8.318	0.116
	Banks	0.091	4.645	0.123
	Insurers	0.068	3.730	0.115
Small	Asset Managers	0.062	7.448	0.164
	Banks	0.046	6.792	0.051
	Insurers	0.085	22.492	0.051
<i>Out Crisis</i>				
	Sector	Exp- $\Delta CoVaR$	ILLIQ	DGC
Large	Asset Managers	0.061	5.926	0.091
	Banks	0.054	3.190	0.084
	Insurers	0.043	3.048	0.086
Small	Asset Managers	0.039	6.022	0.102
	Banks	0.034	5.642	0.031
	Insurers	0.064	13.744	0.036

Table III.7: **Values for Systemic Risk Profiles: Differences in crises.**

Values computed to plot the Systemic Risk Profile in Figure III.6. We separate the values of our indicators for stable times and crisis periods, and detail each crisis. From top to bottom: Baseline is the out-crisis sample, which is the small dark triangle in the SRP. Then Dot-Com, Subprimes, European Sovereign Debt and Covid. . Exp- Δ CoVaR measures the 1% worse return; DGC the percentage of total connectedness; and the higher ILLIQ is, the higher is illiquidity.

	Sector	Exp- Δ CoVaR	ILLIQ	DGC
Baseline	Asset Managers	0.044	7.990	0.098
	Banks	0.051	5.489	0.057
	Insurers	0.058	5.942	0.064
Dot-Com	Asset Managers	0.063	23.179	0.086
	Banks	0.059	16.664	0.054
	Insurers	0.075	19.262	0.067
Subprimes	Asset Managers	0.080	6.458	0.194
	Banks	0.091	7.427	0.141
	Insurers	0.125	5.488	0.162
Sovereign	Asset Managers	0.056	5.558	0.125
	Banks	0.067	4.769	0.060
	Insurers	0.074	4.383	0.071
Covid	Asset Managers	0.064	6.284	0.110
	Banks	0.086	3.066	0.072
	Insurers	0.095	5.424	0.063

Table III.8: **Significance of differences**

The table summarizes F-statistics produced from a one-way ANOVA for the test of differences of mean between each type of financial institutions, as for all types of financial institutions. The significance tests are given for each Systemic Dimensions at different statistical levels (the one used in the study are the 1% measurements). The ILLIQ indicator was computed using the Asymmetric MEM (ILLIQ_Asy) and the Spline MEM (ILLIQ_Spline) for robustness, as explained on the Volatility-Lab (NYU) website. All series have been transformed to be stationary using log difference of order 1 for CoVaR and DGC; of order 2 for ILLIQ_Asy and ILLIQ_Spline. The p-value associated with the F-statistic is given in form of stars: ***:10%, **:5% and ***:1%**.

		Banks/Asset Managers	Banks/Insurers	Asset Managers /Insurers	ALL
1%	CoVaR	0.0067*	0.0068*	0.0000***	0.0044***
	DGC	0.0015**	0.0000***	0.0019**	0.0011***
5%	CoVaR	0.0069*	0.0064*	0.0000***	0.0043***
	DGC	0.0041*	0.0004**	0.0066*	0.0036***
10%	CoVaR	0.0069*	0.0066*	0.0000***	0.0044***
	DGC	0.0039**	0.0003***	0.0060*	0.0033***
	ILLIQ_Asy	0.0000***	0.0000***	0.0000***	0.0000***
	ILLIQ_Spline	0.0002***	0.0003***	0.0000***	0.0001***

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Table III.9: **Significance of differences: Firms of different size.**

The table summarizes *F*-statistics produced from a one-way ANOVA for the test of differences of mean between large and small companies of the same sector (ex: *B.big/B.small*, stands for comparing the mean of large banks against small banks); as for all large companies against all small firms. The significance tests are given for each Systemic Dimensions at different statistical levels (the one used in the study are the 1% measurements). The *ILLIQ* indicator was computed using the Asymmetric MEM (*ILLIQ_Asy*) and the Spline MEM (*ILLIQ_Spline*) for robustness, as explained on the Volatility-Lab (NYU) website. All series have been transformed to be stationnary using log difference of order 1 for *CoVaR* and *DGC*; of order 2 for *ILLIQ_Asy* and *ILLIQ_Spline* The *p*-value associated with the *F*-statistic is given in form of stars: *:10%, **:5% and ***:1%.

		B.big/B.small	IN.big/IN_small	AM.big/AM_small	all.big/all_small
1%	CoVaR	0.0008**	0.0036**	0.0022**	0.0005**
	DGC	0.0222	0.0007**	0.0036**	0.0133*
5%	CoVaR	0.0009 **	0.0032**	0.0021**	0.0005**
	DGC	0.0219	0.0003**	0.0014**	0.0136*
10%	CoVaR	0.0007**	0.0031**	0.0032**	0.0003**
	DGC	0.0207	0.0058*	0.0008**	0.0145*
	ILLIQ_Asy	0.0002***	0.0000***	0.0000***	0.0000***
	ILLIQ_Spline	0.0002***	0.0001***	0.0000***	0.0001***

Note: B: Banks, AM: Asset Managers, IN: Insurers

Table III.10: **Significance of differences: crises**

The table summarizes *F*-statistics produced from a one-way ANOVA for the test of differences of mean between stable periods and a specific crisis for each type of financial institution. The significance tests are given for each Systemic Dimensions at different statistical levels (the one used in the study are the 1% measurements). The *ILLIQ* indicator was computed using the Asymmetric MEM (*ILLIQ_Asy*) and the Spline MEM (*ILLIQ_Spline*) for robustness, as explained on the Volatility-Lab (NYU) website. All series have been transformed to be stationnary using log difference of order 1 for *CoVaR* and *DGC*; of order 2 for *ILLIQ_Asy* and *ILLIQ_Spline* The *p*-value associated with the *F*-statistic is given in form of stars: *:10%, **:5% and ***:1%.

		Dot-Com			Subprime			Sovereign Debt			Covid		
		B	IN	AM	B	IN	AM	B	IN	AM	B	IN	AM
1%	CoVaR	0.1475	0.5928	0.0904	3.8759**	3.6516*	2.7851*	0.1578	0.3244	0.2316	1.4187	0.5192	0.4107
	DGC	1.8656	2.1027	3.2170*	0.8579	0.8632	0.8259	0.1206	0.0227	0.0134*	0.1532	0.0047*	0.0010**
5%	CoVaR	0.1745	0.7018	0.0635	3.7911*	3.6686*	2.7836*	0.1517	0.3402	0.2572	1.4054	0.5324	0.4075
	DGC	1.8204	1.9665	2.8169*	0.7321	0.5085	0.5050	0.2484	0.0911	0.0800	0.0026**	0.0599	0.2444
10%	CoVaR	0.1692	0.7106	0.0574	3.6832*	3.6664*	2.8175*	0.1530	0.3458	0.2659	1.3618	0.5247	0.3986
	DGC	1.6525	1.7212	2.4709	0.5958	0.3137	0.3538	0.3303	0.1653	0.1464	0.0553	0.2111	0.6510
	ILLIQ_Asy	0.0017**	0.0066**	0.0293	0.0000***	0.0000***	0.0000***	0.0009**	0.0003**	0.0022**	0.0135*	0.2161	0.0048*
	ILLIQ_Spline	0.0043*	0.0001***	0.0002**	0.0003**	0.0000***	0.0001***	0.0018**	0.0000***	0.0000***	0.0021**	0.0025**	0.0001***

Note: B: Banks, AM: Asset Managers, IN: Insurers

Table III.11: **Values for Risk Profiles: Differences in continent**

Values computed to plot the Risk profile in Figure III.8. We separate the values of our indicators for stable times and crisis periods, and separates European firms (EU) and American firms (U.S.). $Exp-\Delta CoVaR$ measures the 1% worse return; DGC the percentage of total connectedness; and the higher ILLIQ is, the higher is illiquidity.

<i>In Crisis</i>				
	Sector	Exp- $\Delta CoVaR$	ILLIQ	DGC
EU	Asset Managers	0.053	11.008	0.153
	Banks	0.056	6.802	0.105
	Insurers	0.063	7.937	0.122
U.S.	Asset Managers	0.082	10.268	0.104
	Banks	0.087	8.689	0.072
	Insurers	0.093	10.151	0.089
<i>Out Crisis</i>				
	Sector	Exp- $\Delta CoVaR$	ILLIQ	DGC
EU	Asset Managers	0.037	6.687	0.114
	Banks	0.044	5.320	0.067
	Insurers	0.043	6.232	0.088
U.S.	Asset Managers	0.052	10.064	0.075
	Banks	0.056	5.414	0.050
	Insurers	0.057	5.822	0.058

General Conclusion

Since the subprime crisis, the academic world has left no stone unturned when it came to coming up with new ways to assess **Systemic Risk (SR)**. From network theory (Cont, Moussa, & Santos, 2013; Acemoglu, Ozdaglar, & Tahbaz-Saheli, 2015; Amini, Cont, & Minca, 2016) to econometric models (White, Kim, & Manganelli, 2015; Adrian & Brunnermeier, 2016; Etesami, Habibnia, & Kiyavash, 2017) passing by default measures (Chan-Lau & Sy, 2007; Duffie et al., 2009; Giesecke & Kim, 2011b; Azizpour, Giesecke, & Schwenkler, 2018) the academic literature on **SR** measurement is tentacular. The multitude of approaches, studies, theses, conferences on the matter is still growing. The fact that so much effort did not lead to a general solution is baffling. The lack of a conceptual framework on the nature **SR** has led to this variety of measures and definitions. This dissertation tackles that precise issue. We first propose a conceptual framework presenting a definition for **SR** based on the process of a **Systemic Event (SE)**. Our proposition is henceforward named: the **Systemic Event Hypothesis (SEH)**. Furthermore, we put forward two chapters that, each, aim to empirically validate specific aspects of the **SEH**. We present in the next section the contributions stemming from our work, before exposing the limitations of our researches as well as future research endeavors.

Main Findings & Contributions

Our first chapter lays the foundation for the rest of the dissertation. It tackles three major aspects. First, in order to be able to develop a coherent measure of **SR**, we have to define it. To that purpose, we propose an initial conceptual framework for assessing **SR**: the **SEH**. It provides definitions for each of the underlying concepts of **SR**, following a systemic approach, as proposed by Walliser (1977). It defines **SR** to be the *‘risk associated with the occurrence of systemic event’* and consequently

constructs the chronology of a [SE](#)⁹. The [SEH](#) postulates that a [SE](#) initially starts with a structural displacement (Minsky, 1992). The displacement creates a new opportunity of profit, in which capitalistic firms will engage. This common investment strategy directly translates into a phase of increase in the financial fragility of the system that will end up in a wide systematic shock. The shock will worsen through contagion and amplification mechanisms, before creating negative externalities for the real economy. Second, the chapter presents optimal intervention timing for regulatory/oversight instances according to the [SEH](#). It classifies such instances in three categories, regarding their scope of action. Structural regulators ([Basel Committee on Banking Supervision \(BCBS\)](#), [European Systemic Risk Board \(ESRB\)](#), etc.) should intervene at the very beginning of a [SE](#), as well as should continue to make financial institution more robust in regard the realization of systemic losses, and contagion/amplification effects. Monetary authorities ([European Central Bank \(ECB\)](#), [Federal Reserve Bank \(Fed\)](#)) should limit the creation of large imbalances in the phase of build-up of financial fragility, and act as [Lender of Last Resort \(LOLR\)](#). Lastly, market authorities ([European Securities and Market Authority \(ESMA\)](#), [Securities and Exchange Commission \(SEC\)](#), etc.) have the responsibility to limit the effect of the shock on financial markets, hence mitigating the potential contagion/amplification effects. The third, and last, point of the chapter regards the empirical validity of the [SEH](#) on the U.S. market during the Subprime crisis. We provide a sample consisting in daily market data (price, volume and capitalization) of 53 of the largest financial institutions in the U.S. over the 2006-2011 period. We use various measures from the literature in order to identify the differences phases in a [SE](#), put forward in the [SEH](#). For the build-up of financial fragility, we use a [Principal Component Analysis \(PCA\)](#) à la Kritzman et al. (2011). We identify the initial shock using the [Conditional AutoRegressive Value-at-Risk \(CAViAR\)](#) of Engle and Manganelli (2004) and the [ΔConditional Value-at-Risk \(CoVaR\)](#) of Adrian and Brunnermeier (2016). We have two measures for the contagion and amplification stage. First, the [Average Chi \(ACHI\)](#) of Balla, Ergen, and Migueis (2014) for assesing the potential of contagion. Second, the [Roll Implicit Spread \(RIS\)](#) of Roll (1984) and [ILLIQ](#) of Amihud (2002), for the amplification of losses through illiquidity. Eventually, we proxy the negative externalities on the U.S. real economy using the U.S. real GDP and the U.S. unemployment rate. As [Figure I.5 \(p.64\)](#) shows,

⁹For a schematic representation of the chronology of a [SE](#), see [Figures 3 \(p.18\)](#) and [I.2 \(p.50\)](#).

we can segment the Subprime crisis according to the **SEH**. We observe, first, an increase in the commonality of returns. In a second time, large systemic losses follow. Eventually, the contagion and amplification effect come in play, shortly followed by a worsening of the real economic variables.

The chapter contributes to the existing literature in two different ways. First, it is the first, in our knowledge, attempt to provide a comprehensive conceptual framework of **SR** that comprises all definitions required to understand **SR**, that proposes a specific chronology in **SEs** and that organizes the existing regulatory instances regarding their role in the unfolding of a **SE**. In particular, the chronology has a strategic importance for regulators as it allows for a better understanding of the process that **SEs** follow. Secondly, it advocates for the multidimensionality of **SR** and shows, empirically, that the **SEH** holds for the Subprime crisis, and that **SR** is a complex combination of multiple types of risk. The fact that **SR** is multidimensional has direct implications for the literature on **SR** measurement, as well as for prudential authorities.

Chapter II takes a closer look on the empirical validity of the **SEH**. In particular, it examines the multidimensionality of **SR**, and the chronology that **SE** follows. First, in order to assess the multidimensional character of **SR**, the chapter introduces the concept of Systemic Dimensions. Systemic Dimensions are different types of risk that compose **SR**. This chapter considers that, individually, Systemic Dimensions are noisy signals for **SR**. They are composed of noise, that is specific to the underlying risk, and signal, that is the systemic component. In essence, Systemic Dimensions should be uncorrelated in stable times, as the signal for **SR** should be null and specific noises are, by definition, uncorrelated. In crisis periods, however, the proportion of noise-to-signal decreases and the Systemic Dimensions should be correlated. We base our analysis on a **PCA** applied over two samples, a U.S. and a European, over the 2001-2020 and 2005-2017 periods respectively, using proxies of Systemic Dimensions: ΔCoVaR for systemic losses, **ILLIQ** for systemic losses and **DGC** for systemic connectedness. Our results show that Systemic Dimensions are indeed not correlated during stable times and lose that orthogonality during crisis periods. Moreover, we provide evidence that an increase in the explained variance of the first principal component is a signal for **SR** if it is caused by a concomitant decrease in the

explained variance of other principal components. In a second time, we introduce a specific lagging procedure (see Figure 4, p.20) that tests the chronology of a **SE**. We find that, by lagging accordingly Systemic Dimensions, we improve the signal for **SR** provided by the inertia of the first component. The implications of these results are twofold. First, **SR** is a combination of different risks, called Systemic Dimensions that become correlated during crisis periods. Second, the systemic connectedness occurs first during a crisis, it relates to the creation of a large common exposure. Systemic losses follow that build-up in financial fragility and worsen through systemic illiquidity.

The contribution of this chapter are twofold. It is the first paper to propose the concept of Systemic Dimensions, and, hence, to study the correlation of **SR** measures between each other. By doing so, it is also the first study to show that **SR** can be assessed via the correlation of different measures, thus, providing initial evidences corroborating the **SEH**. Furthermore, it provides additional empirical evidences of a specific timeline of **SE**. By doing so, the research opens up a new path for research for the literature that centers on the temporal dynamics between **SR** measurements. Consequently, the chapter brings forward evidences, both concerning the multidimensionality and temporality of **SR**, that advocate for the validity of the **SEH**.

Chapter III addresses one of the limits of the **SEH**. Indeed, the first chapter exposes in details our proposition of conceptual framework, the **SEH**. However, the **SEH** does not include the diversity of types of financial institutions in the development of a **SE**. We assume that, with different types of core activity, different types of risk emerge. In other words, different types of financial institution should incur different types of risk. Chapter III studies the type of **SR** carried by each institution. We collect daily prices, volumes and market capitalization of 483 European and American firms over the 2001-2021 period. Accordingly to the previous chapters, we compute the Systemic Dimensions for each types of firm. We use the ΔCoVaR to proxy systemic losses, and the **DGC** for systemic connectedness. In order to take into account the fact that illiquidity should be worse when returns are negative, we apply a Multiplicative Error Model (MEM) on the **ILLIQ** measure¹⁰,

¹⁰The use of a MEM for extracting the conditional mean of a timeseries is proposed by the Volatility-Lab of NYU. It allows to ‘filter’ the noise out of the measure, and to add more weight to illiquidity when returns are negative.

proxying systemic illiquidity. In order to simplify the interpretation of our results, we introduce the **Systemic Risk Profile (SRP)**¹¹. The **SRP** consists in a graphical representation of the levels of Systemic Dimensions, in and outside of a crisis, for a type of firm. Our results are fourfold. First, we provide evidences that the **SRP** differs given the type of firm considered. Insurers are largely exposed to losses, while investment funds are more interconnected. Secondly, we show that the **SRP** also varies according to the size of the firm¹². Large financial firms tends to be highly exposed to systemic losses and are more interconnected, while smaller firms presents higher illiquidity. Thirdly, and correspondingly to the **SEH**, the tendency of financial firms to be more prone to one type of Systemic Dimensions implies that large firms will be involved in the beginning of the crisis, during the build-up of financial fragility and the realization of latent losses. However, smaller firms will suffer high illiquidity and will act as contagion channels. Finally, we show that each crisis in our sample is different, and that the **SRP** is a simple, yet powerful, tool to assess the type of a crisis. In particular, we observe that a systemic crisis, translates by a concomitant increase in all Systemic Dimensions, confirming the results put forward in Chapter I and Chapter II.

This final chapter contributes to the current literature in two ways. First, it constitutes the first study, in our knowledge, to propose a graphical representation of the levels in Systemic Dimensions¹³ for various types of financial firms. It is the first study to point out the existing differences in **SR** given the type of financial firms considered. Hence, it advocates for using different types of measure, when assessing **SR** for different types of firm. Second, it put forward yet additional evidences for a specific chronology of **SEs**. The chronology corresponds to what the **SEH** postulates, as well as what Chapter II finds empirically.

In essence, this dissertation brings three main contributions. The first one is of a theoretical nature. We assessed that the difficulty in measuring **SR** stems from a lack of conceptual framework that led to an overabundance of measures. We address that matter by proposing a conceptual framework, the **SEH**. It is one of the first research, that develop a full chronology of **SEs**, and define **SR** accordingly. We

¹¹To have a schematic representation of a **SRP**, see Figure 5 (p.22).

¹²See Figure III.4 (p.139).

¹³The graphical representation of Systemic Dimensions refers to the **SRP**.

also provide empirical evidences, over multiple samples and measures, that the **SEH** holds for the Subprime crisis. The **SEH** offers a clarification on how systemic crises emerge, on how to assess **SR** and on how regulators can mitigate it. It expands the existing literature on **SR**, and allows for a more precise understanding on how **SEs** unfold. The second contribution is methodological. By aiming to validate the **SEH**, Chapter II proposes a novel approach to measure **SR**. Until now, most of the existing measures are unidimensional, and, hence, assess one specific Systemic Dimension. More recently, new researches have come up with a multidimensional assessment of **SR** (Hollo, Kremer, & Lo Duca, 2012). However, none, in our knowledge, have approached **SR** by examining the correlation between Systemic Dimensions, or **SR** measures. By doing so, this thesis proposes to examine further the temporal dynamics of Systemic Dimensions. Finally, this dissertation offers a contribution for regulators. By describing in details the chronology of a **SE**, the composition of **SR** in terms of Systemic Dimensions, the role of the type (and size) of financial institutions during a crisis, we offer precious information for regulatory instances. More specifically, we propose timing of regulatory intervention during a **SE** for different types of regulatory bodies. Each oversight instance has a specific role to play during the whole development of a crisis. This thesis specifically organizes these regulatory actions.

Limits & Future Research Agenda

The framework on **SR** measurement, that this dissertation proposes, is by no means complete, nor final. The current proposal is a framework that needs to gain maturity and to be refined. We account for four main limitations, and expose in what ways our future research agenda will address these.

The first relates to our proposal of a conceptual framework, the **SEH**. The current version consists in an initial proposal, that aims to fuel a renewed interest in theoretical aspects of **SR**. By its lack of maturity, it needs to be refined, completed and would benefit from a more comprehensive assessment of its empirical validity. Consequently, we aim to collect larger sets of data in order to investigate further the empirical validity, and to confirm the presence of a chronology in a systemic crisis. By doing so, we also plan to integrate in the **SEH** the role of each type of financial

institution in a crisis. Moreover, a conceptual framework is often created in order to lead the construction of a coherent measurement. While the SEH provides its share of contributions, it lacks the development of a model for measuring SR that is coherent with the definitions and the chronology proposed by the framework. On that matter, we already have considered a few leads. Among those, we considered the construction of Hidden Markov Model (HMM) with a constrained transition matrix. The constraints applied over the transition matrix would help the model to identify the succession of stages of a SE. From that point, we could perform prediction and assess the validity of the SEH in the forecasting of financial crises. We also considered another method based on Vector AutoRegression (VAR) models in order to infer the states of the financial system. We plan to explore both approaches.

A second limitation comes from the nature of the data used in this dissertation. The research in SR measurement exhibits a peculiar tradeoff. A study must make a choice between using daily market based data or quarterly/annual accounting based data. The first kind allows to have a dynamic view of SR and to examine the short-term changes and evolution of the risk. However, the measures proposed for market based data are usually proxies. In other words, we approximate a given risk, by using stock data of financial firms. The second choice allows addressing that issue, by looking directly at the fundamentals of a firms, it, however, comes with the cost of diminished frequency. This doctoral work chose the first option. It is now required to explore the coherence, and validity of this work by using accounting based data. One of the related issue will become then the accessibility of such datasets. However, the construction of Systemic Dimensions and the examination of their correlation through time would be validated, if evidences were to be found using accounted-based measures.

Our third limitation comes with the creation of Systemic Dimensions. The introduction of the concept that SR consists in a combination of various risks, have serious implications for both regulators and academics. However, our work suffers from the gigantic amount of measures available, which translates into the arduous task of choosing a specific measure to represent a Systemic Dimension. For the sake of this dissertation, we had to make a choice on what measures to use as a proxy for what Systemic Dimension. The choice was made by taking well-known loss, liq-

uidity and connectedness measures. However, we did not explore all of the possible measure for each dimensions. We plan to address those limitations by performing an exploratory study on the construction of Systemic Dimensions. One method considered would be to apply a [PCA](#) on a set of [SR](#) measures, in order to categorize measures between each other and to extract our Systemic Dimensions. Furthermore, there is an additional need to assess the predictive power of Systemic Dimensions on the distress of financial firms. Intuitively, we could consider that the levels of Systemic Dimensions are positively correlated with a firm's distress. However, it is possible that, especially for [TBTF](#) firms, the Systemic Dimensions are positively correlated with the distress of the system. It is currently unknown, whether high levels of Systemic Dimensions for a given firm imply the future failure/distress of that firm. Moreover, the extent to which each Systemic Dimension participates to financial distress is also unknown. Such relationship must be further examined.

Finally, although the results put forward this thesis have serious regulatory implications, there is still a need to formalize and develop them. The regulatory proposals presented were constructed from a financial perspective. Hence, a collaboration with academics specialized in financial regulation would allow to improve the relevance and applicability of our suggestions.

More generally, we intend to improve the work proposed in this thesis by performing robustness tests over our results, and continue to examine the dynamics of [SR](#) over multiple sample and measures. In particular, we need to address the multiple comparisons problem¹⁴ when performing tests over a large set of data. In particular, the construction of the [DGC](#) requires bilateral regressions performed for each pair of firms in the system considered and that for each rolling-forward window. For the tests in Chapter [III](#), the [DGC](#) was computed over, roughly, 800 millions regressions in total. Even though, we compute the [DGC](#) at the 1% level of confidence, the amount of remaining errors is significant.

[SR](#) is one of the most interesting topics in finance nowadays. Despite the extent of literature present on regulatory or measurement aspects, [SR](#) remains a topic of utmost importance. Understanding it requires tremendous knowledge of interna-

¹⁴It is also known as the '*look else-where effect*'.

tional economics, finance, mathematics, law and many other fields. It is precisely why, the opportunities of research in [SR](#) are insatiable. The discovery of knowledge is not a continuous process. Quite oppositely, it experiences large pushes, jumps, caused by the unexpected work or point of view of an academic that allows a renewed expansion. The literature on [SR](#) may seem, at the moment, saturated. We argue however, that, until a sustainable solution addressing financial crises has been reached, we are merely waiting for an unexpected push.

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Résumé en Français

Le risque de système

Le risque systémique, ou risque de système¹, n'a rarement été autant d'actualité qu'aujourd'hui. Au regard des répercussions multiples et imprévisibles de la crise sanitaire mondiale, nous avons pu observer l'importance de l'interconnexion de notre système, le poids des faiblesses structurelles qui, avec le temps, se développent et fragilisent l'économie mondiale. Par le passé, le risque de système est apparu à travers la défaillance d'*Herstatt*, en 1974. Cet événement a mis en exergue les implications systémiques des activités bancaires. Dans ce cas spécifique, le risque systémique s'est matérialisé via le marché des changes. La banque ayant été mise en liquidation, n'a cependant pas ou régler ses paiements/règlements sur le marché américain. De ce fait, les créances des contre-parties américaines furent annulées, résultant en une cessation du système de paiements interbancaires de New York, de plusieurs jours. Herstatt est notamment connue pour être à l'origine de l'intérêt des instances réglementaires pour le risque systémique. Par la suite, le développement des normes de Bâle I et II permit, en premier lieu, la création d'un cadre réglementaire concernant le risque de système, et, dans un second temps, son renforcement. Ce développement, néanmoins, échoua à empêcher la réalisation de la crise systémique du 21^{ème} siècle, la crise des Subprimes. Cette dernière est reconnue comme étant l'archétype d'un événement systémique. Son développement a été particulièrement complexe, se construisant sur la bulle immobilière et la dérégulation du système bancaire américain, présentant divers mécanismes d'amplification des pertes ainsi que des effets de rétroaction² entre le monde financier et économique. Elle a, entre autres, causé le gel momentané du marché interbancaire, une diminution

¹Aglietta, 1993.

²Plus connus sous le nom de: *feedback effects*.

significative de la croissance économique et une augmentation du taux de chômage dans la majorité des pays impliqués. Les conséquences, selon Aglietta (1993), sont appelées d'externalités négatives, qui sont les processus poussant l'économie réelle hors de la plage des équilibres normaux³. En connaissant la dangerosité d'un tel type de crise, il paraît essentiel d'empêcher leur réalisation. Or, pour tenter de gérer un risque, encore faut-il d'abord savoir le mesurer.

La définition du risque systémique devient alors une préoccupation capitale pour les autorités prudentielles. En effet, il faut déterminer, en premier lieu, ce qu'est le risque de système, avant de pouvoir proposer une réglementation efficace pour limiter ce dernier. Ce travail portant sur la définition du concept remonte à la fin du 20^{ème}. Aglietta (1993, 1996) et Aglietta and Moutot (1993) proposent une définition assez large, qui ne précise pas le type d'acteur considéré, mais qui se concentre sur le dysfonctionnement de la capacité d'allocation optimale des risques sur les marchés financiers. La définition formelle est la suivante: *'Le risque de système est l'éventualité qu'apparaissent des états dans lesquels les réponses des agents aux risques qu'ils perçoivent, loin de conduire à une meilleure répartition des risques individuels, conduisent à élever l'insécurité générale'* (Aglietta and Moutot, 1993, p. 22, paragraphe 6). De leur côté, De Bandt and Hartmann (2000) vont séparer le risque système en deux concepts adjacents. Le risque systémique horizontal d'une part, qui ne concerne que les marchés financiers. Par là, il se réfère aux crises et chocs restreints au monde financier. Et, d'autre part, le risque systémique vertical, créé dans le système financier et qui engendre des conséquences dans l'économie réelle. Il mettent alors en avant la relation entre les concepts de risque systémique et d'instabilité financière⁴. Parmi les nombreuses autres définitions existantes, il ne semble pas y avoir de consensus sur une en particulier. Ce qui n'est pas sans poser problème. Comme le note Aglietta (1993), le risque systémique *'est un domaine où l'approche théorique peut, et doit, guider l'action publique'*.

Dû à la profusion de différentes définitions proposées par la littérature mais aussi par les instances de supervision, une vague de recherche concentrée sur la mesure du risque systémique est apparue à partir du début des années 2000. Certains

³Aglietta, 1993.

⁴De Bandt, Drumetz, and Pfister, 2013.

chercheurs se sont concentrés sur les aspects de contagion et d'interconnexion présents durant une crise, donnant ainsi lieu à une littérature abondante sur des mesures basées sur la théorie des réseaux (Billio et al., 2012; Hautsch, Schaumburg, & Schienle, 2014; Diebold & Yilmaz, 2014; Acemoglu, Ozdaglar, & Tahbaz-Saheli, 2015; Amini, Cont, & Minca, 2016; Hué, Lucotte, & Tokpavi, 2019). D'autres se sont focalisés sur l'aspect de pertes extrêmes qui pourraient pousser une institution Too Big To Fail (TBTF) dans la faillite (Acharya, Engle, & Richardson, 2012; Brownlees & Engle, 2017; Adrian & Brunnermeier, 2016; Acharya et al., 2017). Kritzman et al. (2011), Blei and Ergashev (2014), and Balla, Ergen, and Migueis (2014) se concentrent sur la commonalité existante entre les rentabilités financières et leurs queues de distribution. La notion d'illiquidité systémique et ses différentes mesures (Roll, 1984; Amihud, 2002) ont aussi trouvé leur place dans la littérature existante. La variété et le nombre de mesures proposées est tel, que certains chercheurs ont opté pour une mesure basée sur l'agrégation de multiples mesures (Allen, Bali, & Tang, 2012; Hollo, Kremer, & Lo Duca, 2012). Bien que la multiplicité de mesures permet de mieux comprendre le risque de système, de par la diversité des approches, elle a aussi tendance à porter à confusion. En effet, quelles sont les mesures les plus à même d'évaluer le 'vrai' risque systémique ? Le manque d'accord à propos de la définition du risque de système s'est traduit par une hétérogénéité des mesures proposées, complexifiant le choix des indicateurs pertinents pour sa gestion. Ce problème constitue un enjeu central pour la réglementation prudentielle.

Le cadre réglementaire prudentiel existant a un large champ d'action, des exigences de liquidité aux *stress tests* en passant par les procédures de résolution⁵. Bien que le cadre prudentiel actuel ait prouvé son efficacité, notamment pendant la crise actuelle, certains aspects peuvent être encore développés. Schwarcz (2019) fait valoir que le fait que la réglementation macroprudentielle reste focalisée sur les entités constitue une limite importante. En effet, la plupart des réglementations actuelles visent à atténuer l'impact d'une défaillance d'une Institution Financière d'Importance Systémique, ou Systemically Important Financial Institution (SIFI), sur le système financier. Même si les SIFI sont liées à l'instabilité financière, les défaillances de ces dernières ne sont qu'une partie des déclencheurs possibles d'une crise systémique. Par exemple, les marchés financiers sont moins réglementés en ce

⁵Schwarcz (2008) propose une introduction complète à la réglementation prudentielle

qui concerne le risque de système. Bien qu'il soit connu que les paniques ou krach boursiers sont généralement liés aux crises financières et aux crises systémiques, ils sont considérés comme des conséquences plutôt que des causes.

En outre, Schwarcz (2019) identifie les principaux déclencheurs et mécanismes de transmission qui devraient être mieux régulés. Les déclencheurs du risque systémique sont nombreux. La question de la complexité, et de l'opacité qui en découle, pose l'un des plus grands défis du 21st siècle. Le degré de complexité des marchés financiers a atteint un tel niveau que les expositions existantes deviennent difficiles à identifier. En outre, les coûts d'agence⁶ et les limitations comportementales⁷ sont des menaces sérieuses pour la robustesse des SIFI. En outre, la rigidité du cadre réglementaire par rapport à l'évolution rapide du système réglementé, pose un certain nombre de problèmes. Sans une surveillance constante, dont la mise en place serait très complexe, il est difficile pour un cadre réglementaire de rester cohérent sur une longue période.

Le cadre réglementaire doit également prendre en compte les différents mécanismes de transmission. Le système financier est de plus en plus interconnecté, et la diversité des interconnexions augmente en conséquence. L'interconnexion peut porter sur des obligations financières et des expositions communes aux risques. De surplus, la taille d'une SIFI a une relation directe avec la quantité de connexions qu'elle possède. Dans certains cas, un choc peut être transmis par des chambres de compensation centrales qui agissent comme un noeud central dans un réseau⁸, ou par les marchés de dérivés. Les transmissions de chocs d'un marché à l'autre jouent un rôle important dans un événement systémique, d'où la nécessité d'une surveillance prudentielle.

'La réglementation macroprudentielle est également soumise, bien entendu, à notre compréhension limitée du risque systémique, notamment de ses déclencheurs et de ses mécanismes de transmission' (Schwarcz, 2019, p.23, paragraphe 2). Il y a et il y aura toujours, surtout en ce qui concerne le risque systémique, un besoin

⁶Les coûts d'agence proviennent d'un mauvais alignement des objectifs entre les gestionnaires et les propriétaires. Les gestionnaires sont souvent rémunérés en fonction d'objectifs à court terme qui vont à l'encontre des intérêts à long terme de l'entreprise.

⁷Les limitations comportementales comprennent, entre autres, le comportement moutonnier (cf. *Herding behavior*) et les biais cognitifs.

⁸Acemoglu, Ozdaglar, and Tahbaz-Saheli, 2015.

de compréhension plus approfondie sur la façon dont un événement systémique se déroule. Le risque de système continue d'évoluer et de changer en même temps que les marchés financiers et les structures de l'économie. Modéliser un phénomène dynamique d'une telle complexité devient alors une tâche particulièrement difficile.

Comment mesurer le risque de système ?

Cette thèse va répondre, de manière générale, au questionnement suivant : Comment mesurer de manière cohérente le risque systémique ? Les enjeux qui découlent de cette question sont multiples. D'un côté, il existe des enjeux réglementaires forts. En effet, les instances de supervision prudentielle ont besoin d'avoir des indicateurs à la fois globaux, c'est à dire une mesure du niveau de risque systémique en général, et individuels, c'est à dire au niveau d'une institution en particulier, et ce, pour pouvoir assurer la stabilité du système financier. Une connaissance plus fine de la dynamique du risque de système permettrait un fonctionnement plus efficace du système financier. D'un autre côté, mais toujours intimement lié, le risque systémique pose un challenge de taille pour la communauté académique. Le défi consiste à découvrir les mécanismes intrinsèques à notre économie et système financier qui mènent à des états d'instabilité chronique.

Répondre à ces enjeux représente un devoir sociétal. Limiter le risque systémique permettra de limiter, voire d'annuler, les externalités négatives provenant du système financier et d'aborder les causes intrinsèques de l'instabilité récurrente de notre système. In fine, la maîtrise du risque de système permettra aux marchés financiers d'effectuer leur fonction première : l'allocation efficiente des ressources.

Comment mesurer de manière cohérente le Risque Systémique ? Pour répondre à cette problématique, il nous faut d'abord la décomposer. En premier lieu, pourquoi, malgré la quantité d'articles et de recherches portant sur le sujet, n'y a-t-il toujours pas d'accord sur une définition (ou mesure) du risque systémique ? Et, par conséquent, comment peut-on définir le risque de système ? Notre premier chapitre répond à ces deux questions.

En effet, le risque systémique est un concept particulièrement difficile à définir.

C'est par son caractère dynamique et sa complexité qu'il échappe à des définitions trop précises, centrées sur des acteurs ou des mécanismes particuliers. Pour pallier ces limites, cette thèse se base sur une approche dite *systemique*⁹. Dans un premier chapitre, nous redéfinissons tous les concepts associés au risque systemique, et construisons notre raisonnement pour proposer un cadre théorique, une grille de lecture novatrice d'un événement systemique. Nous nommons ce cadre théorique : l'Hypothèse des Événements Systemiques (HES). Cette hypothèse formalise le déroulement d'une crise systemique, et en détaille chaque étape. À partir de cette chronologie, nous proposons des fenêtres de temps spécifiques pour une intervention réglementaire d'une instance de supervision. Nous offrons, ensuite, une démonstration empirique de notre hypothèse appliquée à la crise des subprimes. Rappelons que ce cadre théorique se base sur certaines hypothèses sous-jacentes, qui se doivent d'être explicitées. Parmi elles, l'HES décrit le risque systemique de manière dynamique. Plusieurs risques se réalisent à différentes étapes d'une crise, et interagissent entre eux via des relations de rétroaction. Ou encore, le fait que le risque de système croît avec la réalisation de chaque étape. Et surtout, l'HES suppose que le risque de système est une association de différents types de risque, appelés : *Dimensions Systemiques*.

Notre deuxième chapitre est dédié à l'étude de ce point en particulier. La logique sous-jacente à notre approche est de considérer les Dimensions Systemiques comme des signaux bruités du risque systemique. Chaque Dimension capte un type particulier de risque, la spécificité du risque évalué induit l'orthogonalité du bruit inhérent à chaque Dimension. En période stable, où le risque de système est bas, le ratio bruit-signal est élevé et les Dimensions Systemiques paraissent non-corrélées. En période de crise, ce ratio se réduit, et les Dimensions deviennent alors corrélées. En utilisant des mesures largement reconnues afin d'approximer les Dimensions Systemiques¹⁰, nous étudions plus particulièrement deux questions. Premièrement, il nous faut vérifier si les Dimensions Systemiques mesurent en effet des risques différents en période stable, et servent de signal pour le risque de système en période de crise. Pour ce faire, nous utilisons la Delta Value-at-Risk Conditionnelle (ΔCoVaR) de Adrian and Brunnermeier (2016) pour approximer les Pertes Systemiques, ILLIQ

⁹Walliser, 1977.

¹⁰Dans notre cas, les Dimensions Systemiques sont les suivantes: Pertes, Illiquidité et Interconnexion.

(Amihud, 2002) pour l'illiquidité Systémique, et le Degré de Causalité de Granger (DCG) (Billio et al., 2012) pour l'Interconnexion Systémique. Notre échantillon comprends 75 entreprises Américaines, comprenant des Banques, Assurances et des Fonds d'investissement sur la période de 2001-2020. Les corrélations entre les Dimensions Systémiques sont représentées par l'inertie de la première composante principale estimée par une Analyse en Composante Principale (ACP). Dans un deuxième temps, nous analysons différents délais dans la corrélation des Dimensions Systémiques. En effet, dû à la chronologie proposée par l'HES, chaque Dimension devrait atteindre un pic de manière successive. Ainsi, en décalant certaines Dimensions Systémiques dans le temps, de telle sorte qu'elles s'alignent par rapport à leur pics respectifs, nous devrions trouver une meilleure corrélation entre ces dernières lors d'une crise. Cette partie se concentre donc sur l'étude des corrélations entre les Dimensions Systémiques décalées, pour mettre en avant cette succession d'occurrences de risque.

L'HES présente les différents risques intervenant lors d'un événement systémique, mais ne se focalise que peu sur le rôle spécifique de chaque acteur du système financier. Chaque type d'institution financière a un fonctionnement propre, une finalité spécifique et des mécanismes particuliers. Il ne serait donc pas surprenant que chaque type d'institution soit plus enclin à être associé à une Dimension Systémique en particulier. Le dernier chapitre de cette thèse répond à cette limite de l'HES. Nous proposons ainsi une étude empirique visant à étudier le niveau des Dimensions Systémiques de plusieurs type d'institutions financières américaines et européennes: banques, assurances et fonds d'investissements. Nous examinons les différences sur un échantillon complet de 417 entreprises, et sur des sous-échantillons comprenant les plus grandes, et petites, entreprises financières en fonction de leur capitalisation boursière. Nous mettons en exergue un effet de taille sur les niveaux des Dimensions Systémiques, et retrouvons la séquentialité d'une crise systémique proposée par l'HES et démontré par notre deuxième chapitre.

L'Hypothèse des Événements Systémiques

La définition du risque systémique constitue le premier et principal problème dans la gestion du risque de crise d'envergure systémique. En effet, les instances de su-

pervision prudentielle se doivent, de par leurs fonctions, d'atténuer du mieux que possible le risque de système. Pour ce faire, il convient de définir le risque de système de manière précise, et, dans un second temps, de développer une mesure cohérente qui dirigera les décisions et interventions réglementaires.

Il existe pourtant une littérature foisonnante sur les définitions de ce concept, et encore plus sur ses mesures. D'où peut donc venir ce manque de consensus ? Il provient d'une caractéristique intrinsèque au risque systémique, ainsi qu'à la réaction à un besoin urgent. Tout d'abord, le risque de système est concept extrêmement dynamique, qui change en fonction du *système* considéré. Vu que le système financier évolue, et particulièrement durant ces dernières décennies, à une vitesse croissante, la notion de risque de système évolue en conséquence. Ensuite, du fait de la crise des Subprimes, de nombreux chercheurs se sont penchés sur la question de la mesure du risque systémique. Ce faisant, la question de la définition de ce dernier a été éludée. C'est précisément sur ce point que nous apportons notre contribution, avec l'Hypothèse des Événements Systémiques (HES). Cette dernière constitue une proposition de cadre théorique pour analyser les crises systémiques. Elle reprecise, tout d'abord, les concepts sous-jacents, tels que la fragilité financière (Allen & Gale, 2007), la stabilité financière (Schinasi, 2004; De Bandt, Drumetz, & Pfister, 2013) ou encore les crises financières. Elle construit une chronologie d'un événement systémique basée initialement sur la vision de Minsky (1991, 1992), et en détaille les étapes, se basant sur la littérature existante.

Tout d'abord un événement systémique naît lors d'un changement structurel. Ce changement, présent dans la théorie de Minsky (1992), peut revêtir diverses formes : changement de cadre réglementaire (que ce soit un affermissement ou une vague de dérégulation), apparition d'une innovation financière, ou d'un nouveau type d'activité (par exemple le Trading Haute Fréquence). C'est à partir de ce dernier qu'apparaît une nouvelle opportunité de profit. Comme toute nouvelle opportunité, cette dernière est accompagnée de risques, parfois connus, parfois moins. Nous appellerons la partie inconnue de ces risques, 'risque latent'. À l'inverse des risques 'usuels', l'incertitude liée au risque latent s'intéresse à *quel moment* ce dernier se

réalisera¹¹. Les institutions financières, agissant de manière rationnelle dans un contexte capitaliste, investissent dans cette nouvelle opportunité de profit. Ainsi, et à leur insu, de nombreuses entreprises financières s'exposent, communément, à un même facteur de risque. C'est le début de la phase de création de fragilité financière.

La fragilité financière fait référence au degré avec lequel le système financier réagira en conséquence d'un choc donné¹². Dans un système capitaliste, les institutions financières sont principalement en quête de rentabilité, et sont donc poussées à chercher de nouvelles sources de profit. C'est précisément pour cette raison, qu'une partie significative du système financier se trouve exposée au risque latent. Cette montée en fragilité est observable, empiriquement, par l'apparition d'un facteur commun aux rentabilités boursières (Kritzman et al., 2011). Cette construction progressive de fragilité continue jusqu'au '*Minsky Moment*'¹³. Par ce terme, Minsky (1992) fait référence à l'arrivée d'un événement macroéconomique '*not-so-unusual*'¹⁴, qui marquera le début de la crise. Dans notre cadre, nous dénommerons cet événement, l'événement déclencheur. Ce dernier entraînera la réalisation du risque latent, poussant le système financier dans un état d'instabilité. La difficulté de l'évaluation et la gestion du risque systémique provient de la relation entre le type d'événement déclencheur et la nature du risque latent, autant que celle entre le risque latent et le changement structurel. En effet, le changement structurel aura un effet certain sur la nature du risque latent, qui, à son tour, sera intrinsèquement lié à la nature de l'événement déclencheur.

La réalisation des pertes latentes¹⁵ sera par définition, inattendue et poussera le système financier dans un premier état d'instabilité. D'autres pertes usuelles (liquidité, crédit, opérationnelles, etc.) s'ajoutent à ces dernières et aggravent l'état d'instabilité. Ce choc financier est de nature systématique, dans le sens où il touche toutes les entreprises qui se sont engagées dans l'opportunité de profit. De plus, la mise à mal de certaines institutions se traduira par la survenance de défauts groupés.

¹¹Les risques usuels sont ceux globalement connus tels que le risque de liquidité, de marché, opérationnel, etc. L'incertitude de ces risques réfère à *est-ce que* le risque se réalisera.

¹²Allen and Gale, 2007.

¹³Le Moment de Minsky ou *Minsky Moment* en anglais, fait référence à l'éclatement d'une bulle spéculative.

¹⁴Traduction de l'auteur: *Pas si inhabituel*.

¹⁵Nous appelons 'pertes latentes', toutes pertes relatives au risque latent.

Les tentatives de recapitalisation, via des ventes d'actifs liquides, conduisent à une pression à la vente faisant chuter les prix boursiers. La combinaison de différents mécanismes de ce type, transforme le choc financier en une crise financière. Le système subit alors des effets d'amplification des pertes (ventes à pertes, assèchement de la liquidité, etc.) et de contagion (cascade de défauts), entremêlés par des effets de rétroaction. Cette phase ne peut se dénouer que par trois issues. Premièrement, une intervention des pouvoirs publics permettant la résolution de la crise. En fonction de la gravité de cette dernière, l'économie réelle subira plus ou moins d'externalités négatives. Deuxièmement, la crise finit par se résorber d'elle-même. Les effets de répartition du risque et effets de réseaux (Acemoglu, Ozdaglar, & Tahbaz-Saheli, 2015) internes au système financier permettent de revenir naturellement à un état stable. Enfin, la troisième issue est la chute du système financier. Cette dernière possibilité est improbable, puisque, au regard de l'importance du système financier dans notre économie, les pouvoirs publics interviendront systématiquement en dernier ressort. Ce n'est alors que par l'étendue des externalités négatives qu'une crise financière peut-être déclarée d'importance *systémique*. Ici réside une nouvelle complexité dans la mesure du risque de système. Ce dernier ne peut être confirmé qu'*a posteriori*.

Ayant présenté la chronologie complète d'un événement systémique nous pouvons maintenant proposer une définition pour le risque systémique. Ce dernier représente le risque associé à la réalisation d'un événement systémique. Cette définition rappelle celle proposée par Zigrand (2014). Bien que la définition paraisse simpliste ou tautologique, la contribution de ce chapitre réside dans la chronologie proposée d'un événement systémique. Le risque systémique est ainsi décrit par sa dynamique et sa manière de se manifester.

En supposant que l'HES soit vraie, il existe alors des fenêtres d'intervention optimale¹⁶ pour différents types d'instance de supervision. Nous séparons ces derniers en trois groupes distincts. Premièrement, les régulateurs structurels sont des instances qui, de par leur fonction, auront un impact direct sur la structure du système. C'est à dire sur la manière dont les agents évoluent et interagissent entre eux. Parmi

¹⁶Pour une représentation graphique des fenêtres d'intervention pour chaque instance de régulation voir Figure I.4, page 55.

lesquels, on trouve le Comité de Bâle (BCBS), le Conseil de Stabilité Financière (FSB) ou encore le Conseil Européen du Risque Systémique (ESRB). Leur rôle est double. D'un côté, ils sont responsables de la résilience du système financier, et, par conséquent, d'imposer les réglementations prudentielles qui pèsent sur les institutions financières. D'autre part, étant donné l'implication systémique de leurs actions, ces instances se retrouvent en charge d'évaluer la nature du risque latent, qui émerge du changement structurel initial. Deuxièmement, les autorités monétaires, telles que la Federal Reserve (Fed) ou encore la Banque Centrale Européenne (ECB), sont chargées de deux principales tâches. La première étant d'éviter la construction d'un niveau d'endettement excessif dans l'économie, intervenant dans la phase d'accroissement de fragilité financière. La deuxième est d'agir en temps que '*prêteur en dernier ressort*'. Elles agissent alors comme filet de sauvetage de dernier recours pour secourir une institution, dite TBTF. Troisièmement, le rôle des autorités de marchés, telles que la Security and Exchange Commission (SEC) ou encore l'Autorité Européenne des Marchés Financiers (ESMA), est centré sur une intervention de court terme ayant pour objectif de limiter l'impact de l'événement déclencheur. En effet, ces instances jouent un rôle clé dans la maîtrise des effets de contagion et de propagation des pertes.

Enfin, nous construisons une étude empirique visant à mettre en évidence les étapes d'un événement systémique. L'étude se réalise sur deux échantillons. Le premier est constitué de 53 des plus grandes entreprises financières américaines. Le deuxième regroupe 50 des plus grandes firmes financières européennes. Les deux échantillons recouvrent, largement, la période de la crise des Subprimes (2006-2011). Nous utilisons de nombreuses mesures destinées à évaluer, individuellement, une étape spécifique d'une crise systémique. Une ACP sur les rentabilités boursières des entreprises vise à mesurer la montée d'un facteur commun (Kritzman et al., 2011). Les CAViaR (White, Kim, & Manganelli, 2015) et Δ CoVaR (Adrian & Brunnermeier, 2016) mettent en lumière la réalisation de pertes extrêmes. L'Average Chi (ACHI) mesure le potentiel de contagion présent dans le système financier (Balla, Ergen, & Migueis, 2014). Pour les effets d'amplification des pertes via l'illiquidité de marché, nous utilisons ILLIQ (Amihud, 2002) et le Roll Implicit Spread (RIS) (Roll, 1984). Enfin, nous choisissons le taux de chômage et le PIB réel. Nos résultats mettent en exergue la présence d'étapes consécutives dans une crise systémique, et

ceci, autant sur le marché américain qu'europpéen (voir Figures I.5, p.64 et I.6, p.83).

Corrélation des Dimensions Systémiques

L'HES soulève de nombreuses questions quant à sa validité. Le chapitre II et le chapitre III visent à répondre à quelques unes d'entre elles. Ce deuxième chapitre se concentre sur la multidimensionnalité du risque de système. La raison d'être de cette étude est de se demander si le risque systémique est réellement une combinaison de différents risques, et donc si les mesures actuellement utilisées dans la littérature sont colinéaires, ou si elles apportent réellement de nouvelles informations utiles sur le risque systémique.

Nous commençons par postuler que le risque de système est en fait une combinaison de différents risques. Plus précisément, nous supposons trois dimensions systémiques : Pertes, Liquidité et Connectivité. Chaque dimension est supposée capturer un type spécifique de risque systémique qui apparaîtra lors d'un événement systémique. Au vu de la littérature existante, il apparaît que les pertes, l'illiquidité et l'interconnexion sont des composantes majeures du risque de système. L'objectif est donc d'évaluer ce dernier à travers ces dimensions. En sachant que les marchés financiers ne sont pas efficaces, il semblerait alors surprenant que tout indicateur, ou mesure, issu des données du marché, évalue parfaitement ce qu'il est censé évaluer. L'hypothèse sous-jacente de cette partie de la thèse consiste dans le fait que les mesures du risque (systémique) sont des signaux bruités. En d'autres termes, chaque mesure est composée, d'un côté, de bruit spécifique à la mesure, et, d'un autre côté, d'un signal représentant le risque systémique. Les bruits (de chaque mesure) ne sont pas corrélés, car ces derniers sont spécifiques à une dimension¹⁷, mais les signaux, du risque systémique, doivent être en quelque sorte corrélés. Pendant un événement systémique, lorsque le risque de système augmente, toutes les dimensions systémiques devraient alors augmenter en conséquence, d'où une diminution de la proportion de bruit par rapport au signal. Comme le bruit est dominant dans les périodes 'stables', nous nous attendons à observer empiriquement une absence de

¹⁷Ici, la dimension spécifique fait référence aux dimensions systémiques. Un bruit spécifique à une dimension correspond à une augmentation de la dimension systémique, ou de la mesure du risque, en question qui n'est pas liée à une augmentation correspondante du risque de système.

corrélations entre les dimensions systémiques. En conséquence, comme le signal devient prédominant en période de crise, le bruit diminue et nous nous attendons alors à trouver des preuves d'une corrélation supérieure à celle des périodes stables. L'apparition d'une augmentation de corrélation entre les mesures du risque systémique pendant une crise confirmerait, dans les faits, la multidimensionnalité du risque de système¹⁸. Toutefois, cette première analyse ne tient pas compte de la chronologie d'un événement systémique, telle qu'exposée dans l'HES. Afin de valider davantage l'HES, nous devons non seulement mettre en avant les preuves de la multidimensionnalité du risque de système mais aussi montrer des preuves significatives d'une chronologie particulière dans un événement systémique. Pour ce faire, nous proposons de nous concentrer sur la corrélation des dimensions systémiques décalées. La procédure de décalage est décrite dans la Figure 4 (p. 20).

Nous calculons les dimensions systémiques en utilisant des mesures connues sur un échantillon de 75 entreprises financières américaines, composé de banques, de compagnies d'assurance ainsi que de sociétés de gestion d'actifs, de 2000 à 2020. Nos dimensions systémiques sont représentées comme suit. La ΔCoVaR (Adrian & Brunnermeier, 2016) représente les pertes systémiques, le proxy d'illiquidité, ILLIQ , de Amihud (2002) pour l'illiquidité systémique et, enfin, le DCG issu de Granger (1969) et Billio et al. (2012) pour l'interconnexion systémique. Nous étudions l'évolution temporelle de la corrélation entre les dimensions systémiques à l'aide d'une ACP réalisée sur une fenêtre glissante (*rolling-forward*). Une rotation orthonormale spécifique (*quartimax*) est appliquée sur la matrice de corrélation. Nos résultats sont de trois ordres. Premièrement, nous constatons que la variance expliquée de la première composante principale, d'une manière similaire à celle de Kritzman et al. (2011), peut agir comme un signal du risque de système. Plus précisément, l'augmentation de la variance expliquée de la première composante est un signe de risque systémique si cette augmentation est due à une diminution de la variance expliquée des deux autres composantes principales. La mesure comporte encore une quantité significative de bruit, qui, selon nous, est due à la non prise en compte de la chronologie d'un événement systémique. Notre deuxième résultat répond à cette limite. Nous montrons que, en retardant de manière appropriée nos

¹⁸Si nous observons (1) la corrélation des mesures du risque systémique en période de crise et (2) l'absence de corrélation en période stable, cela confirmerait que le risque de système est une combinaison de divers risques, c'est-à-dire de dimensions systémiques.

dimensions systémiques, nous sommes en mesure de réduire la quantité de bruit, ce qui permet à la mesure de capturer plus clairement les périodes de crise. Enfin, nous montrons que la mesure peut également fonctionner pour identifier le risque de système dans tout type de système considéré. Nous appliquons notre procédure à des parties distinctes du secteur financier. Ce faisant, nous sommes en mesure d'observer quels types d'entreprises financières étaient les plus déterminantes, sur le plan systémique, lors de crises bien connues (DotCom, Subprimes ou la crise de la dette souveraine européenne). Nous effectuons aussi toutes nos analyses sur un échantillon européen afin de démontrer leur robustesse.

À chaque institution son Risque Systémique

Notre troisième chapitre vise à étudier le rôle spécifique des différents types d'agents financiers dans un événement systémique. En effet, l'HES propose une chronologie des événements systémiques, et décrit largement les mécanismes en jeu. Cependant, elle ne tient pas compte du rôle spécifique de chaque type d'institutions financières. Le système financier est un éco-système complexe, et chaque agent y appartenant fonctionne d'une manière propre. Le risque systémique étant un risque commun à tous les agents d'un système, et étant le résultat, endogène, d'une succession d'événements prenant racine dans les interactions entre ces agents, il paraît alors logique que chacun de ces derniers ait un rôle précis dans la réalisation d'un événement systémique. L'hypothèse sous-jacente de ce chapitre consiste dans le fait que différentes institutions fonctionnent et interagissent de manière spécifique. Par conséquent, chaque type d'institutions doit avoir un rôle particulier à jouer dans une crise systémique.

Nous basons notre analyse sur nos résultats précédents, et supposons que le risque systémique est composé de trois Dimensions Systémiques : Pertes, Liquidité et Interconnexion. Les Dimensions Systémiques sont approximées au travers de diverses mesures. La ΔCoVaR (Adrian & Brunnermeier, 2016) pour les pertes systémiques, ILLIQ (Amihud, 2002) pour l'illiquidité systémique et, enfin, DCG (Billio et al., 2012) pour l'interconnexion systémique. Ces dernières sont appliquées sur un échantillon de 417 entreprises financières Européennes et Américaines, du 01-01-2001 au 21-01-2021. Les entreprises financières sont des banques, des compagnies

d'assurance et des sociétés de gestion d'actifs. L'objectif principal de l'étude est de découvrir les dimensions systémiques spécifiques à chaque type d'entreprise. À cette fin, nous proposons le concept de Profil de Risque Systémique (PRS). Un PRS est une représentation graphique des niveaux des dimensions systémiques, pour un type d'entreprise donné (voir Figure 5, p. 22). Il représente les niveaux en période 'stable' ainsi qu'en période de crise. Ce faisant, il permet d'avoir rapidement une vue d'ensemble du risque systémique encouru par un type d'entreprise.

À cet objectif initial, s'ajoutent trois buts parallèles. Le premier consiste à examiner l'effet de la taille sur le PRS d'une institution. En effet, découlant du même processus logique qui nous a permis de déterminer que différents types d'entreprises doivent avoir différents types de risques, des entreprises identiques de différentes tailles peuvent également avoir différents types de risque systémique. Pour ce faire, nous séparons notre échantillon initial en deux sous-échantillons. Le premier contient les 10 % des entreprises ayant la plus forte capitalisation boursière, tandis que le second contient les 10 % d'entreprises ayant la plus faible capitalisation. La seconde consiste à découvrir l'effet de chaque crise de notre échantillon (DotCom, Subprimes, dette souveraine européenne et Covid) sur le PRS. Comme nous l'avons dit plus haut, les crises financières peuvent être de différentes sortes. Ainsi, leurs conséquences respectives sur le risque de système devraient alors différer, et le PRS fournira alors un moyen simple d'observer ces conséquences. Enfin, il s'agit de confirmer (ou d'infirmier) la présence d'une chronologie dans les dimensions systémiques lors d'un événement systémique. L'HES fait l'hypothèse qu'il existe différents types de risque systémique (Dimensions Systémiques), et, de plus, que chaque type se produira dans une séquence spécifique. Il s'agira enfin d'examiner la dynamique des dimensions systémiques au cours des deux dernières décennies .

Nos résultats sont nombreux. Répondant à notre question initiale, nous montrons que les PRS diffèrent selon le type d'institutions. Les compagnies d'assurance ont tendance à être largement exposées aux pertes systémiques, tandis que les sociétés de gestion d'actifs sont plus interconnectées et tendent à être plus exposées à l'illiquidité. De manière surprenante, les banques n'apparaissent pas comme le type d'institution le plus important sur le plan systémique dans notre échantillon. Nous observons qu'il existe un effet de taille significatif. Les grandes entreprises auront

tendance à être plus exposées aux pertes systémiques et à être plus interconnectées. Les entreprises plus petites auront tendance à être plus exposées à l'illiquidité. Enfin, nous montrons que chaque crise financière est différente de l'autre, mais qu'une crise systémique est caractérisée par une augmentation concomitante de ses dimensions systémiques. De plus, nous confirmons que ces Dimensions culminent successivement au cours d'un événement systémique, comme le suppose l'HES. En combinant nos résultats, nous montrons que les grandes entreprises, notamment les compagnies d'assurance et les sociétés de gestion d'actifs, auront tendance à accumuler une exposition commune au début de la crise et seront les plus touchées par le choc financier qui suivra. Les petites entreprises, notamment les banques et les assureurs, subiront la hausse de l'illiquidité vers la fin de la crise.

Contributions, Limites & Perspectives

En substance, cette thèse apporte trois contributions principales. La première est de nature théorique. Nous avons affirmé que la difficulté de mesurer le risque systémique provient d'un manque de cadre conceptuel, lequel a conduit à une surabondance de mesures dans la littérature. Nous répondons à cette limite en proposant un cadre conceptuel, l'Hypothèse des Événements Systémiques (HES). Il s'agit de l'une des premières recherches à développer une chronologie complète des événements systémiques, et à définir le risque de système en conséquence. Nous fournissons également des preuves empiriques, sur de multiples échantillons et mesures, que la HES est cohérente pour la crise des Subprimes. L'HES offre une clarification sur la manière dont les crises systémiques émergent, sur la manière d'évaluer le risque systémique et sur la manière dont les régulateurs peuvent l'atténuer. Elle élargit la littérature existante sur la mesure du risque de système, et permet une compréhension plus précise du déroulement des crises systémiques.

La deuxième contribution est d'ordre méthodologique. En visant à valider l'HES, le chapitre II propose une nouvelle approche pour mesurer le risque systémique. Jusqu'à présent, la plupart des mesures existantes étaient uni-dimensionnelles, et n'évaluaient donc une seule dimension systémique. Plus récemment, de nouvelles recherches ont proposé une évaluation multidimensionnelle, comme le Composite Indicator of Systemic Stress (CISS) de Hollo, Kremer, and Lo Duca (2012). Cepen-

dant, aucune recherche académique n'a, à notre connaissance, abordé le risque systémique en examinant la corrélation entre les dimensions systémiques. Ce faisant, cette thèse propose d'examiner plus précisément la dynamique temporelle des Dimensions Systémiques.

Enfin, cette thèse offre une contribution d'ordre réglementaire. En décrivant en détail la chronologie d'un événement systémique, la composition du risque de système en termes de Dimensions Systémiques, le rôle du type et de la taille des institutions financières pendant une crise, nous offrons des informations précieuses pour les instances de réglementation. Plus précisément, nous proposons des fenêtres d'intervention réglementaire à l'intérieur d'un événement systémique pour différents types d'instances réglementaires. Chaque instance de surveillance a un rôle spécifique à jouer durant le développement d'une crise. Plus spécifiquement, cette thèse organise les actions réglementaires de chaque type de régulateurs.

Néanmoins, le cadre de mesure du risque de système que cette thèse propose n'est en aucun cas complet, ni définitif. La proposition actuelle consiste en un cadre qui doit gagner en maturité et être affiné avec le temps. Nous présentons ci-dessous quatre limites principales de ce travail doctoral et exposons les moyens par lesquels notre recherche future les abordera.

La première concerne notre proposition de cadre conceptuel, l'HES. La version actuelle consiste en une proposition initiale, qui vise à alimenter un intérêt renouvelé pour les aspects théoriques de la mesure de risque systémique. Par son manque de maturité, elle doit être affinée, complétée et bénéficierait d'une évaluation plus complète de sa validité empirique. Par conséquent, nous souhaitons collecter des ensembles de données plus importants afin d'en approfondir la validité empirique et de confirmer la présence d'une chronologie spécifique aux crises systémiques. Ce faisant, nous prévoyons également d'intégrer dans l'HES le rôle de chaque type d'institution financière dans une crise. Par ailleurs, un cadre conceptuel est souvent créé afin de diriger la construction d'une mesure cohérente. Dans ce cadre, si l'HES apporte sa part de contributions, elle pâtit cependant du manque d'un modèle de mesure du risque de système cohérent avec les définitions et la chronologie proposées par le cadre. À ce sujet, nous avons déjà envisagé quelques pistes. Parmi celles-ci, nous

avons envisagé la construction d'un modèle de Markov caché (HMM) ajusté par des contraintes spécifiques sur la matrice de transition. Les contraintes appliquées à la matrice de transition aideraient le modèle à identifier la succession des étapes d'un événement systémique. À partir de là, nous pourrions effectuer des prédictions et évaluer la validité de l'HES dans la prévision des crises systémiques. Nous avons également envisagé une autre méthode, basée sur les modèles d'autorégression vectorielle (VAR) afin d'inférer empiriquement les états du système financier. Nous prévoyons d'explorer ces deux approches.

Une deuxième limite provient de la nature des données utilisées dans cette thèse. La recherche sur la mesure du risque systémique présente un compromis cornélien. Une étude doit faire un choix entre l'utilisation de données quotidiennes basées sur le marché ou des données comptables trimestrielles/annuelles. Les premières permettent d'avoir une vision dynamique du risque de crédit et d'examiner les changements à court terme et l'évolution du risque. Cependant, les mesures proposées pour les données de marché sont généralement des approximations. En d'autres termes, nous nous rapprochons d'un risque donné en utilisant les données boursières des entreprises financières. La deuxième option permet de résoudre ce problème en examinant directement les fondamentaux d'une entreprise, mais au prix d'une fréquence réduite. Ce travail de doctorat a choisi la première option. Il est maintenant nécessaire d'explorer la cohérence et la validité de ce travail en utilisant des données comptables. L'une des questions connexes sera alors l'accessibilité de ces ensembles de données. La construction des dimensions systémiques et l'examen de leur corrélation dans le temps seraient validés si les résultats étaient confortés en utilisant des mesures comptables.

Notre troisième limite concerne la création des dimensions systémiques. La définition du concept selon lequel le risque de système consiste en une combinaison de divers risques, a de sérieuses implications pour les chercheurs et régulateurs. Cependant, notre travail souffre de la quantité gigantesque de mesures disponibles, ce qui se traduit par la tâche ardue de choisir une mesure spécifique pour représenter une Dimension Systémique. Pour les besoins de cette thèse, nous avons dû faire un choix sur les mesures à utiliser pour représenter une dimension systémique. Le choix a été fait en prenant des mesures bien connues de perte, de liquidité et d'interconnection.

Cependant, nous n'avons pas exploré toutes les mesures possibles pour chaque dimension. Nous prévoyons de remédier à cette lacune en réalisant une étude exploratoire sur la construction des dimensions systémiques. Une méthode envisagée serait d'appliquer une ACP sur un ensemble de mesures du risque systémique, afin de catégoriser les mesures entre elles et d'extraire nos dimensions systémiques. En outre, il est nécessaire d'évaluer le pouvoir prédictif des dimensions systémiques sur la détresse des entreprises financières. Intuitivement, nous pourrions considérer que les niveaux des Dimensions Systémiques sont positivement corrélés avec la détresse de l'entreprise en question. Cependant, il est possible que, surtout pour les entreprises dénotées comme TBTF, les Dimensions Systémiques soient positivement corrélées avec la détresse du système. On ne sait pas actuellement si des niveaux élevés des Dimensions Systémiques, pour une entreprise donnée, impliquent la défaillance ou la détresse future de cette entreprise. De plus, la mesure dans laquelle chaque Dimension participe à la détresse financière du système est également inconnue. Une telle relation doit être examinée de manière plus approfondie.

Enfin, bien que les résultats présentés dans cette thèse aient de sérieuses implications réglementaires, il est encore nécessaire de les formaliser et de les développer. Les propositions réglementaires présentées ont été construites à partir d'une perspective financière. Ainsi, une collaboration avec des chercheurs spécialisés dans la réglementation financière permettrait d'améliorer la pertinence de nos suggestions, ainsi que leur applicabilité.

Plus généralement, nous avons l'intention d'améliorer le travail proposé dans cette thèse en effectuant des tests de robustesse sur nos résultats, et de continuer à examiner la dynamique du risque de système sur plusieurs échantillons et mesures. En particulier, nous devons aborder le problème des comparaisons multiples¹⁹ lors de la réalisation de tests sur un grand ensemble de données. En particulier, la construction du DCG nécessite des régressions bilatérales effectuées pour chaque paire d'entreprises dans le système considéré et cela pour chaque fenêtre glissante. Pour les tests du chapitre III, le DCG a été calculé sur, approximativement, 800 millions de régressions au total. Même si nous calculons le DCG au niveau de confiance de 1%, la quantité d'erreurs subsistantes reste significative.

¹⁹Également connu sous le nom de '*look else-where*' effect

Le risque systémique reste un sujet central en finance de nos jours. Malgré l'étendue de la littérature présente traitant des aspects réglementaires ou sur ses mesures, le risque de système reste un sujet de la plus haute importance. Sa compréhension nécessite des connaissances approfondies en économie internationale, en finance, en mathématiques, en droit et dans de nombreux autres domaines. C'est précisément la raison pour laquelle les opportunités de recherche dans ce domaine sont infinies. La découverte de connaissances n'est pas un processus continu. Bien au contraire, elle connaît de grandes avancées, des sauts, provoqués par le travail ou le point de vue inattendu de chercheurs, qui permet une expansion renouvelée. La littérature sur le risque systémique peut sembler, à l'heure actuelle, saturée. Nous soutenons cependant que, tant qu'une solution durable aux crises financières n'a pas été trouvée, nous sommes simplement dans l'attente d'une avancée inattendue.

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List of Abbreviations

[A](#) | [B](#) | [C](#) | [D](#) | [E](#) | [F](#) | [G](#) | [H](#) | [I](#) | [L](#) | [M](#) | [N](#) | [O](#) | [P](#) | [R](#) | [S](#) | [T](#) | [V](#)

A

ACHI Average Chi.

ADR Asymptotic Dependence Rate.

ASRF Asymptotic Single Risk Factor.

B

BCBS Basel Committee on Banking Supervision.

BSMD Banking System Multivariate Density.

C

CAViAR Conditional AutoRegressive Value-at-Risk.

CIMDO Consistent Information Multivariate Density Optimizing Methodology.

CoVaR Conditional Value-at-Risk.

CRD Capital Requirement Directive.

D

DGC Degree of Granger Causality.

DIP Distress Insurance Premium.

E

EBA European Banking Authority.

ECB European Central Bank.

EMH Efficient Market Hypothesis.

ES Expected Shortfall.

List of Abbreviations

ESMA European Securities and Market Authority.

ESRB European Systemic Risk Board.

ETF Exchange Traded Fund.

F

Fed Federal Reserve Bank.

FIH Financial Instability Hypothesis.

FSB Financial Stability Board.

FSOC Financial Stability Oversight Council.

G

G-SIB Global Systemically Important Banks.

G-SII Global Systemically Important Insurers.

H

HLA Higher Liquidity Absorbency.

I

IAIS International Association of Insurance Supervisors.

IMF International Monetary Fund.

ISD Investment Services Directive.

L

LCR Liquidity Coverage Ratio.

LOLR Lender of Last Resort.

M

MiFiD Markets in Financial Instrument Directive.

N

NSFR Net Stable Funding Ratio.

O

O-SII Other Systemically Important Institutions.

OFR Office of Financial Research.

P

PCA Principal Component Analysis.

R

RIS Roll Implicit Spread.

S

SCCA Systemic Contingent Claims Analysis.

SE Systemic Event.

SEC Securities and Exchange Commission.

SEH Systemic Event Hypothesis.

SES Systemic Expected Shortfall.

SIFI Systemically Important Financial Institution.

SLRI Systemic Liquidity Risk Indicator.

SR Systemic Risk.

SRP Systemic Risk Profile.

T

TBTF Too Big To Fail.

V

VaR Value-at-Risk.

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