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On the origin of systemic risk

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Abstract

Systemic risk in the banking sector is usually associated with long periods of economic downturn and very large social costs. On one hand, shocks coming from correlated exposures towards the real economy may induce correlation in banks' default probabilities thereby increasing the likelihood for systemic-tail events like the 2008 Great Financial Crisis. On the other hand, financial contagion also plays an important role in generating large-scale market failures, amplifying the initial shocks coming from the real economy. To study the sources of these rare phenomena, we propose a new definition of systemic risk (i.e. the probability of a large number of banks going into distress simultaneously) and thus we develop a multilayer microstructural model to study empirically the determinants of systemic risk. The model is then calibrated on the most comprehensive granular dataset for the euro area banking sector, capturing roughly 96% or EUR 23.2 trillion of euro area banks' total assets over the period 2014-2018. The output of the model decompose and quantify the sources of systemic risk showing that correlated economic shocks, financial contagion mechanisms, and their interaction are the main sources of systemic events. The results obtained with the simulation engine resemble common market-based systemic risk indicators and empirically corroborate findings from existing literature. This framework gives regulators and central bankers a tool to study systemic risk and its developments, pointing out that systemic events and banks' idiosyncratic defaults have different drivers, hence implying different policy responses.

Keywords: Systemic risk, financial contagion, microstructural models

JEL Codes: D85, G17, G33, L14.

Non-technical summary

The calibration of policies aiming to contrast the build-up of systemic risk and preserve the stability of the financial system is an increasingly relevant task for regulators world-wide. The development of sound analytical tools for the interpretation and forecasting is therefore of paramount importance, and microstructural contagion models represent a promising tool, especially considering the fact that very granular datasets are increasingly available to regulators.

One of the main limits of such literature is the lack of an agreed and usable definition of systemic risk, leading to several models that are difficult to compare, or that are suitable only for answering specific research questions. In particular the microstructural contagion model literature is mostly focused on measuring amplification and contagion effects, while the generation of shocks and the relationship between the financial system and the real-economy is less studied.

In this work, systemic risk is defined as the probability for a systemic event to materialize in the financial system, over a specified time period. In turn, systemic event is characterized by a clear and measurable indicator, i.e. the number of financial institutions going bust simultaneously over a certain time period. Systemic risk is then estimated based on the information set available to regulators and policy makers. We stress that the manifestation of systemic risk is related to the cross-sectional correlation of banks' default, and we investigate the determinants of these correlations considering both the correlation of economic shocks to banks' balance sheets and financial contagion.

We set up a microstructural contagion model that integrates three contagion channels. Such model is feeded with correlated shocks to banks' assets and allows to measure and decompose systemic risk. The model is calibrated using a comprehensive novel dataset that includes granular exposure data for a large panel of European banks. According to the model, the main drivers of systemic risk are the presence of correlated shocks from the real economy and market contagion that manifests in terms of fire sales of assets. We also highlight how the interaction amongst different contagion channels can significantly increase the level of systemic risk. The findings of our model match the ones in the literature, and we contribute by providing a unified framework for the analysis of different determinants.

From a policy perspective, the model represents a particularly powerful and flexible tool for regulators, thanks to the ability to estimate the level of systemic risk endogenously, the microstructural fundations, and the possibility of running counterfactual exercises by changing different parts of the system in isolation. Examples of possible applications are: the assessment of costs and benefits of potential bail-in, the calibration of regulatory capital buffers, the identification of the financial institutions most likely to cause systemic events, or the ones most affected by it. We also highlight how average default risk and systemic risk have very different origins (the former related mostly to credit risk, the latter to correlation in shocks and contagion). They therefore require different policies.

1 Introduction

The 2008 Great Financial Crisis revealed, once again, the endogenous instability of our economic and financial system. Size, interconnectedness, opacity and complexity were among the traits of the financial industry which caused a real economic shock to become a systemic financial event, where a very large number of banks and other financial institutions world-wide were affected with large social and public costs. A core message has been indeed that financial stability can't be analyzed by looking at banks in isolation, but instead must be observed as intrinsically related to the micro structure of the financial system and its connection to the real economy. When studying systemic risk, it is therefore necessary to have an holistic view of the financial system to encompass the internal and external feedback dynamics at the very core of financial systemic events. As those feedbacks have been proven to be driven by the way financial institutions interact with each other and the real economy, it is necessary to have microstructural a model to reproduce financial crisis.

Nevertheless, despite the growing interest, the concept of systemic risk remains difficult to measure and quantify (Hansen, 2012). Referring to the literature, we see indeed that several theoretical frameworks have been proposed to assess systemic risk. Some focus on measuring tail interdependence between assets market indices (e.g. Acharya et al., 2017; Adrian and Brunnermeier, 2016) or on gauging the risk stemming from interconnectedness (Billio et al., 2012; Diebold and Yilmaz, 2008). Other models encompass the multidimensionality of systemic risk by aggregating multiple market indicators to assess the level of stress in the system (Hollo et al., 2012; Committee, 2011). Finally, an increasingly popular class of models use microstructural approaches in which interactions among agents are individually modelled, in order to describe the evolution of a complex system and to study the diffusion of financial contagion via multiple channels in reaction to an exogenous initial shock (see e.g. Allen and Gale, 2000; Gai and Kapadia, 2010; Acemoglu et al., 2012; Montagna and Kok, 2016).

To present our interpretation of systemic risk and to guide our choices in the model, we first introduce what we believe represents the most natural and measurable quantity to define a systemic event. Among all the possible financial variables one may look at, we focus on the number of banks' defaults or credit events over a particular time period. This choice is motivated by the empirical fact that, historically, credit events in the banking sector such as defaults, government interventions, and loans of last resorts are typically concentrated in relatively short periods of time, and are followed by substantial financial and economic turmoil. Fig. 1 represents the time series of the fraction of banks that experienced default or other credit events for the US (left panel) and for the euro area (right panel), and the peaks of the series track closely the manifestation of systemic banking crises identified by Laeven and Valencia (2013). Looking at these historical series, two statistical properties are striking. First, there is clearly a very large clusterization of banks distress and default events in certain quarters, implying strong correlations among banks' default probabilities in the cross-section. Second, there is also a large auto-correlation over time, meaning that the effects of a systemic event in the banking sector leaves significant aftermaths. When looking at these figures, it becomes clear the importance to have models able to reproduce these two properties, and so disentangle the origins of these events.

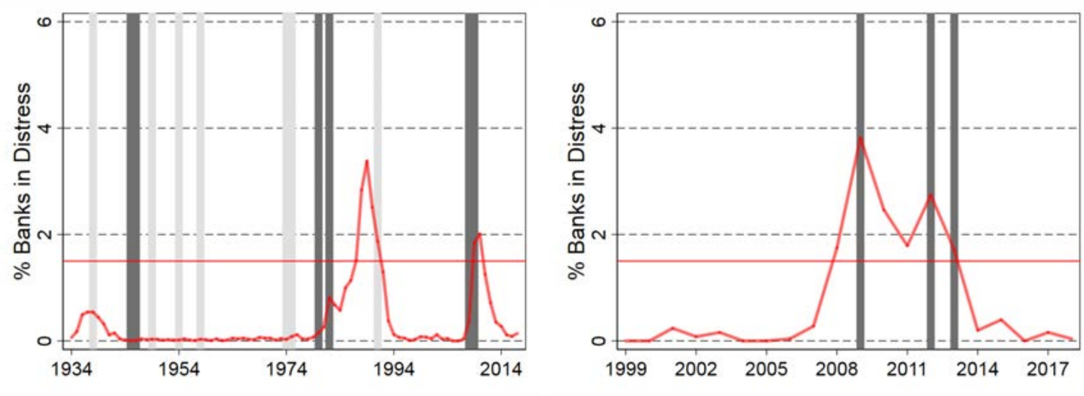


Figure 1: Historical series of percentage of distressed banks in the United States (left panel), and in the euro area (right panel). Bank distress is defined as one among the following events: capital injection, asset protection scheme, loan guarantee, state aid, bankrupty. Light grey and dark grey areas represent respectively mild and deep economic recession periods. Source: Lang et al. (2018) for the European bank distress time series, and Federal Deposit Insurance Corporation for the US time series.

The time series in Fig.1 are particularly challenging for modelization frameworks based on the analysis of the time series of market data (equity prices or CDS spreads) (e.g. Adrian and Brunnermeier, 2016; Acharya et al., 2017; Brownlees and Engle, 2016), due to difficulty in modeling and calibrating highly correlated and non-stationary time series, and the limited availability of historical data on series that characterize extreme events such as banks' default correlations. The high level of cross-sectional correlations in banks' defaults, that potentially generates the peaks in the time series, can instead be studied on a cross-sectional basis by means of microstructural approaches and network analysis using banks' balance-sheet data and their bilateral exposures (Eisenberg and Noe, 2001; Elsinger et al., 2006; Gai and Kapadia, 2010). The latter approach, granted the availability of granular exposure data, are therefore in our opinion more suitable to study systemic risk, also because they allow a much greater flexibility in the analysis, allowing for instance the possiblity to simulate policy interventions or simulate adverse scenarios.

shock like a bank default.[1] Differently from these works, mostly focusing on the contagion component, we highlight the role of correlation among banks' economic shocks, as one of the main contributors to systemic risk. In the real world, economic shocks tend to weaken banks' balance simultaneously via common and individual exposures towards the real economy, both subject to a high level of correlation among non-financial corporations' performance across countries and sectors. To capture this endogenous feature of our economic and financial system and its systemic risk implications, we model the initial triggers of systemic events introducing stochastic correlated defaults in the real economy by means of Monte Carlo simulations. Thanks to this modelling device, we characterize the initial trigger as a distribution of banks' losses stemming from exposures towards the real economy. We then borrow from the existing literature solvency, liquidity and fire-sales contagion mechanisms to model deterministically how economic losses are amplified by the financial system - the euro area interbank network in this framework.[2] In the end, this approach allows us to decompose the results into its sources, (i.e. direct economic credit risk, correlations of economic shocks, financial contagion mechanisms, and their interaction), and to assess their relative importance in the generation of systemic risk in the banking system. Finally, we underline that our model can be used to compute not only the probability of systemic events (related to the tail of the distribution of number of banks' default), but also the average bank default probability (corresponding to the expected percentage of defaults in the system)

The model is then calibrated and estimated on a unique granular exposure-level dataset of euro area banks in the world economy, capturing roughly EUR 23.2 trillion (96%) of banks' assets using quarterly data over the horizon 2014-2018. Specifically the dataset covers both banks' loan and security exposures towards non-financial sector corporations, bank and non-bank financial corporations as well as aggregate exposures by country towards the households sector. This dataset is among the most comprehensive available to regulators to date and, to our knowledge,

[1] The contagion literature usually uses this shock as a trigger for setting dynamics into the system, and uses bilateral exposures in the interbank market to track the propagation and amplification of risk across banks.

[2] The financial system can be further expended to capture via the very same contagion channels interactions and amplification across non-bank financial corporation like funds and insurances.

this work represents the first attempt and first step to empirically assess and quantify the level of systemic risk using a quasi-complete network dimension.[3] These new features in terms of systemic risk definition, modelling tool, and data allows us also to provide a rich set of results and policy implications. First of all, we estimate that the level of systemic risk defined as the probability of experiencing a systemic event in which 1.5% of all the banks in the system default or experience distress in the same quarter is 358 basis points in Q4-2018. To this respect, correlated economic shocks contributes for 45.8% of the total systemic risk, emphasizing the importance of modelling the initial trigger as granular correlated economic shocks. The three interbank contagion channels considered (solvency, liquidity and fire-sales) account for 44.8%, and almost half of this contribution derives from the interaction among the channels, thereby highlighting the importance of the multilayer network dimension and the role played by financial contagion. To a lesser extent, economic credit risk contributes for only 8.7% of the total. The findings are aligned to many of the previous findings ins the literature. Moreover, we highlight that the relative contribution of these determinants to systemic risk is quite different from their contribution to the average banks' default probability, endogenously computed using the same model. Indeed, we estimate that such measure is mostly driven by economic credit risk (68.3%), while financial contagion mechanisms play a secondary role, and correlated economic shocks play no role at all. Finally, our systemic risk measure and the average bank default probability nicely resemble market-based measures: the Composite Systemic Risk Indicator (CISS) and the average 5-year senior CDS spreads for the European banking sector, respectively.

Results showcase a fundamental dichotomy in terms of policy targets for achieving the financial stability objective: a reduction in the average bank default probability does not imply a reduction of the level of systemic risk, whereas a reduction in banks' asset return correlation is a sufficient condition. The intuition that we provide emphasize that the mean of the distribution is not affected by a weakening in the correlation of banks' default probabilities, contrary to the mass of the tail of the distribution, which is strongly and negatively affected. From this follow that regulators need to think carefully about their intermediate target for monitoring and assessing systemic risk developments.

[3] This network is constructed using confidential ECB supervisory data, respectively euro area banks' large exposures dataset (LE) and the security holding statistics dataset (SHS). Complementary supervisory data sources such as COREP and FINREP are also used to retrieved banks' balance sheet information and their capital structure, as well as solvency and liquidity regulatory thresholds to model banks' distress and defaults. All data sources are detailed and discussed in Appendix B.

The reminder of the paper is organized as follows. Section 2 presents our definition and quantifiable measure of systemic risk, describing the underlying generating process of systemic events. Section 3 presents the microstructural model, the dataset on which the model is calibrated, as well as the systemic risk decomposition in its main outputs. Next, Section 4 follows with the presentation of the main results and Section 5 provides discussions in relation to the literature. Section 6 concludes.

2 Measuring systemic risk

Although widely recognized as crucial in the analysis of financial systems, systemic risk is still an elusive concept, and it is described in many different ways by scholars and regulators. In the most general terms, systemic risk can be described as "the risk of threats to financial stability that impair the functioning of a large part of the financial system with significant adverse effects on the broader economy" Freixas et al. (2015). Alternatively, it can be described as "the risk that (i) an economic shock such as market or institutional failure triggers (through a panic or otherwise) either the failure of a chain of markets or institutions or 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." Schwarcz (2008).

To make the definition operational, it is necessary to quantify the probability that an event assumes systemic proportions, as well as to identify the potential sources of distress and the amplification channels. A relevant challenge is related to the wide variety of data used to model systemic risk, ranging from market prices of financial securities, macroeconomic factors, balance sheet data and bilateral exposures data. Several attempts have been made to classify systematically the literature. Bisias et al. (2012) proposes to classify systemic risk measures in multiple taxonomies, defined in terms of data required, supervisory scope and decision time horizon. Benoit et al. (2017) suggest a categorization based on four classes based on the source of systemic risk: *systemic risk-taking*, *contagion*, *amplification mechanisms*, and *global measures of systemic risk*. The complexity of the phenomenon and the plurality of its manifestations render difficult the task of measuring and monitoring systemic risk. Among the most used measures, Adrian and Brunnermeier (2016) consider the contribution of a specific institution to the tail risk of the system, Acharya et al. (2017) measure the propensity of an institution to be undercapitalized when the system as a whole is undercapitalized, Brunnermeier and Cheridito (2014) propose a measure that captures the a priori cost to society for providing tail-risk insurance to the financial system, and Battiston et al. (2012) focus on the identification of the institutions that are the most relevant for the transmission of systemic shocks.

The models in the literature show some recurring themes: several frameworks stress the role of the transmission of distress across financial entities, or financial contagion (Schwarcz, 2008; Diebold and Yilmaz, 2008; Billio et al., 2012), the attention on tail co-movement of financial institutions and market returns, in particular credit institutions (Adrian and Brunnermeier, 2016; Acharya et al., 2017), and the issue of dealing with rare and sudden events, that are therefore difficult to grasp using traditional econometric tools for the analysis of time series (Montagna and Kok, 2016).

2.1 A new definition

The need of a clear and, most importantly, measurable definition of systemic risk is fundamental for the implementation of adequate macroprudential policies (Hansen, 2012; Acharya et al., 2017). We propose here an alternative definition that is measurable and allows to focus on extreme events with high impact and low probability. We underline that our work is mostly concerned with the banking sector, and aims to identify the determinants of systemic risk in the cross-section on the basis of information available to regulators.

Then, it becomes natural to describe systemic risk as: *the probability of a systemic event E_t at time t, conditional to an information set $\boldsymbol{I}_{t-\Delta t}$ that characterizes the state of the system available in a previous time*, or in simbols:

$$\boldsymbol{SR} = Pr(E_t|\boldsymbol{I}_{t-\Delta t}) \tag{1}$$

The measurement of systemic risk requires three components: first, the identification of a clear and observable definition of a systemic event E_t, second, a methodology to estimate the probability of the manifestation of such events, and finally, the information set $\boldsymbol{I}_{t-\Delta t}$ at time t to compute the probability. We now introduce the definition of systemic event, while in Section 2.2 we discuss the modelization aspects and the identification of the information set, in relation to the determinants of systemic risk.

In our framework we define a systemic event as the realization of a scenario in which a large number of banks default or get into distress in the same time period.[4] As introduced in Section 1, such events are quite rare, occurring only few times in a century, and they are always related to deep economic downturns and require significant policy intervention measures. Numerous studies indeed show how banking crises are characterized by relevant economic and social implications, and are often followed by currency and sovereign debt crises, requiring relevant governmental interventions (Laeven and Valencia, 2013). The ratio of distressed banks reported in Figure 1 for both the US and Europe provides clear evidence of the impact of banking crises and the role played by the banking system in our economic system. The peaks in distress events are associated with the savings and loans crisis that hit the United states across the year 1986 to 1995, the subprime mortgages crisis started in 2007, and the European Sovereign Crisis. Hence, the ratio of the number of banks in distress or default (D) over the total number of banks in the sample (N) at a specific point in time (a year or a quarter) can be used as a simple yardstick to classify systemic events. We can compare the peaks in the distribution of defaults to the banking crises identified by Laeven and Valencia (2013) with the US series, and both the levels and the position of the peaks are remarkably similar.[5]

Although it may seem simplistic to use such a plain counting measure to identify systemic events, we opted for such approach, instead of more complex ones such as counting the losses incurred by the system, or weighting the defaulted banks by their assets, for several reasons. First of all, in practice, the default of a large bank in our framework would generate chain effects leading to the default of other institutions. Therefore, such scenario would most likely qualify as systemic both in terms of losses, and in terms of number of defaults. Moreover, as our interpretation of systemic risk is based on the idea that a large part of the financial system faces troubles, by considering losses, or weighting banks by assets, we could end up to undesirable settings in which the default of a large number of medium-sized banks in distress may not be accounted as a systemic event if their balance sheets are relatively small compared to the system. On the contrary, the default of a single, large institution with limited effect on the rest of the system would qualify spuriously as a systemic event. Finally, in defense to our approach, as Haldane (2012) emphasizes, sometimes it is wiser not to fight complexity with complexity, as

[4] In our empirical analysis, as it will better clarified in Section 3.1, default happens when the capital of a banks is below the minimum capital requirement, and distress when it is below the capital buffers imposed by regulators.

[5] We underline that the US and the European Economy are significantly different, the former relying more on capital financing, while the latter on banks' financing for roughly 80% of the total financing needs. Our systemic risk measure seems to be even more appropriate given our euro area centric perspective.

complexity requires a regulatory response grounded in simplicity. Introducing this additional layer of complexity in terms of measuring losses, may add bias to our estimate without adding a relevant contribution to our approach for the identification of systemic events.

Despite the simplicity of our definition, the fine tuning of the systemic risk threshold for the identification of systemic events is challenging. In this respect, we think that the precise definition of the cut-off is more related to the economic goal of the regulator that uses the model, that could be interested in identifying certain types of systemic events, rather than a parameter that could be tuned objectively to real data. Drawing a parallelism to risk management, we can relate the choice of the threshold for systemic events to the choice of a percentile α for computing the VaR_{α} (Value at Risk): $VaR_{99\%}$ denotes a more conservative evaluation of risk compared to $VaR_{95\%}$, but the choice of a value or the other is up to the policy of the risk management, or the regulatory constraints. For this specific analysis we identify a threshold on the basis of historical data, in such a way to include the major peaks in defaults and distress events observed in the US and Europe. In particular, although the sample is arguably too small to determine a statistically significant threshold identifying systemic events, we consider a threshold of 1.5% of defaulted or distressed banks. The issue of the threshold will be addressed in Appendix C, where a sensitivity analysis shows that the results qualitatively hold for a range of values around such threshold.

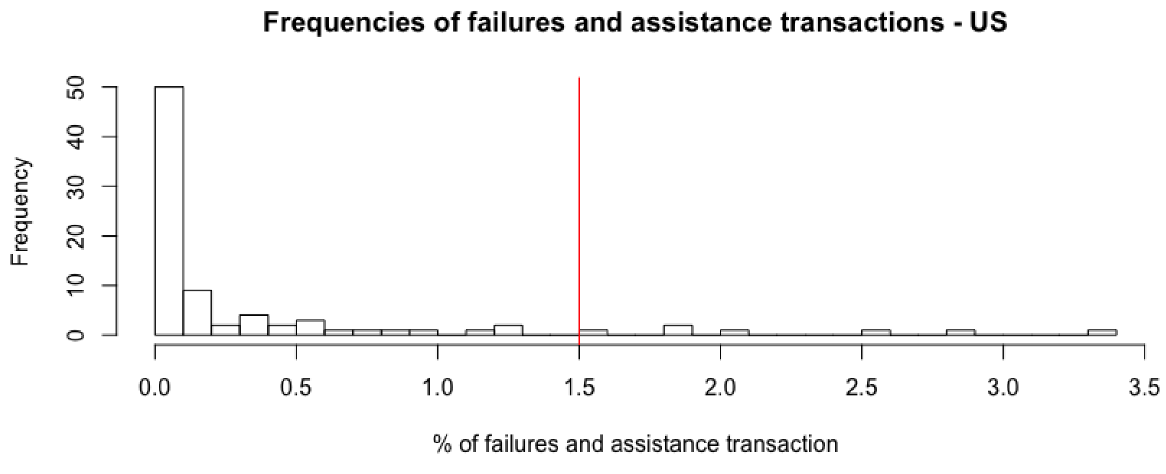


Figure 2: Distribution of the percentage of failures and assistance transactions per year in the US in the period 1934 – 2017. Source: Federal Deposit Insurance Corporation. In red the threshold of 1.5% of defaulted or distressed banks per year to identify a systemic event.

In this respect, by plotting the histogram of the historical distribution of the percentage of banks' failures and assistance transactions in the US (Figure 2), we point out that the distribution is characterized by a very long right tail. This denotes a non-negligible probability of periods with a large number of failures.

The shape of the distribution in Figure 2, together with the clusterization of defaults over time, suggests that traditional econometric techniques may have limited ability in describing systemic risk as defined here, suggesting instead to focus on the cross sectional correlations of banks' defaults. To formalize this point, we introduce a more rigorous definition of systemic event. Consider a system with N institutions and, for each bank i, we define the default variables $\chi_{i,t}$ as follows:

$$\chi_{i,t} = \begin{cases} 1 & \pi_{i,t} \\ 0 & 1-\pi_{i,t} \end{cases}, \tag{2}$$

where $\pi_{i,t}$ is the probability that each bank i experiences default or distress in the period t. We also introduce the variable $D_t = \sum_{i=1}^{N} \chi_{i,t}$ that denotes the number of defaults or distress events in period t. A systemic event is then defined as a state in which the ratio D_t/N of defaults or distress over the total number of institutions is higher than the threshold $\bar{D} = 1.5\%$:

$$E_t = \mathbb{I}_{\frac{D_t}{N} > \bar{D}} \tag{3}$$

where $\mathbb{I}_{\{\cdot\}}$ is an indicator function. Considering Equation 1, systemic risk is so defined as:

$$\boldsymbol{SR} = Pr\left(\frac{D_t}{N} > \bar{D} \middle| \boldsymbol{I}_{t-\Delta t}\right). \tag{4}$$

2.2 The determinants of systemic risk

Given Equation 4, the problem of estimating systemic risk boils down to the estimation of the distribution of the number of defaults or distress events D_t. Such distribution is function of the probabilities of default $\pi_{i,t}$ and, more importantly, the dependency structure across such probabilities. In particular, we want to reproduce the extremely skewed distribution of defaults witnessed in the real world, that is, a two-state system where either there are no banks in distress at all, or many banks run into troubles at the same time. This stylized fact can only be explained via correlations among banks' distressed probability, which must therefore play a crucial role for financial stability.

We know that, the higher their correlations, the fatter the tails of the distribution of D_t. For example, in the limit case of independent and identically distributed $\chi_{i,t}$s, their sum is distributed as a binomial distribution, that has thin tails and converges quickly to a Gaussian distribution. On the other hand, the presence of correlated $\chi_{i,t}$s leads to a distribution of D_t characterized by fatter tails.[6]

We immediately see that the expected value of D_t is not a function of the correlations due to the linearity of expectations:

$$\mathbb{E}\left[\frac{D_t}{N}\right] = \frac{\mathbb{E}\left[\sum_{i=1}^{N} D_{i,t}\right]}{N} = \frac{\sum_{i=1}^{N} \mathbb{E}\left[\pi_{i,t}\right]}{N} = \bar{\pi}_t, \tag{5}$$

where $\bar{\pi}_t$ is the average default probability of the banks in the system.

This highlights that the interconnected structure of the $D_{i,t}$s is the relevant factor for the analysis of systemic risk, while the average default probability of the banks in the system has limited relevance in terms of realization of extreme events. This feature has important implications for micro and macro-prudential regulation, that will be discussed in more details in the following sections. Indeed, adopting a micro-prudential perspective, and considering only the default probabilities of banks in the system in isolation (consistently with the analysis of the expected value of the number of defaults), does not bring any significant information on the probability of extreme events that qualify as systemic, even after considering the amplification effect due to financial contagion. To identify the determinants of systemic risk from a macro-prudential perspective, we need therefore to understand the sources of banks' defaults cross-correlations. That is, we need to determine why banks default together.

Interconnection is expected to play a significant role in the determination of banks' default correlations (and consequently systemic risk). We underline that interconnectivity is not limited to the direct credit exposures among banks, but relates also to indirect channels, such as the exposure to common counterparts, or to correlated asset classes. Figure 3 exemplifies graphically the multiplicity of interaction sources that can be identified between two banks B_1 and B_2, causing default correlations and systemic risk. In Panel 1 the two banks are related indirectly, through the exposures towards non-financial corporations (NFC) correlated to each other, for

[6]Note that the joint distribution of $\chi_{i,t}$s cannot be fully determined by the probabilities $\pi_{i,t}$ and the cross correlations. However, thinking in terms of correlations provides some intuitive backgroud on the properties of the system.

instance via their input-output production matrix or due to the exposure to common factors. In Panel 2 instead the two banks have a direct debt exposures, and are also indirectly connected as they are linked to two banks (B_3 and B_4) that are exposed in the short term debt market. Finally, Panels 3 and 4 depict an intertwined economic and financial system with multiple layers of interactions. This complex set of relationships, both direct and indirect, leads to a strengthening of the initial correlation of banks' asset returns described in Panels 1 and 2. Their contribution to our systemic risk measure is actually what we want to study and quantify. Overall, each of this link represents the channels of shock transmission, which by their interaction, amplify the initial shock coming from the real economy.

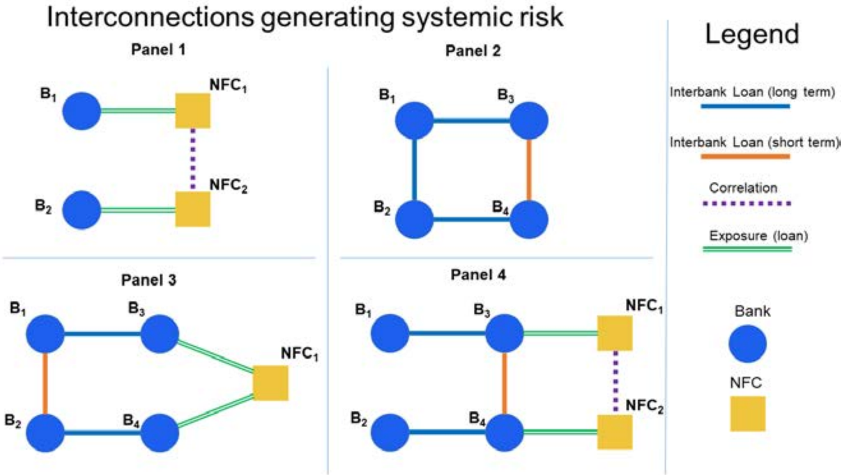


Figure 3: The picture shows graphically the interaction among different determinants that can generate correlation across banks defaults in a system with overlapped and correlated exposures towards the real economy (NFC), and an interbank network of banks (B) in which banks are linked to each other via loan and security exposures.

The literature on microstructural contagion models has grown substantially in recent years, shedding light on several potential mechanisms responsible of the transmission of shocks via direct and indirect connections. Among the most important direct channels there are solvency contagion (Eisenberg and Noe, 2001; Gai and Kapadia, 2010; Battiston et al., 2012) and liquidity contagion (Allen and Gale, 2000; Gai et al., 2011). Indirect ones are instead related to market effects driven by changes in investors' perceptions such as fire sales mechanisms, in which the sudden sales of large amount of assets by distressed banks affect the price of the securities, generating more problems for other financial institutions (Caccioli et al., 2014; Greenwood et al., 2015; Clerc et al., 2016; Cont and Schaanning, 2019). Other contagion channels driven by information spillovers are related to bank runs Diamond and Dybvig (1983) and complexity contagion Caballero and Simsek (2013).

Contagion however is not the only determinant of systemic risk. Freixas et al. (2015) identify three factors that together concur in the origination of a systemic crisis: first, the presence of macro fragilities that make financial institutions prone to losses, second, contagion and other spillovers that spread the troubles of a bank to the rest of the system, and finally a trigger that leads the sudden convergence of investors' expectations to a new equilibrium. While the second factor has been widely studied, the literature gave less attention to the triggering of financial distress, that has been typically modelled as random shocks applied to individual banks (Gai and Kapadia, 2010; Espinosa-Vega and Solé, 2011), or shocks targeted to specific institutions (Battiston et al., 2012). These approaches, although useful to measure *contagion*, have little power in measuring *systemic risk*, defined as the probability of the manifestation of a systemic event. This probability, in fact, is not calibrated according to the characteristics and state of the economic system, and it stems from an exogenous shock hitting the interbank network structure.[7] Overall, the estimation of systemic risk should be based on the correct characterization of the shocks hitting the system and conditional to the current state of the banking system, not exclusively on the modeling of contagion channels.

We can relate this discussion to the definition of systemic risk in Equation 4 by considering that the distribution of the shocks applied to banks, together with the relevant variables that describe the system and the modelization of contagion channels constitute the information set $\boldsymbol{I}_{t-\Delta t}$. Ideally, the information set should be as complete and realistic as possible to capture accurately the sources of systemic risk, including therefore the entire state and dynamics of the system (leading then to the measurement of *unconditional* probability of a systemic event). Still, we maintain the conditioning in the notation since, due to data availability or incompleteness of the contagion channels, in practice the estimation of systemic risk is necessarily conditional to a sub-set of the information on the system. Moreover, it may be interesting to regulators to perform counterfactual exercises by modifying certain types of inputs (as in a systemic stress test framework) or by altering the characteristics of the contagion model (i.e. by deactivating some of the channels) or by simulating potential policy interventions (i.e. higher capital or liquidity buffers) in order to assess the impact of these changes on the level of systemic risk. We underline that contagion models in which shocks are applied to random banks in the system can

[7] Some exceptions, that consider distributional shocks from banks' exposure are Elsinger et al. (2006); Glasserman and Young (2015); Roukny et al. (2018).

be also described using this framework, simply by considering a narrower information set.

In practical terms, the estimation of systemic risk can be obtained by feeding a microstructural contagion model with the distribution of shocks coming from the real economy and all the relevant information of the system, in a Monte Carlo simulation scheme. This allows us to compute the distribution of banks' default and then to quantify systemic risk as in Equation 4, factoring in the contagion dynamics, as well as the distribution of shocks from the market. In this framework, shocks are endogenous, and can be generated on the basis of the (correlated) distributions of banks' exposures towards the real economy. We underline that by modeling the shocks from the banks' exposures in probabilistic terms, and tuning the model on real data, our framework includes endogenously not only the triggering of the model, but also the macro fragilities that can contribute to the origination of systemic events. Concerning the contagion model, we use a multi-layer framework conceptualized in Montagna and Kok (2016), and characterized by three separate channels: solvency, liquidity and market contagion (fire sales), as described in Section 3.1.

Our approach is related to the work of Elsinger et al. (2006), Glasserman and Young (2015) and Roukny et al. (2018), that also feed microstructural contagion model with the distribution of shocks coming from banks' exposures. We go beyond these works in several ways. First, we consider a more complete contagion model, that includes multiple channels, while the aforementioned works consider only solvency contagion. Second, we center our analysis on the estimation of systemic risk that, as discussed, focuses on extreme events and the estimation of their probabilities. Moreover, thanks to our unique dataset, we have the possibility to measure systemic risk in the European banking system using real-data, studying the evolution over time of the level of systemic risk and, more importantly, to identify empirically the main determinants of systemic risk.

In the literature consensus is still lacking on the relative importance of these determinants. Some studies suggest that indirect contagion plays a more prominent role compared to solvency contagion (Elsinger et al., 2006; Cont and Schaanning, 2019), and Glasserman and Young (2015) find that solvency contagion is less relevant than the correlation of economic shocks. Moreover, Montagna and Kok (2016) show that the presence of multiple contagion channels active at the same time may have a significant role in the amplification of distress and in the determination of systemic events, underlying the importance of considering comprehensive models to avoid potential underestimation of risk. A decomposition of systemic risk according to different determinants may be of use to regulators to better understand the relative contribution of each risks, and in turn design more accurate policy tools or better calibrate the existing ones. Within the Monte Carlo simulation scheme, it is possible to implement such decomposition by changing the setting of the model and run the simulation multiple times. For instance by deactivating some of the contagion channels, or changing the level of correlation of economic shocks. The decomposition can then be computed by comparing the measures of risk under different specifications. Thanks to the decomposition, our model can shed light on the relative role played by each component in relation to the level of systemic risk.

We are interested in two main research questions. The first is to investigate the role of economic shocks (i.e. the shocks coming from the portfolio exposures to non banking institutions, that in our model represent the triggering factor) in the generation of systemic risk, dividing such effect in two parts: one for the purely idiosyncratic shocks (computed considering all the shocks to the banks as independent), and one accounting for the correlations of shocks and portfolio overlaps. The second research question focuses on the transmission of shocks in the banking system, assessing the role of each of the three contagion channel considered in the analysis to systemic risk, and to measure the effect of their interaction. The details of the decomposition are discussed in Section 3.1. For the sake of comparison, in Section 4 we provide not only a decomposition of systemic risk, but also an analogous decomposition of the expected percentage of defaulted institutions over a period of time ($\bar{\pi}_t = \mathbb{E}[\frac{D_t}{N}]$), that can be interpreted as the average default probability for the banks in the system (see Equation 5). The comparison of the decomposition of these two measures will allow us to interpret the impact of each determinant both on the level of systemic risk (that relates to the field of macroprudential policy), and on the average bank default probability (that relates to microprudential policies).

3 Empirical analysis: microstructural model implementation

Considering the framework for the measurement of systemic risk presented in Section 2.1, and the discussion on its determinants in Section 2.2, we propose here a model in which shocks from the real-economy affect the balance sheets of banks, and are then transmitted through three intertwined contagion channels to the rest of the system: solvency contagion, liquidity contagion and market contagion (fire sales). The model is calibrated using real data for European banks, and systemic risk is computed and decomposed using Monte Carlo simulations. In particular, the multi-layer contagion model is inspired by the framework of Montagna and Kok (2016) and the CoMap model by Covi et al. (2020).

The analysis is based on a unique dataset of granular data recently developed within the European Central Bank that includes bilateral interbank exposures, exposures to non-bank financial corporations, and security holdings issued by banks, NFCs, FCs, and governments.[8] The data are updated with quarterly frequency, and cover the period Q1-2015 to Q4-2018.

Table 1: Summary Statistics for Q4-2018. Values are reported in EUR trillion for columns (3) to (6), while columns (8) and (9) report amounts in EUR billion. Granular exposures (Gran.) refer to the exposure amount mapped with exposure-specific information, securities (Sec.) refer to the exposure amount mapped with ISIN information, while aggregate exposures (Agg.) refer to the exposure amount mapped on aggregate sector-country counterparty basis. LGD reports the share of total exposure amount used to impute credit risk losses. Avg. edge refers to the average exposure amount per edge, while Avg. node reports the average exposure amount per counterparty.

Sector	Edges	Nodes	Gran.	Sec.	Agg.	Tot.	LGD	Avg. edge	Avg. node
CI	8580	1175	3.0	0.6	-	3.6	14%	0.4	3.1
NFC	14497	5866	1.9	0.7	0.9	3.5	22%	0.2	0.6
FC	7762	4324	1.3	0.9	3.6	5.9	10%	0.8	1.4
GOV	4823	1257	2.9	2.0	-	4.8	24%	1.0	3.8
HH	820	297	0.04	-	5.3	5.3	17%	6.5	17.8
Total	36482	12919	9.1	4.3	9.8	23.2	18%	0.6	1.8

Table 1 reports the summary statistics of the euro area banks' network of exposures used to estimate the propagation of shocks from the real economy and within the interbank market. The overall coverage of the our data is EUR 23.2 trillion for the last quarter available, covering roughly 96% of euro area banks' total assets. With our data we map banks' exposures vis-á-vis five major sectors of the economy, and we decompose the dataset into two types of exposures: granular bank-to-entity exposures, and aggregate exposures by counterparty country-sector when the granular dimension is not available. (see Appendix 3 for a description of the sources of the data and the details on the construction of the variables).

We notice that the global network of euro area banks' exposures consists in almost 36 thousand directed linkages (edges) spread across 13 thousands counterparties (nodes), with an average edge and node exposure of EUR 0.6 and 1.8 billion, respectively. In our dataset, the sector with the higher percentage of exposures reported at granular level for the counterparty

[8]To increase the coverage of the dataset, especially for households component, we also considered aggregate and sectorial exposures. Moreover, non-bank financial corporations are treated like exposures to NFCs since we do not directly model contagion channels across financial corporations that are non-bank.

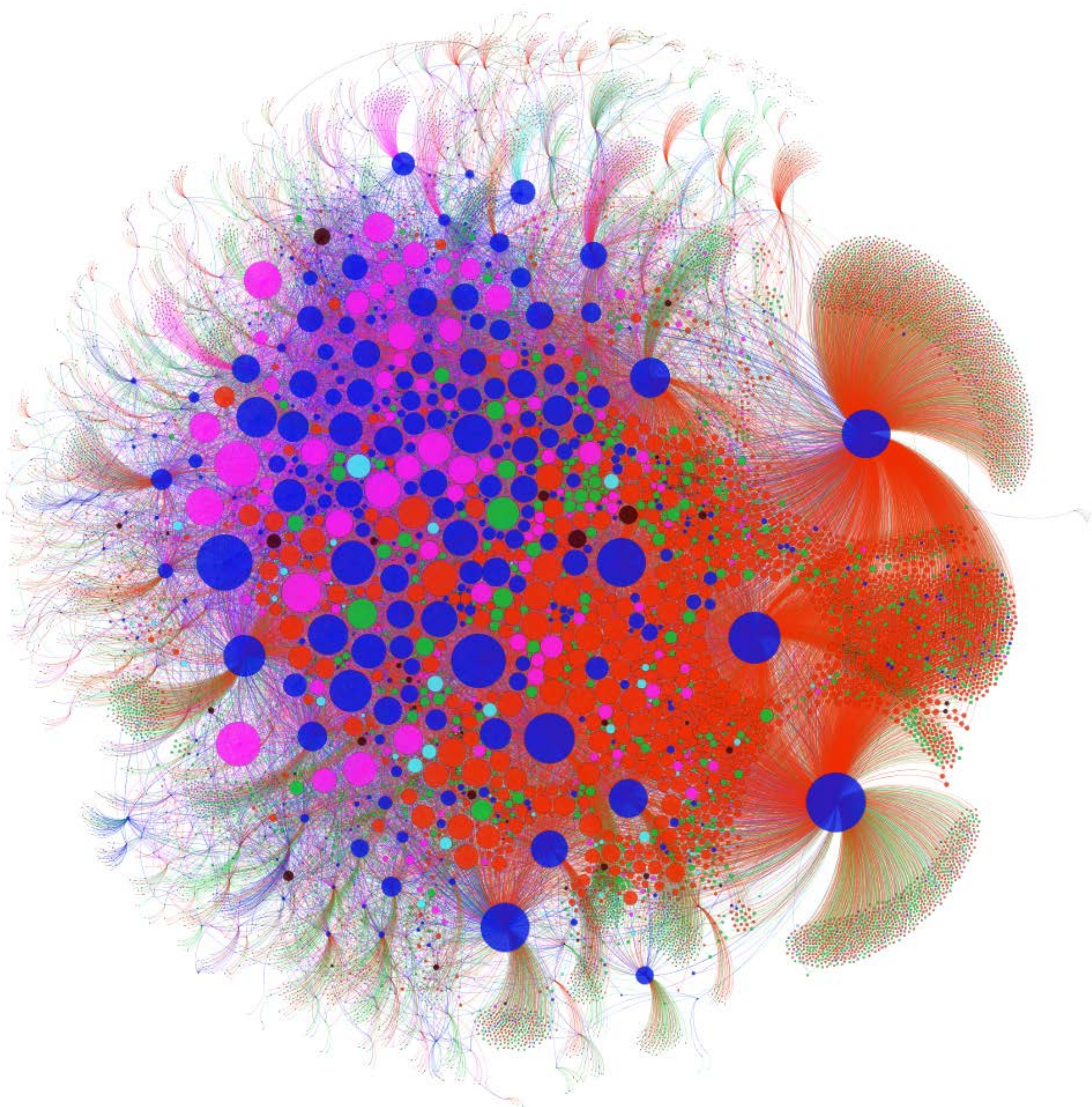


Figure 4: Network of the granular and aggregate exposures captured by our data. The total amount of exposures for Q4-2018 is EUR 23.2 trillion. The network is built by assigning the eigenvector centrality metrics to the size of the nodes, while the colour of the edges to the node reporting the exposure on the asset side. Blue nodes represent the banking sector, red nodes non-financial corporates, purple nodes the government sector, green nodes the financial corporate sector, and finally the light blue nodes the household sector.

is government (GOV), followed by credit institutions (CI), non-financial corporations (NFC) and financial corporations (FC). The household sector is covered granularly only in a negligible amount. Overall, there is both a strong heterogeneity in terms of exposures amount across sectors and within sectors.

Fig. 4 depicts the global network of euro area banks' exposures by assigning the eigenvector centrality metrics to the size of the nodes, while the colour of the edges to the node reporting the exposure on the asset side. This set up highlights the relevance of the counterparty sector in terms of euro area banks' common exposures and overlapping portfolios of securities. Hence, we detect two main sectoral clusters, respectively exposures towards non-financial corporates (red) and towards governments (purple). On top of this, the banking sector's nodes size (blue) also stands out from the graph, highlighting the intermediary role played across the sectors and banking-centric perspective of the European financial system. Although households (light blue) and financial corporate (green) sectors show a higher total amount of exposure relatively to the NFC and GOV sectors (Table 1), they don't play a key role for the propagation of shocks to the interbank network. On one hand, banks tend to be exposed only domestically to households, thereby reducing the degree of common exposures towards the same household sector, here aggregated by country. On the other hand, few financial corporates are central to the network, while many of them are clustered around large banks, leaving the majority of the banks in the network without connections to this sector, hence reducing the degree of interconnectedness via direct and indirect exposures.

The global network of euro area banks' exposures, capturing the multilayer dimension across types of exposures and sectors, allows us to model comprehensively the microstructure of the banking system.

3.1 Description of the model

The dynamics of the model for the estimation of systemic risk can be conceptually divided in two parts: one consisting in the engine for the generation of shocks coming from the real economy, and one consisting in the multi-layer contagion model that transmits and amplify the initial shocks. These two steps are implemented in a Monte Carlo simulation scheme to obtain an estimate of the probability density function of the distribution of the number of defaults and distress events. We underline that the stochasticity in the model is rooted in the first step (the generation of the scenarios), while the second step (contagion mechanism) operates as a deterministic (and highly non linear) function to estimate the banks' defaults.

More in detail, the generation of shocks consists in the default of some of the companies included in banks' portfolios, reflecting the actual default probabilities of these counterparties, and an estimate of their correlation structure inferred from market data. Additionally to individual companies, we also model the exposures to households by country, and a residual groups of non financial corporations not covered by the granular dataset. The details of the generation process are described in A.2.

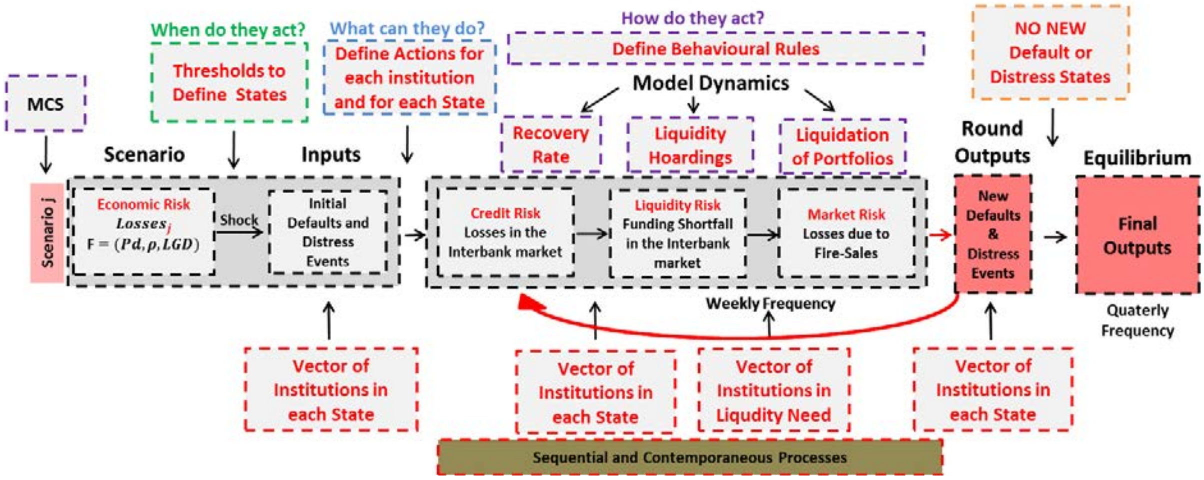


Figure 5: Flow chart of the contagion mechanisms. The representation shows the building blocks of each simulation.

Concerning the modelization of the contagion mechanism, following Montagna and Kok (2016), each layer of interconnectedness is characterized by specific dynamics based on the behaviours of the agents as a consequence of previous events. The series of events is based on subsequent blocks that unfold over time, and repeat iteratively until no new default or distress event manifests. Figure 5 shows the structure of the contagion process, highlighting the main building blocks. The losses incurred by banks can then trigger further consequences through the other layers of interconnectedness. In particular, if the losses are high enough to push the capital below its minimum requirements, the company defaults. A bank can instead go in distress if the capital goes below a distress threshold, that includes also banks' capital buffer requirements. The losses are then transmitted to the other banks via long term interbank linkages on the basis of exposure-specific loss given default (LGD), eroding their capital and potentially triggering their default or distress. After this round, we model the dynamics in the short term interbank market, where the withdrawal of liquidity by defaulted and distressed banks, together with precautionary hoardings from other institutions, may generate liquidity risk. This mechanism results in a potential liquidity shortage, requiring institutions to sell securities abruptly in order to obtain liquidity. Such security sell-off (that may result in a fire-sale mechanism), is modelled in the third block, where the sales of securities by banks in liquidity shortage and by banks in a liquidation process as a consequence of default generate a decrease in market prices of such securities, resulting in further capital erosion. This sequence of events is then iterated until no more banks default or go in distress, and then the number of distressed or defaulted banks is stored in order to compute its distribution across all the Monte Carlo simulations. The details are explained in Appendix A.

3.2 Model outputs

The main output of the Monte Carlo simulations is the estimate of the distribution of the number of defaults or distress events, computed on the basis of a realistic distribution of real-economic shocks, balance sheet informations, and the contagion mechanism implemented. Once the distribution is estimated, it is possible to compute systemic risk as the probability of a systemic event (Equation 4). We point out that the procedure adopted here is not a stress test exercise, as here we are not assessing the response of the system to one (or few) adverse scenario. Instead, this approach allows us to identify the most extreme scenario arising from the distribution of a set of shocks, not requiring therefore to make any assumption of the distressed distribution.

As introduced in Section 2, the Monte Carlo framework allows to decompose systemic risk in order to assess its determinants. In particular, we decompose systemic risk in an *economic risk* component, and in a *contagion* component. The former is further divided in two parts: *baseline* (uncorrelated shocks) and *economic correlations* (accounting for correlation among shocks and overlaps in the portfolios). Contagion is instead divided in four parts: *interbank solvency contagion*, *interbank liquidity contagion*, *market contagion (fire sales)* and an interaction component. Schematically:

- Economic risk – Solvency risk given by exposures to agents from the real economy (non financial corporations and households).
  - $\boldsymbol{SR}^0$ – Baseline economic risk – independent shocks
  - $\boldsymbol{SR}^E$ – Economic correlations – effect of correlation of economic shocks and portfolio overlappings.
- Contagion risk – Risk attributable to amplification mechanism in the banking system.

- $\boldsymbol{SR}^S$ – Interbank solvency contagion – Bilateral long term exposures among credit institutions.
- $\boldsymbol{SR}^L$ – Interbank liquidity contagion – Bilateral exposures on the interbank short term market.
- $\boldsymbol{SR}^M$ – Market contagion risk (fire sales) – Losses related to the sale of common securities holdings.
- $\boldsymbol{SR}^I$ – Interaction factor – Component that accounts for the interaction among different contagion channels.

Concerning the practical implementation of the systemic risk decomposition, we can proceed by running the Monte Carlo simulations and computing systemic risk under six different specifications of the model, changing the active channels and determinants:

- $\boldsymbol{SR}^0$ (baseline) – independent shocks to each banks' assets and no contagion channels.
- $\boldsymbol{SR}^\alpha$ (economic) – Correlated shocks and overlapping p.folios, but no contagion.
- $\boldsymbol{SR}^\beta$ (solvency) – Correlated shocks and overl. p.folios, only solvency contagion
- $\boldsymbol{SR}^\gamma$ (liquidity) – Correlated shocks and overl. p.folios, only liquidity contagion
- $\boldsymbol{SR}^\delta$ (market) – Correlated shocks and overl. p.folios, only market contagion
- $\boldsymbol{SR}^{TOT}$ (all) – Correlated shocks and overl. p.folios, all active contagion channels

We can then compute the specific role of correlation and overlapping of economic shocks $\boldsymbol{SR}^E$, the net contribution of solvency, liquidity and market contagion $\boldsymbol{SR}^S$, $\boldsymbol{SR}^L$, and $\boldsymbol{SR}^M$, respectively, and the interaction component between the contagion channels $\boldsymbol{SR}^I$ as follows:

$$\begin{aligned}
\boldsymbol{SR}^E &= \boldsymbol{SR}^\alpha - \boldsymbol{SR}^0 \\
\boldsymbol{SR}^S &= \boldsymbol{SR}^\beta - \boldsymbol{SR}^\alpha \\
\boldsymbol{SR}^L &= \boldsymbol{SR}^\gamma - \boldsymbol{SR}^\alpha \\
\boldsymbol{SR}^M &= \boldsymbol{SR}^\delta - \boldsymbol{SR}^\alpha \\
\boldsymbol{SR}^I &= \boldsymbol{SR}^{TOT} - (\boldsymbol{SR}^0 + \boldsymbol{SR}^E + \boldsymbol{SR}^S + \boldsymbol{SR}^L + \boldsymbol{SR}^M)
\end{aligned}$$

Analogously, it is possible to perform the decomposition of the expected percentage of defaults ($\bar{\pi}_t = \mathbb{E}[\frac{D_t}{N}]$), corresponding to the average default probability of the banks in the system (see Equation 5).

4 Results

We present the estimation and decomposition of systemic risk based on the model and the dataset outlined above. We first analyse the characteristics of systemic risk diffusion in the last available quarter in our sample (Q4-2018), and then monitor the evolution over time. The results are based on 50,000 runs of Monte Carlo simulations for each of the specification.[9] Together with the measurement and decomposition of systemic risk $\boldsymbol{SR}_t$, we also study the average default probability of the banks in the sample $\bar{\pi}_t$ computed as the expected percentage of defaults (see Equation 5). The former indicator is relevant for macro-prudential policies, while the latter carries information useful for micro-prudential policies. Both these measures are computed endogenously in the model.

Table 2: Decomposition of systemic risk, $\boldsymbol{SR}$, and of the average default probability $\bar{\pi}_t$, for Q4-2018. All the figures are reported in basis points. The interaction term is approximated by the difference between each contagion channel and economic risk, thereby providing a conservative estimate of amplification effects (source: own calculation).

Sources	$\boldsymbol{SR}$ – Systemic risk	$\bar{\pi}_t$ – Avg. def. prob.
Economic Risk	**195.2**	**9.9**
Baseline	31.2	9.9
Correlation of shocks	164.0	0.0
Contagion Risk	**166.6**	**4.6**
Market contagion	83.4	0.7
Liquidity contagion	0.6	0.8
Solvency contagion	2.0	1.3
Interaction	77.0	1.8
Total	**358.2**	**14.5**

Table 2 summarizes the results for the last quarter available (Q4-2018). The total probability to have a systemic event is estimated at around 3.6% (358.2 bp), while the average default probability for the banks in the sample is estimated as 0.145% (14.5 bp). Looking at the decom-

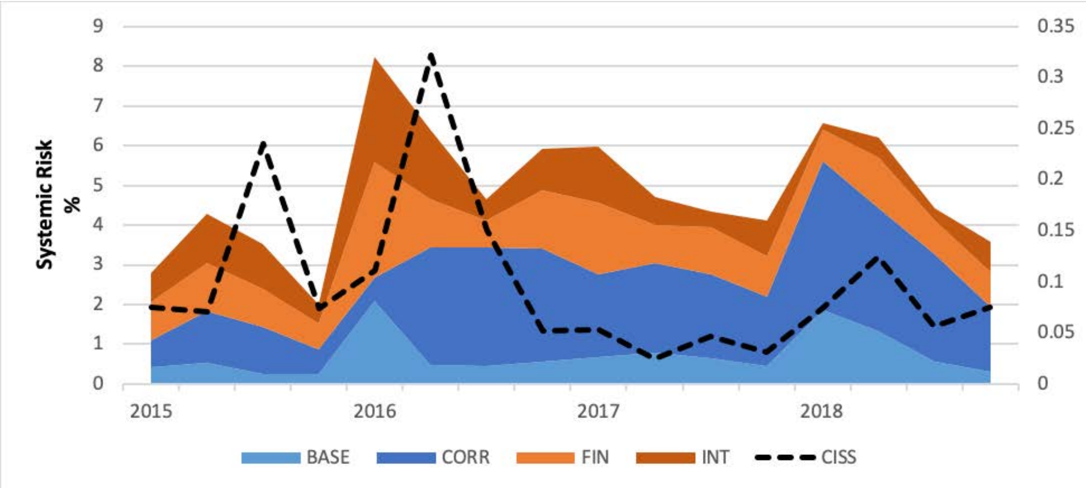
[9] In Appendix C we presents, as robustness analysis, the results for different numbers of Monte Carlo simulations.

position, we see that the two measures are affected by the determinants in a very different way. Starting from systemic risk, we see that, according to our model, almost half of the total risk is related to the presence of correlated shocks from the real economy (164 bp). Financial contagion accounts for 166.6 bp, of which 83.4 deriving from market contagion (i.e. fire sales of assets). Interbank liquidity and solvency contagion, give a small contribution to the total systemic risk when considered individually (0.6 and 2 bp, respectively), nevertheless, the interaction of the considered contagion channels accounts for additional 77 bp of systemic risk, underlining the importance of considering all the contagion channels, even if their individual contribution is small.

By stripping down the effect of correlated shocks and financial contagion, we see for the baseline estimate that the level of systemic risk is roughly 31.2 bps, more than 10 times lower than the complete model with all the activated channels. We remind that such baseline is affected by the same level of economic shocks, but such shocks are independent and there are no active contagion channels. This result confirms that, as postulated in Section 2.2, the level of systemic risk is mostly affected by factors affecting banks' defaults correlations, rather than the expected probability of default of individual banks.

Concerning the average default probability, we see that the decomposition is rather different than the one of systemic risk: the correlation of shocks and the contagion effects have a significantly smaller effect,with the baseline level accounting for more than two thirds of the total (9.9 bp over 14.5 bp). As expected by the linearity of the expectation, correlation of shocks do not play a role at all, as in presence of correlated shocks banks will tend to default more frequently together (increasing systemic risk), but at the individual level the probability of default does not change. Contagion effects instead increase the average default probability due to the presence of non-linear effects. The individual channel that contributes the most is the solvency contagion (1.3 bp), followed by liquidity contagion (0.8) and market contagion (0.7). Also in this case, the interaction of contagion channels has a relevant role (1.8 bp). We underline that the relative importance of these channel is different compared to the decomposition of systemic risk, where market contagion was much more relevant compared to the other channels. An intuitive explanation is that market contagion has on average a smaller effect, but it manifests seldomly and with a more disruptive effect. On the contrary, solvency contagion manifests relatively more frequently, but without enough power to sustain contagion cascades strong enough to cause systemic events.

Panel A – Probability of Systemic Event



Panel B – Average Probability of Bank Default

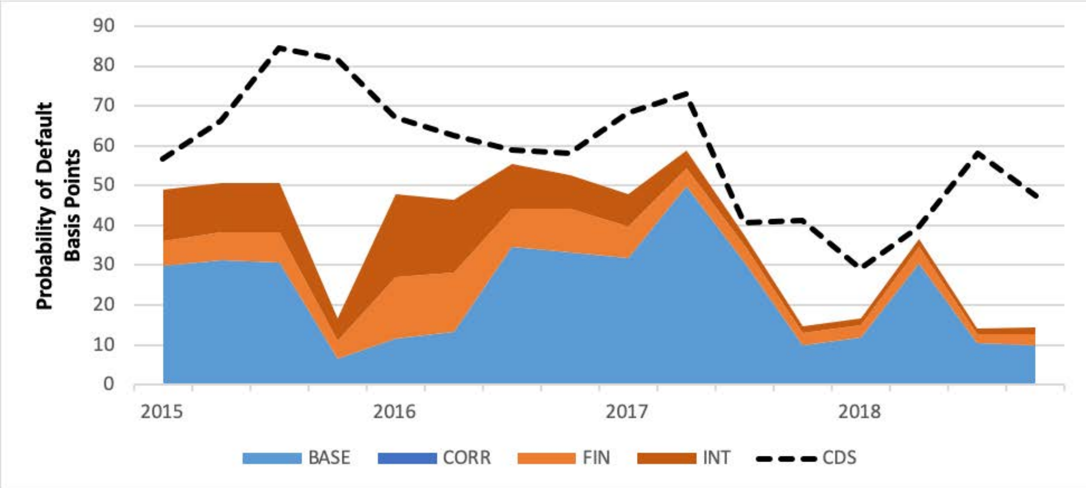


Figure 6: Probability of a systemic event ($\boldsymbol{SR}$) and average expected probability of a bank default ($\bar{\pi}_t$). BASE refer to the baseline model with no contagion and independent shocks, CORR to the effect of correlation of economic shocks and portfolio overlappings, FIN to the cumulated effect of solvency, liquidity and market contagion (without accounting for their interaction), INT to the interaction of financial contagion channels (Source: own calculation). CISS is the level of the Composite Index of Systemic Stress (source: ECB), and CDS is the average credit risk spread for European banks (source: Thomson Reuters Datastream).

Figure 6 reports the evolution over time of our estimate of systemic risk $\boldsymbol{SR}_t$ (Panel A), and of the average default probability of banks $\bar{\pi}_t$ (Panel B), together with the decomposition (to improve readability we merged market, liquidity and solvency contagion in a single component). Concerning the decomposition of risk, the results qualitatively confirm the results for Q4-2018: correlations of shocks and financial contagion account for the largest component of systemic risk, while concerning the average default probability the effect of contagion and correlations is relatively smaller. More in detail, we see that the evolution of the indicators is particularly unstable in the period before Q2-2016, in part due to regulatory changes in the definition of capital buffers, that led to temporary situation of fragilities for some banks during the transition process: the increase in capital buffer requirements reduced banks' distance to distress, and only after the banks implemented policies to increase their capital base, their distance to distress increased again, thereby reducing the likelihood of being in distress. Since Q3-2016, we see a relatively stable level of systemic risk, with a peak in Q1-2018 driven by increase in baseline risk, and a moderate decline until Q4-2018. Concerning the average default probability (Panel B), we see that the contribution of correlations and contagion is decreasing over time. The dip in Q4-2015 may be, also in this case, partially explained by the temporary adjustments to banks' capital base and capital requirements. Interestingly, we see that the evolution over time of $\boldsymbol{SR}_t$ and $\bar{\pi}_t$ is different, with the former witnessing an increase in 2018, while the latter shows a sharpe decline in the same period. This underlines how the two indicators, despite being computed using the same model, are driven by substantially different dynamics, requiring therefore different analytical tools for their analysis, and different policy strategies from regulators.

Figure 6 also compares the evolution over time of our indicators with two market-based measures: the Composite Indicator of Systemic Stress (CISS, source: ECB) (Hollo et al., 2012) as a benchmark for our systemic risk measure (Panel A), and the average spread for senior CDS for European banks (source: Thomson Reuters Datastream), that proxies credit risk in the banking sector. Concerning systemic risk, our measure seems to move with the CISS indicator, sometimes anticipating it by one quarter. We also see that the shifts are much less pronounced compared to the CISS. Concerning the average default probability, we see a certain level of comovement between the series and the level of CDS spreads, suggesting that the model can capture correctly the evolution of average default probability in the market.[10]

Finally, we underline that the results here are robust to several checks, as detailled in Appendix C. In particular, we tested the effect of changing the correlation structure of the shocks, finding similar results for small variations in the correlations ($\pm 10\%$). We also tested the role of the threshold for the definition of systemic events by considering values in the range from 1.2 to

[10] We want to underline that banks' CDS spreads do not enter as inputs into the model. Moreover, we point out that CDS spreads are measures of risk-neutral default probabilities, while our microstructural model computes real-world default probabilities. For this reason the absolute value of the two series are not directly comparable (see Lando, 2009).

1.8, finding a moderative sensitivity to the threshold, but overall a comparable evolution over time. Finally, we tested the numerical convergence of the Monte Carlo scheme, finding that the estimates of systemic risk are very similar to the ones discussed here even with as low as 6,250 simulations (an eight of the 50,000 used in the main analysis).

4.1 Correlations of banks losses and banks defaults

The focus of our systemic risk analysis on the co-occurrence of banks' default, highlights the need of measuring and modelling the correlations among banks' default probabilities, especially among large institutions. Regulators may be interested in assessing the default correlations between specific institutions, for instance in the evaluation of the stability of national banking systems. The empirical estimation of such correlations is challenging due to the limited number of default events (see e.g. De Servigny and Renault, 2002; Lee et al., 2009), especially for banks with relatively high credit ratings. Our model, given a proper calibration, allows to derive the banks' default correlations endogenously using the simulation scheme proposed in Section 3.1. In particular, it is possible to compute the sample correlation matrix of the defaults across the simulation runs.

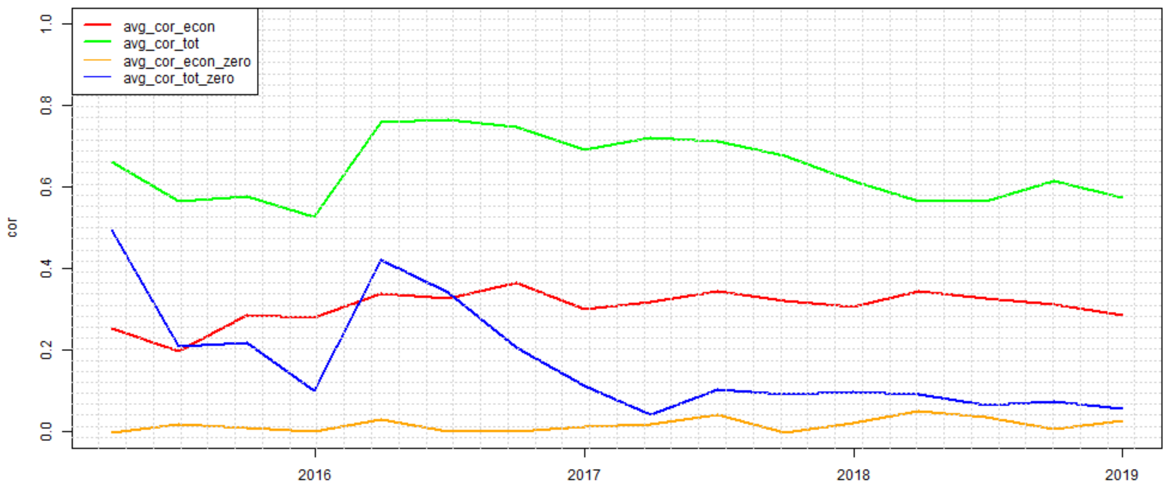


Figure 7: Average default correlation for the 15 largest banks in the system. *Total* refer to the simulation scenario with economic shocks from the real economy and interbank contagion dynamics, while *econ. shocks* to the scenario without contagion. *zero* refer to an alternative set of simulation in which the default correlation among non-financial corporation is set to zero. Simulation are repeated for each quarter on the basis of 50,000 runs.

Fig. 7 reports the evolution over time of the average banks' default correlation among the 15 largest banks in the system, again computed over the 50,000 simulation runs for each quarter, for different specifications of the model. The green line represents the average correlation among the banks when the complete model is used, i.e. the correlation due to both common exposures to the real economy and contagion channels. The red line, on the other hand, represents the average default correlation among top 15 banks only due to common shocks from the real economy. Note that correlated economic shocks can happen both because banks are exposed to the same set of non-financial corporations, or because they are exposed to different corporations which in turn have a correlated default probability (see Fig. 3 for a graphical representation). It is striking to see the levels of these correlations, which amounts to values as high as 80% in the peak at the end of the first quarter of 2016. One can see from Fig. 6 (top panel) that the peak is reflected in a similar maximum of systemic risk for the same quarter, though the total amount remains relatively low due to small idiosyncratic default probabilities (Fig. 6, bottom panel). From Fig. 7 it is also clear that the increase in systemic risk in that quarter is only partially due to the increase in economic risk, as already discussed above when looking at Fig. 6, but instead an increase in financial contagion and amplification drives a great part of these results.

It is interesting to compare the above situation with the case where the economic system is composed by non-financial corporations which are totally uncorrelated among each other. In this universe, banks' correlated shocks from the real economy can only be attributed to common exposures, i.e. exposures towards the same sources of risk. In fig. 7 the yellow line reports the average correlation among banks' defaults when the correlation among non-financial corporations is set to zero. The levels are now considerably lower than the previous scenario (red line in the same plot). The blue line shows instead the total correlation among banks' defaults when the correlation matrix among economic shocks is set to zero, highlighting the strong role played by banks' common exposures towards the real economy, financial contagion, and their interaction. Focusing at the last quarter, Fig. 8 reports the heatmap of loss and default correlations for the top 15 largest banks in our sample. We see that the default correlation matrix appears to be characterized by groups of correlated banks, while the losses have a more uniform structure, with a large group of strongly correlated banks and a set of less connected ones. This set of results emphasize relevant policy implications that will be discussed in the following and concluding sections.

Finally, the correlation matrix presented above can be interpreted as an undirected network in which the nodes are the banks and the edges are the bilateral default (or losses) correlations, and they can be used to represent synthetically the relationships among banks and to define appropriate policies. Notably, they establish a bridge between microstructural models and market based networks, as correlations may also be estimated using market data. This connection may be useful for the validation of market based networks estimated on time series data, such as Diebold and Yilmaz (2008); Billio et al. (2012); Torri et al. (2018). We leave this stream of research for future analysis.

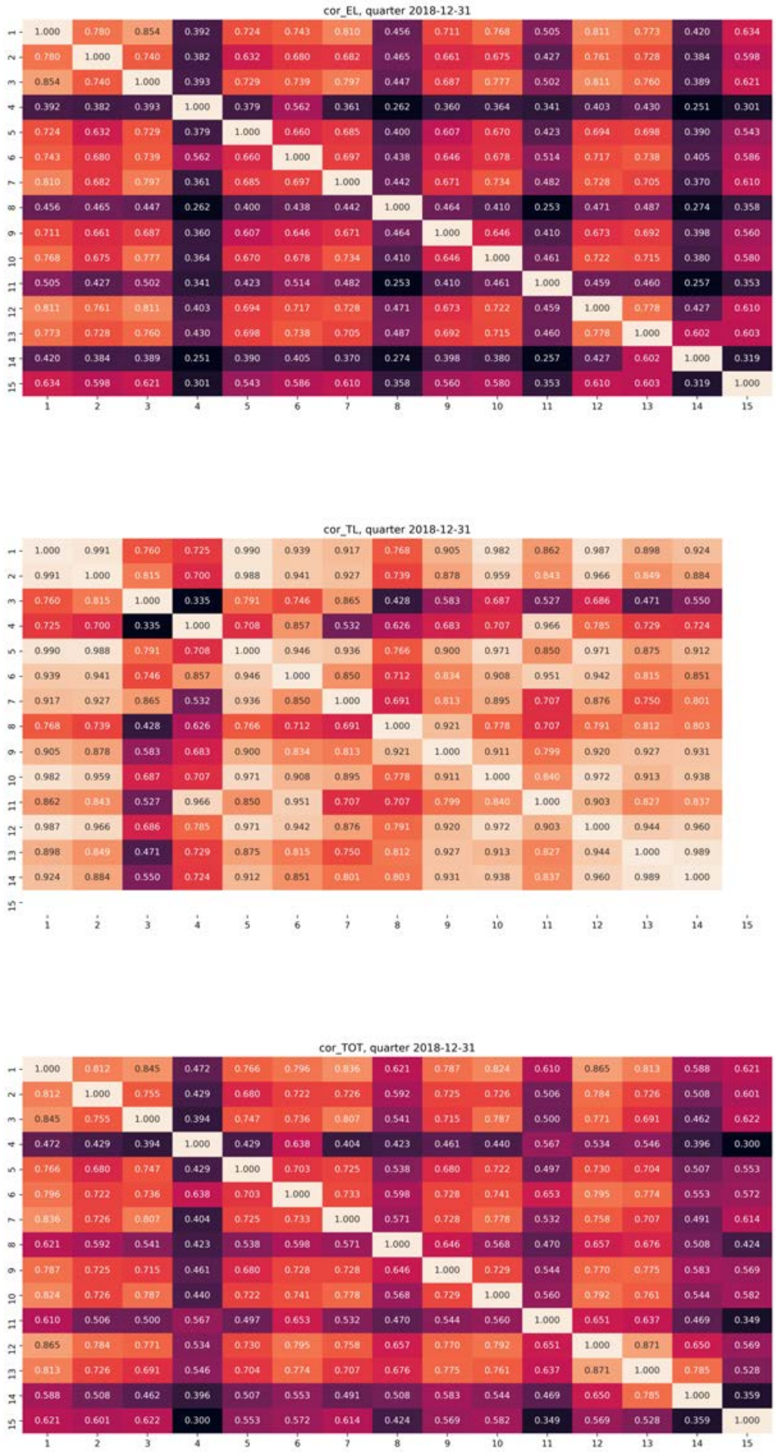


Figure 8: Heatmaps of the correlation matrix for the variables economic losses (top), total losses (center), and default event (bottom). Simulations refer to the fourth quarter of 2018 and are based on 50,000 Monte Carlo runs.

5 Discussion

In this paper, we propose a systemic risk analysis framework based on a multi-layer microstructural contagion model calibrated on a rich dataset of euro area banks' granular exposures. The methodology is grounded on a new and rather intuitive definition of systemic risk, which is the starting point of our investigation. The aim of our approach is to study and model the drivers of systemic risk, that is, the economic and financial factors affecting the probability to have a large number of banks going into distress simultaneously in the same period. The focus of this paper is placed upon the process and conditions generating and strengthening the cross-sectional correlation in banks' default probabilities. Why do banks fail jointly leading to events such as the 2008 Great Financial Crisis? This is the research question we intended to answer and so we contribute to the literature in multiple ways.

We emphasize that to fully characterize the probability of the manifestation of systemic events (i.e. systemic risk), we need to model both the potential sources of distress, and the amplification channels. Hence, we structure the analytical framework into two core blocks which serve different purposes. The first is the modelization of the source of the shocks, that represents the stochastic component of the model, and is the distinguishing feature of our work. In particular, the trigger event is modelled as a distribution of initial economic shocks coming from the real economy, thereby weakening jointly banks' balance sheet. The second block consists of a multilayer financial contagion mechanism that includes three intertwined channels: solvency, liquidity and fire-sales used to assess how economic losses are amplified by the financial system. A large part of the literature focuses more on the transmission of contagion (the second block) rather than on the sources of the distress (the first block), among others: in Gai and Kapadia (2010); Gai et al. (2011); Espinosa-Vega and Solé (2011) the contagion dynamics are analysed by applying random shocks to individual nodes, and in Battiston et al. (2012) the authors study the systemic relevance of individual institutions by assessing the potential effect on the system to them going in distress. Contrary, the shocks in our framework are computed endogenously on the basis of the actual exposures of banks to non-banking institutions. We underline that such approach is fundamental to measure *systemic risk*, and not only *contagion*. In this sense, our work relates to Elsinger et al. (2006), that considers the effect of correlated shocks derived from asset exposures, together with a solvency contagion model. Compared to ours, such model is focused on a much smaller selection of banks (the authors discuss the Austrian banking sector), and considers only the solvency contagion channel. The usage of shocks from asset exposures is also considered by Glasserman and Young (2015), that estimates the potential for contagion and amplification of economic shocks on the basis of node-level quantities and by Roukny et al. (2018), that discuss the role of the structure of the network in the determination of credit risk, studying the role of correlation of the economic shocks affecting the financial system. These models however assume a more theoretical approach, not focusing on the characterization and estimation of such shocks. Moreover, they limit the contagion analysis to the solvency channel, while we include also liquidity and market fire-sales contagion mechanisms. Other works are also limited compared to our in terms of complexity of the contagion channels deployed, since their focus is to assess the relevance of one channel in isolation rather than their interaction. In this respect, Eisenberg and Noe (2001), Gai and Kapadia (2010), and Glasserman and Young (2015) focus on solvency contagion; Allen and Gale (2000), Gai et al. (2011) study the liquidity channel; and Caccioli et al. (2014) as well as Cont and Schaanning (2019) model asset fire-sales and indirect contagion. Our model instead considers three different contagion channels (solvency, liquidity and fire sales), as well as the systemic risk determined by the correlation of economic shocks. As discussed previously, the contemporaneous implementation of multiple contagion channels allows to consider the interaction effects among them, leading to a more complete evaluation of systemic risk.

This narrower focus of the existing empirical literature is mainly due to the limited availability of granular exposure-level data, which are confidential, complex to clean, and most importantly, their collection only started in recent years thanks to the post-crisis regulatory reforms (see for instance the large exposures regulation). Hence, compared to previous analyses, we leverage upon a more complete and extended dataset in terms of granularity, type of assets, sectoral and country dimensions. In this regard, we need to acknowledge the availability of the unique dataset recently structured at the ECB, which allows us to map euro area banks' granular exposures towards the real economy (non-financial corporations, non-bank financial institutions, and households). In the literature, to cope with data limitation Allen and Gale (2000), Acemoglu et al. (2012), Gai and Kapadia (2010) and Montagna and Kok (2016) use simulated data to reconstruct either interbank exposures or banks' portfolios of securities, while Eisenberg and Noe (2001), Puhr et al. (2012), Alter et al. (2015) limited their analysis to national banking systems, whereas Espinosa-Vega and Solé (2011) and Anand et al. (2015) use statistical techniques to estimate the actual bilateral exposures starting from marginal data. Similarly, Fricke and Lux (2015) study exclusively the overnight interbank transactions on the e-MID platform. Finally, Covi et al. (2020) exploit the actual interbank network structure of euro area significant institutions' short and long-term exposures to model liquidity and solvency contagion. In this respect, we augment Covi et al. (2020)'s dataset in terms of banks' exposures towards the real economy, and by adding granular security holdings of banks. To our knowledge, this dataset is the most comprehensive euro area bank-centric dataset available to date to regulators, both in terms of geographical and sectoral coverage as well as granularity and type of asset to model the propagation of shocks across individual entities over multiple layers of risk.

Thanks to this dataset and to our stochastic simulation engine, we are able to provide a rich set of results and insights, and to validate and integrate some of the findings of previous works. First, starting from our main result and research question, we show that economic correlated shocks are the main contributor to systemic risk. This result corroborates the findings of Elsinger et al. (2006), that undelined how correlation in banks' asset portfolios plays a significant role in the generation of systemic risk. Second, fire-sales via overlapping portfolios of securities is the most relevant financial contagion channel, largely more prominent than solvency and liquidity contagion. This finding is consistent with the literature highlighting the role of indirect contagion, derived from the presence of overlapping portfolios and related to market dynamics such as fire sales (Cont and Schaanning, 2019; Clerc et al., 2016; Caccioli et al., 2014; Greenwood et al., 2015), and other information sensitive channels such as bank run (Diamond and Dybvig, 1983) and complexity contagion (Caballero and Simsek, 2013). Third, interaction among channels proved to be quite relevant in our framework, confirming the findings of Montagna and Kok (2016), that also found a relevant increase in the spread of contagion related to fire sales when other contagion channels and systemic risk determinants were considered. This hints scholars and regulators to give even greater focus on the integration of multiple contagion channels and systemic risk determinants, to avoid (potentially severe) underestimation of systemic risk. Last, in relation to solvency contagion, the literature highlights that the potential of systemic risk related to such channel is relatively limited (see e.g.Glasserman and Young, 2015, that compute a bound on contagion and amplification based on bank specific information, finding relatively difficult to generate contagion uniquely on the basis of spillover losses, and Elsinger et al., 2006, that studying the Austrian banking system found that domino effect due to solvency contagion happen rarely, and if contained with crisis resolution strategies they pose minor problem). Such findings are consistent with our work that shows how interbank solvency contagion alone (without considering the interaction with other contagion channels) does not contribute significantly to systemic risk.

The systemic risk framework here proposed, can be viewed as the basis for a system-wide analysis, or for assessing and calibrating macroprudential policy measures. Moreover, by augmenting the methodology with new contagion channels, or by considering newly available data sources, the framework may benefit in terms of accuracy, reducing the estimation bias due to the limited information set available to us. According to this, the main directions for future research are the inclusion of other non-bank financial institutions such as insurances and funds so as to better model market risk via fire-sales, as well as other indirect contagion channels such as news-based contagion, derivative markets and complexity contagion.

6 Conclusions

The calibration of policies aiming at contrasting the build-up of systemic risk and preserve the stability of the financial system is an increasingly relevant task for regulators worldwide. The development of sound analytical tools for the interpretation and forecasting is therefore of paramount importance, and microstructural contagion models represent a promising tool, especially considering the fact that very granular dataset are increasingly available to regulators. One of the main limits of such literature is the lack of an agreed and usable definition of systemic risk, leading to a plurality of works that are difficult to compare, or that are suitable only to answer specific research questions. Moreover, microstructural models also capture the causal relationships among the events, thereby allowing regulators to precisely target critical junctures in the network in order to avoid idiosyncratic risks becoming a systemic event.

In this work we propose a definition where systemic risk is described as *the probability of a systemic event, conditional to a certain information set*, where a systemic event is defined as a scenario in which a large number of banks default or go into distress in the same time period. The definition is based on three elements: a definition of systemic event, a model for the transmission of distress, and a conditioning set of information. Each of these points is discussed in the paper; in particular we explain that the focus on the number of default is motivated by the clusterization of defaults, and by the centrality of the banking system in the current economic system. We highlight that by defining systemic risk in probabilistic terms, the user is forced to turn the attention towards the modelization of tail events starting from the actual distribution of market variates, leading to a more complete assessment of risk. Moreover, we point out the relevance of banks' defaults cross-correlation in the manifestation of systemic events, and thus systemic risk.

We then implement a stochastic microstructural multi-layer model calibrated on a unique dataset that includes data on individual exposures for a large panel of euro area banks. The results highlight that the main determinants of systemic risk according to our model are the correlation of economic shocks and the market based indirect contagion channel (fire sales). Solvency and liquidity contagion instead play a less prominent role when considered alone, but the interaction among all the contagion channels contribute relevantly to systemic risk. On the contrary, the average default probability of the banks in the system are not affected by the correlation of economic shocks, and only marginally influenced by contagion dynamics. The results match the findings of the literature, and the evolution over time of systemic risk and expected default probability matches the evolution of the systemic risk indicator CISS and the average CDS spread for the European banking sector, respectively.

From a policy perspective, the model represents a particularly powerful and flexible tool for regulators, thanks to the ability to estimate the level of systemic risk endogenously, the microstructural foundations, and the possibility to run counterfactual exercises by changing individual aspects of the system. Some examples are: the cost and benefit analysis of prudential mechanisms such as the bail-in, the calibration of regulatory capital buffers and liquidity requirements, the identification of financial and non-financial institutions most likely to cause systemic events, or the ones most affected by it. By highlighting a relevant differences in the determinants of systemic risk and the determinants of average default risk (with the former being much more influenced by correlations of economic shocks and contagion), our analysis suggests that regulators targeting the reduction of banks' default probabilities may have very little effect in reducing the probability of experiencing a systemic crisis. Regulators need to think whether their policy targets, tools and ultimate objective aim for a reduction of the average bank default probability (less frequent bank default) or of systemic risk (fewer banks defaulting simultaneously). These two targets differ from one another, and reducing the former does not imply a reduction of the latter. In particular, for reducing systemic risk regulators need to target correlations among banks' losses. Macroprudential policy measures taking into account the micro-structure of the financial system, and going beyond simple capital requirements, are therefore necessary to properly tackle systemic crises from their origins.

A Microstructural contagion model dynamics

The microstructural contagion model proposed here includes four drivers of systemic risk: overlapping and correlation of exposures to the real economy (economic risk), losses deriving from the default of the counterparties in the interbank network (interbank solvency risk), hoarding of liquidity from short term interbank market (liquidity risk) and risk deriving from the downward spiralling prices due to sales of securities (market risk). All these factors interact with each other, leading to an amplification effect of risk. We underline that the framework presented here can be easily extended in several directions, for instance by incorporating additional risk drivers (interest rates, sovereign risk, etc.), other actors (central banks, insurance companies, etc.) or different dynamics (alternative behavioural rules for interbank liquidity hoarding and sales of securities). The specification that we present here reflects the most commonly considered determinants of systemic risk in the literature, and to leverage as best as possible the data available to us. In particular, the multilayer contagion model reflects the framework in Montagna and Kok (2016).

A.1 Variables definition

Consider N credit institutions, each characterized by a capital level c_i (corresponding to the CET1 capital of an institution) and a liquidity level $cash_i$ (the sum of cash and exposures to central banks). In the model a bank is in distress if, for any reasons during the simulation dynamics, its capital breaches its capital buffer requirements $\bar{c^b}_i$ or its liquidity breach the liquidity coverage ratio (LCR). In the same way, a bank is considered defaulted if its capital is below the minimum capital requirement $\bar{c}_i$ or if does not have enough cash to close a position on the liquidity market. We model two interbank *exposure* networks, one for long term and the other for short term exposures. They are represented by the weighted adjacency matrices of size $N \times N$: $\boldsymbol{M}^{lt}$ and $\boldsymbol{M}^{st}$, respectively. Note that in the long term exposures network we implicitly include a Loss Given Default in the analysis by constructing $\boldsymbol{M}^{lt}$ using not the entire exposure, but only the part the will result in losses (see Appendix B).

consider then M entities from the real economy (non-financial corporations and households), each characterized by a default probability p_j, a loss given default LGD_j, and a correlation structure estimated from market CDS spreads. The exposures of banks to these entities are described by a bipartite network whose weighted adjacency matrix is $\boldsymbol{M}^{re}$ of size $N \times M$.

Similarly to the long-term bilateral network, $\boldsymbol{M}^{re}$ does not reflect the entire exposures, but only the LGD.

Finally, the model envisions a set of L securities that a bank can sell to gather liquidity, characterized by an initial price p_k (set to 1 for convenience). The bipartite network of the exposures to such securities is $\boldsymbol{M}^{sec}$ of size $N \times L$. We assign to each security an initial price equal to one and the, with the dynamic of the model unfolding, the price of security k is affected in accordance to how much of its notional has been sold in the market:

$$p_k = f_k(p_{k,0}, \text{amt}_k, d_k), \tag{6}$$

where amt_k is the amount of the asset sold, d_k is a parameter that determine the market depth of a security and $p_{k,0}$ is the initial price of the security. In line with the literature, we use here a linear specification of f_k of the form:

$$p_k = p_{k,0}(1 - \alpha_k d_k \text{amt}_k), \tag{7}$$

where α_k denotes the sensitivity of each asset to the selling.

The networks $\boldsymbol{M}^{lt}$, $\boldsymbol{M}^{st}$ and $\boldsymbol{M}^{re}$ are constructed using granular and aggregated data as described in Section B.

A.2 Scenarios generation

Each of the simulations is driven by a shock to the real economy, modelled by a vector $\boldsymbol{\varepsilon}$ of length M. Each element $\varepsilon_j \in [0, 1]$ denotes the set of states for non-financial corporation, where 1 represents the default, and 0 non-default. We model three types of entities separately: individual non-financial corporations, households by country, and a residual groups of non financial corporations not covered by the granular dataset.

To model the defaults with a correct default probability and a realistic correlation structure we proceed as follows: first, we obtain a large set of weekly CDS spreads of non financial corporations from Thomson Reuters Datastream, and we group them geographically (for the euro area we consider individual countries, while for other regions we consider broader aggregates). Second, we compute for each group the average correlation of the CDSs within the country, and for each couple of groups the average correlation of the CDSs between the two. Third, on the basis of the country of the non-financial corporations, we model an M-variate distribution with uniform marginals and a Gaussian copula with a covariance matrix characterized by a block structure derived from the previous step. We finally obtain the vector of defaulted entities by sampling from the distribution the vector G, and setting $\varepsilon_j = 1$ if $G_j > p_j$, where p_j is the default probability for the period provided by Moody's Risk Calc. For the household sector and the non-financial corporations not covered by granular data, we consider instead conservative estimations of the probability of default based on country and sectorial averages.

A.2.1 Initial shock

For each run of Monte Carlo simulation, defaults are described by the column vector $\boldsymbol{e}$ of length M described above. The losses incurred by each company are then defined by the vector $l_0 = \boldsymbol{M}^{re}\boldsymbol{\varepsilon}$. The capital is then updated as $c_i = c_{i,0} - l_0$ (where $c_{i,0}$ is the capital at the previous iteration). If it is lower than $\bar{c^b}_i$, the company i is marked as distressed, while if it is lower than $\bar{c}_i$ the company defaults.

A.2.2 Transmission of solvency contagion

Banks that are defaulted transmit the losses to the counterparties in the long term market based on the exposures, generating losses for the counterparties according to $l = \boldsymbol{M}^{lt}\boldsymbol{d}$, where $\boldsymbol{d}$ is a vector of length N, where the element i has value equal to one if the bank i has just defaulted, and zero otherwise. Banks can then default or go into distress if their capital is below $\bar{c}_i$ or $\bar{c^b}_i$, respectively.

A.2.3 Liquidity contagion

After the first round of solvency contagion, we model the dynamics on the short term interbank market that begin with two types of operations: newly defaulted and distressed banks withdraw all the exposures to other counterparties, while all the banks prehentively withdraw their positions to defaulted and distressed banks.[11] The withdrawal are represented by the $N \times N$ matrix $\boldsymbol{M}^w$. These operations may generate liquidity shortage for some banks if their liquidity position goes below the target liquidity. Such shortage is measured by the vector $cash_{need}$, considering

[11] In this modeling framework we assume that no solvency losses occour in the short term market, as we assume that the time scale of solvency default is longer than the maturity of such exposures, giving to the counterparties the time to withdraw their position.

the previously available cash, the amount witdrawn from them, the liquidity gathered in the market and the liquidity threshold:

$$cash_{need} = \max(cash + \boldsymbol{M}^w \mathbf{1} + \mathbf{1}' \boldsymbol{M}^w - LCR, \mathbf{0}) \tag{8}$$

where $\mathbf{1}$ and $\mathbf{0}$ are conformable column vectors of ones and zeros, respectively, and the operation max() is performed elementwise.

banks affected by the shortage then further proceed with further withdrawals from their counterparty. Assuming that the withdrawal is proportional to the size of the exposure, the updated withdrawal matrix is described as follows:

$$ratio_i = \min \left(cash_{need\,i} / \sum_{j=1}^{N} (\boldsymbol{M}_{ij}^{st} - \boldsymbol{M}_{ij}^{w}), 1 \right), \tag{9}$$

where

$$\boldsymbol{M}_{ij}^{st} = \boldsymbol{M}_{ij}^{st\,old} + ratio_i (\boldsymbol{M}_{ij}^{st} - \boldsymbol{M}_{ij}^{w}), \tag{10}$$

and $\boldsymbol{M}^{st\,old}$ is the matrix of withdrawal before this update.

The procedure is then iterated until the 1-norm of the matrix $(\boldsymbol{M}^{st} - \boldsymbol{M}^{st\,old})$ becomes smalle than a threshold ε, that is, when no more liquidity is withdrawn from the market at each new iteration. We underline that the algorithm, although it lends itself to be interpreted as the unfolding of a liquidity crisis (over a period of hours, days or weeks), can also be interpreted as an interative algorithm to get to an equilibrium. Note that the liquidity shortage of the banks may not be fully replenished, as the amount of liquidity required may be higher than their exposures in the interbank market. Such residual shortages will be addressed in the next step.

A.2.4 Securities sales

After the liquidity round, we proceed to model the selling of securities in the market. In the model, sales of securities are done by the defaulted banks (that liquidate all their assets), and by banks that have residual liquidity shortages from the previous round of liquidity contagion. The selling of securities has an effect on the prices, potentially leading to fire-sales mechanism (i.e. selling at a strongly discounted price) and capital losses to the banks. In this implementation we assume that the pricing function is linear, and that each bank sells its assets proportionally to the holdings. The framework could be expanded by considering more complex specifications for the pricing function, and by assuming different behavioural rules for the selling (for instance a bank may choose which securities to sell to minimize its capital losses). These extensions, fundamental for the definition of a model used for policy purposes, are left to future works.

Given the vector of intial prices of securities $\boldsymbol{p}$ of length L, where for convenience we standardized the prices to 1, we compute the value of the asset portfolio and the ratio of assets that each bank has to sell (defaulted banks sell all their portfolio, and banks with liquidity shortage sell as much as possible to replanish the shortage):

$$v_{tot} = \boldsymbol{M}^{sec}\boldsymbol{p}, \tag{11}$$

$$ratio_i = \begin{cases} 1 & \text{bank } i \text{ is defaulted,} \\ \min\left(v_{tot}, cash_{needi}\right)/v_{tot} & \text{otherwise} \end{cases}. \tag{12}$$

Given the matrix of assets to sell, where each element is defined as:

$$\boldsymbol{M}_{ik}^{tosell} = ratio_i \boldsymbol{M}_{ik}^{sec}. \tag{13}$$

We model now the price effect on the security using Equation 6, with the amount $\text{amt}_k = \sum_{i=1}^{L} \boldsymbol{M}_{ik}^{tosell}$ and original price equal to the current price:

$$p_k = p_{k0}(1 - \alpha_k d_k \text{amt}_k). \tag{14}$$

Using the updated market price, the mark-to-market losses l_i^{fs} are estimated for each bank i, and the capital c_i is updated accordingly:

$$l_i^{fs} = \sum_{k=1}^{L} \boldsymbol{M}_{ik}^{sec}(p_{k0} - p_k), \tag{15}$$

$$c_i = c_{0i} - l_{fs}. \tag{16}$$

Finally, the security holdings are updated, by subtracting the amount sold and liquidity position and liquidity shortage are updated with the cash recovered from the selling:

$$\boldsymbol{M}_{ik}^{sec} = \boldsymbol{M}_{ik}^{sec\,old} - \boldsymbol{M}_{ik}^{to\,sell}, \tag{17}$$

$$cash_i = cash_{0i} - \sum_{k=1}^{L} \boldsymbol{M}_{ik}^{to\,sell}, \tag{18}$$

$$cash_{need} = \max(cash_i - LCR_i, 0) \tag{19}$$

where $cash_{0i}$ is the liquidity of bank i before the update.

The procedure is then repeated until no new securities are sold in the market.

A.2.5 Closing of the round

Finally, the positions on the short term market are settled with the cash recovered in the sale of the security. If the liquidity recovered is not sufficient, a bank goes in default. Similarly, if a bank cannot recover the entire amount required to have a cash position above LCR_i, the bank goes in distress.

The matrix of short term exposures gets updated by subtracting the amount withdrawn, and the banks that defaulted in the previous round get marked as inactive.

The process is the repeated from the transmission of solvency contagion, until no new banks goes in distress or default.

At the end of each simulation, the number of distressed or defaulted companies is stored, in order to construct its distribution and compute systemic risk.

A.3 Activation of contagion channels

In order to replicate the decomposition proposed in Section 3.2, we need to run the model with only some of the channels active. In particular, we can deactivate the credit risk channel by setting the LGD of each banking institution to zero, so that any default does not transmit any distress. The liquidity contagion can instead be deactivated by setting all the short term exposures to cash. Finally, the market risk channels can be deactivated by removing any repricing of securities as a consequence of sales in the market.

The marginal contribution of each channel (without considering the interaction factor) can then be estimated by activating one channel at the time, computing the level of systemic risk using Monte Carlo simulations, and subtracting the baseline level of systemic risk driven by the economic shocks alone.

B Dataset description

The empirical analysis in Section 3 is based on a unique dataset constructed using multiple data sources. In particular, the long-term and short term networks of interbank exposures, and the exposures to non-financial corporations are the data reported by banks in the large exposures (LE) framework, a regime introduced in the EU in 2014 that requires banks to report to prudential authorities' detailed information about their largest exposures.[12] The LE data reported capture almost EUR 8.2 trillion of gross exposures in Q4-2018, more than 50% of euro area credit institutions' exposures. Large exposures towards credit institutions, financial corporations, and governments cover respectively for 77%, 67% and 98% of euro area significant institutions' total assets to these sectors. The coverage of non-financial corporations is smaller, approximately 31% of total assets, whereas the household sector is almost missing. The panel of reporting banks include all the euro area Significant Institutions at consolidated level (around 100 groups in Q4-2018), as well as around 300 other Less Significant Institutions. In addition to these banks, we also consider all the other institutions, either European and global, that appear as counterparties of the reporting instituions, leading to a total of over 1000 institutions in the network. For each exposure, the bank has to report the original amount, as well as the net amount after credit risk mitigations and exemptions. Then, we rescaled the banks' exposure-specific LGDs in order to match the averages by country and sector estimated in the 2018 stress test. For the 10 largest exposures to credit institutions, the banks have to report also the maturity split, and we use these data to differentiate between long-term and short-term interbank network.

Together with LE, we consider also data from table C.67 in the COREP framework, where banks report the 10 largest liability counterparties, each greater than 1% of current liabilities.[13]

The long and short term interbank network $\boldsymbol{M}^{lt}$ and $\boldsymbol{M}^{st}$ are constructed using LE data

[12] An exposure is considered a "Large Exposure" when, before applying credit risk mitigations and exemptions, it is 10% or more of an institution's eligible capital vis-à-vis a single client or a group of connected clients (CRR, art. 392). Moreover, institutions that report FINREP supervisory data are also requested to report large exposures information with a value above or equal to EUR 300 million (Committee et al., 2014).

[13] Together with LE, this requirement and the connected exposures limits are aimed at reducing concentration risk and increase the transparency of the market.

Table 3: Interbank network characteristics.

Data Sample	2014	2015	2016	2017	2018
Consolidated banking group	1149	1017	1089	1088	1053
Linkages	4453	4096	4914	4639	4559
Gross amount	2.04	2.27	2.47	2.24	2.32
Net amount	0.82	0.88	0.90	0.85	0.91
short-term amount (¡30 days)	0.52	0.52	0.63	0.54	0.60
Density	0.3%	0.4%	0.4%	0.4%	0.4%
Avg. Path length	3.2	3.2	3.6	3.6	3.8
Diameter	7	9	9	9	9
degree of power law distribution	1.48	1.38	1.35	1.36	1.35

Consolidated banking groups refer to euro area and extra euro area banks. Net amount is the amount of unsecured exposures, and refers to the gross amount after deducting exemptions and credit risk mitigation

merged with data from table C.67. Table 3 reports the main characteristics of the interbank network over time (including both short and long term exposures).

The network of exposures to the real economy $\boldsymbol{M}^{re}$ is also constructed using LE data for the exposures to non-financial corporations. In order to minimize the reporting bias, to cover the exposures to household and non-financial corporation smaller than the threshold required by the LE framework, for which we do not have disaggregated data, we use the exposures reported by FINREP, aggregated by country.

An additional source of granular data comes from the Security Holding Statistics (SHS), a dataset collected on a security-by-security basis, that provides information on securities held by selected categories of euro area investors, broken down by instrument type, issuer country and further classifications. In order to simplify the analysis, we aggregated the counterparties by country and sector, modeling each of these groups as a new security. The market depth parameter has been assigned on the basis of the liquidity and risk profile of the group of securities.

To complete the dataset, we retrive balance sheet information, capital requirements and aggregate exposures from COREP and FINREP for euro area banks, and from Bankscope for banks outside the euro area. We instead obtain default probabilities for real economy actors from Moody's Risk Calc, and CDS spreads using for the generation of correlated scenarios from Thomson Reuters Datastream.

C Robustness analysis

We performed a series of robustness checks on our results, and we report here the most important ones. More in detail, we assess the sensitivity of our systemic risk measure to (i) the level of economic correlation, (ii) the value of the threshold that identify a scenario as systemic and (iii) the number of simulations.

Fig. 9 shows the results for the sensitivity to correlation to economic shocks. We let the correlation matrix describing the relationships among the non-financial corporations default probabilities varying between -10% and +10%, showing that systemic risk estimations are considerably stable. On the other hand, when the correlation among NFCs is set at zero, and therefore common exposures play the only real role in generating commons shocks, the results is still a considerably high level of systemic risk (green line).

Fig. 10 shows the evolution over time of systemic risk for different values of the systemic risk threshold. We let the threshold vary from 1.2% to 1.8%. As one can see from the picture, both the levels and the trend of the systemic risk remains largely unchanged.

Finally, Fig. 11 shows that our results are robust to changes in the number of Monte Carlo simulations, even when the number is reduced to 6,250 runs (an eight of the original ones).

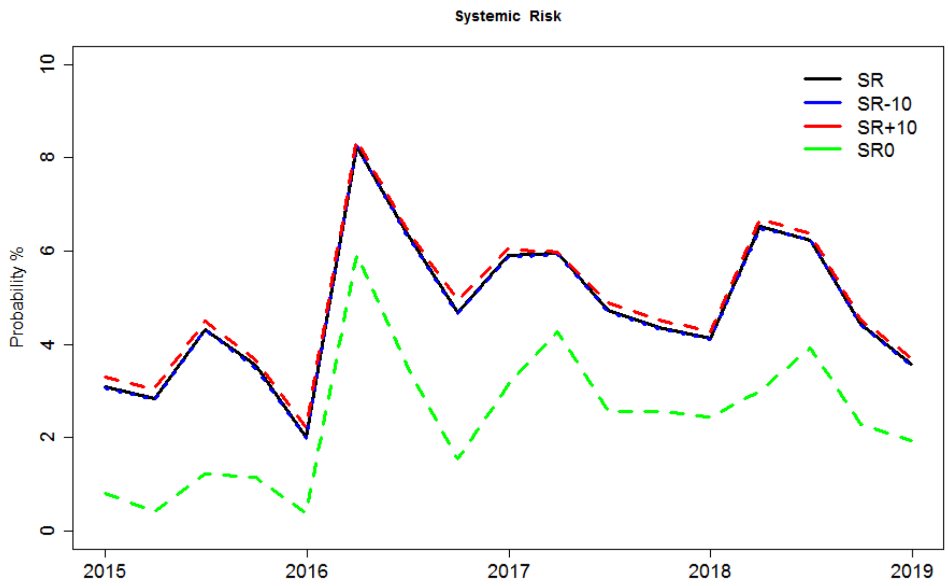


Figure 9: Systemic risk for different levels of correlations. In particular for an increase or decrease of 10% percent, and for zero correlation among non-financial corporations. Simulations are repeated for each quarter on the basis of 50,000 runs.

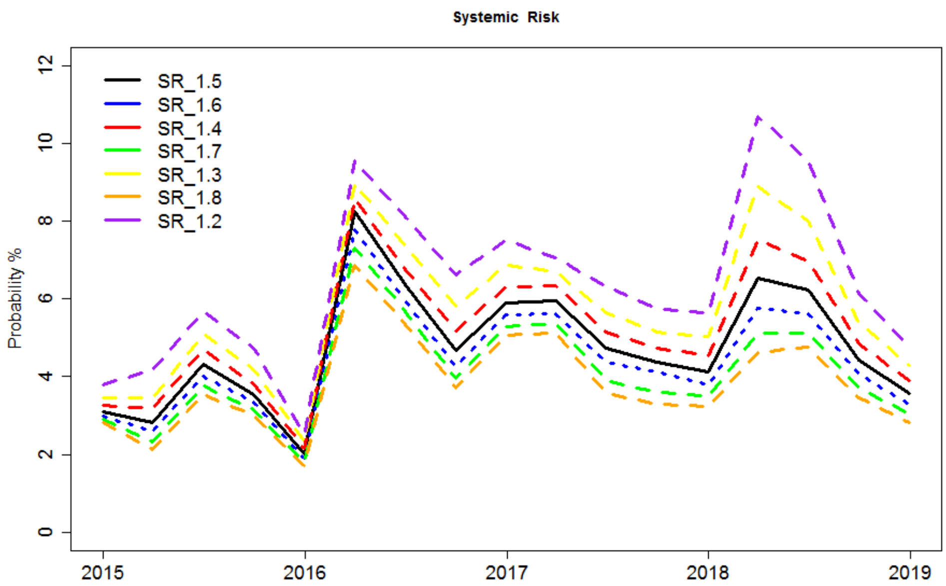


Figure 10: Systemic risk for different levels of the systemic threshold. Simulations are repeated for each quarter on the basis of 50,000 runs.

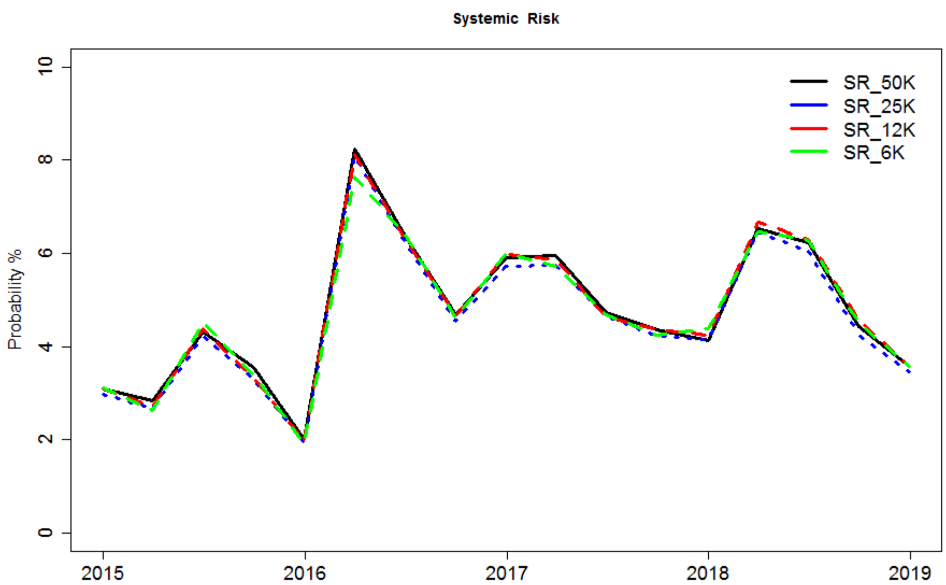


Figure 11: Systemic risk for different number of Monte Carlo simulations.

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