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## Article

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# 15 years of research on systemic risk across the globe: The evolution of the field and its drivers

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## ABSTRACT

This study examines the evolution of research on systemic risk during the 2007–2021 period, encompassing the Global Financial Crisis, European financial crisis, the outbreak of the COVID-19 and a number of other notable episodes undermining global financial stability. Our research goal is two-fold. First, based on Scopus-indexed publications, we identify the most impactful countries, institutions and scholars in the field, revealing a gradual but notable decline in the annual shares of publications on systemic risk associated with major advanced economies. This is offset by the increasing role of emerging markets, primarily, China, which makes this research field more competitive. Second, we are also concerned with the drivers of research on systemic risk in a vast sample of countries during the observation period. By applying a combination of variable selection techniques to 33 indicators that can potentially incentivize research on systemic risk, we find that low bank profitability as well as the general productivity of economic research are the most robust factors stimulating such publications. A higher country's score on the global innovation index also spurs the research in this field. Conversely, countries with a higher power distance index, i.e. favoring hierarchy and low risk-taking, tend to produce less research on systemic risk.

## 1. Introduction

Systemic risk is one of the key concepts in the contemporary macrofinancial analysis. This risk undermines financial stability by impairing the functioning of a large part of the financial system and exerting adverse effects on the real economy (Freixas, Laeven, & Peydró, 2015). The build-up of systemic risk is one of the repercussions of financial globalization, which has increased the interconnectedness across financial markets and institutions (Evanoff, Hoelscher, & Kaufman, 2009). Largely overlooked by researchers and practitioners prior to the 2008 Global Financial Crisis (GFC), systemic financial risk has gained momentum since then, materialising in numerous publications with the findings relevant for bank risk management, regulation and macroprudential policy. Many of them emphasized the global dimension of systemic risk and its adverse effects on the world economy, e.g. Ellis, Haldane, and Moshirian (2014), Kanno (2015), Bostandzic and Weiß (2018), McLemore, Mihov, and Sanz (2022).

The progress in this research field has naturally resulted in a number of studies aiming to generalize the extant literature on systemic risk. For example, Bisias, Flood, Lo, and Valavanis (2012) provide a taxonomy of

systemic risk indicators. Silva, Herbert, and Vinicius (2017) are the first to elaborate an analytical classification and coding of research papers on systemic risk. Based on this classification, they identify major research paths and networks in this field. Benoit, Colliard, Hurlin, and Pérignon (2017) review the literature on systemic risk, focusing on its sources and regulatory challenges. Ellis, Sharma, and Brzezczynski (2022) characterize the universe of existing systemic risk measures, most of which still appear to capture the soundness of individual financial institutions rather than the resilience of the entire system. Finally, Zhou and Chen (2022) carry out a comprehensive bibliometric study on systemic risk, highlighting the most productive countries, journals, scholars in the research field as well as emerging trends.

The objective of this paper goes beyond a systematic bibliometric analysis. By compiling data on 831 publications dedicated to systemic risk from the Scopus database for the period 2007–2021, we pursue a two-fold goal. Firstly, we investigate the evolution of the research field during its most productive 15-year period. This time span is peculiar, as it covers several crisis episodes strongly hitting global financial stability: the GFC, European financial crisis, the outbreak of the COVID-19 pandemic. This period is also essential since it embraces the peak of

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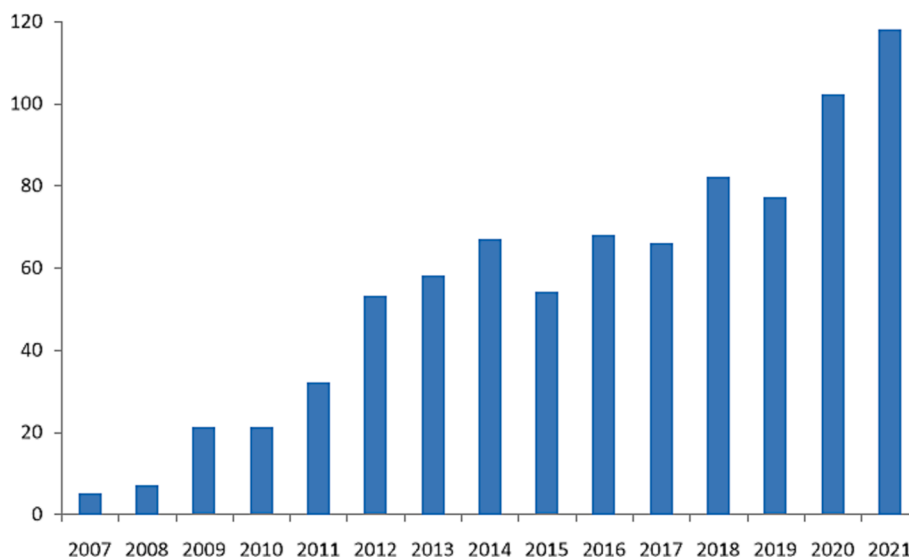


Fig. 1. Dynamics of publications on systemic risk, 2007–2021.

financial globalization and its certain retrenchment, though not a reversal, in the aftermath of the GFC, e.g. Cerutti and Zhou (2017), McCauley, Bénétrix, McGuire, and von Peter (2019). By focusing on this period, we shed light on several aspects overlooked in the previous reviews on systemic risk, e.g. changes in the concentration of publications across countries over the observation period, the evolution of publication quality proxied with the dynamics of weighted average journal impact factors. Secondly and more importantly, we aim to distil the drivers which incentivize researchers to conduct and publish their studies on systemic risk. As far as we know, such research question has not been raised in the academic literature on systemic risk. We address it by performing the analysis in a sample of 67 countries and building on a combination of variable selection techniques, i.e. Bayesian model averaging (BMA), adaptive least absolute shrinkage and selection operator (LASSO), elastic net and variable selection with second-generation p-values. We apply these algorithms to 33 variables which can potentially predict the intensity of research on systemic risk, capturing various country-specific macroeconomic, financial, institutional and cultural features as well as the factors accounting for global economic uncertainty and financial instability.

As regards the bibliometric part of our analysis, we document a gradual, but notable decline in the shares of publications on systemic risk associated with major advanced economies. Since the year 2007, the shares of the USA and the UK have decreased from 50 and 33 % to 12 and 10 %, respectively. As a result, China appears to overtake the global leadership, reaching 23 % and thereby outperforming the US share of publications on systemic risk in the year 2021. By computing a Herfindahl-type index which captures the concentration of publications on systemic risk across the sample countries in 2007–2021, we find a pronounced decline in this indicator since the year 2010. Against this backdrop, other major emerging markets alongside China tend to increase their scientific output on systemic risk, e.g. Brazil, India, Russia. Their shares are so far in the range between 2 and 3 %, though starting virtually from zero in 2007.

As for the Scopus-indexed journals which publish the research on systemic risk most actively, the *Journal of Financial Stability* and *Journal of Banking and Finance* are the undeniable leaders, each representing 7 % of the total number of publications. They significantly outperform the *Journal of Economic Dynamics and Control* and *Finance Research Letters*, both with the shares around 3 %. In the realm of organizations producing research on systemic risk, US universities (Stern School of Business, New York University, MIT) as well as the regulatory bodies (the Federal Reserve System) appear the most prolific. The IMF as an

international financial organization also plays an important role in such research. The European universities and research centers whose affiliates most actively publish on systemic risk are Deutsche Bundesbank, Goethe-Universität (Frankfurt am Main), Tinbergen Institute (Netherlands) and Université d'Orléans (France).

By applying the battery of variable selection techniques, we identify the robust drivers stimulating research on systemic risk in our sample of countries. There are two indicators found significant by all the four variable selection techniques: the cost-to-income ratio and the number of publications in Scopus-indexed journals in the subject area “Economics, Econometrics and Finance” scaled to one million of population. Higher values of the cost-to-income ratio as a proxy of the banking sector profitability are associated with more publications on systemic risk scaled to one million of population. As the literature exploring the link between bank profitability and financial stability posits, lower profitability, i.e. higher cost-to-income ratios, is often an attribute of riskier business models, which involve an over-reliance on wholesale funding and non-interest income (Köhler, 2015; Roengpitya, Tarashev, Tsatsaronis, & Villegas, 2017), and eventually a higher exposure to systemic risk (Bostandzic & Weiß, 2018; Brunnermeier, Dong, & Palia, 2020; Xu, Hu, & Das, 2019). Since bank business models tend to exhibit inertia, the persistence of high cost-to-income ratios in a country over several years can send a signal for policymakers and scholars to care about increasing systemic risk. Thus, growing public concerns may shape researchers’ focus on this matter. Alongside the cost-to-income ratio, the number of publications in Scopus-indexed journals in the subject area “Economics, Econometrics and Finance” scaled to one million of population appears the most consistent driver of research on systemic risk. This measure specifically pins down the productivity of economic research in a country.

There are two indicators which constitute the second tier of drivers fostering research on systemic risk. They are identified by two out of the four variable selection algorithms. The first of them is global innovation index, a composite measure describing multiple dimensions of education, infrastructure and knowledge creation in more than 130 countries. In line with intuition, a higher country’s score of the index is associated with more publications on systemic risk, as a more advanced level of science and innovation in a country in general lays ground for an elevated productivity of research, especially if it is data-intensive and involves sophisticated quantitative methodologies, as is the case of systemic risk analysis. The second indicator in this tier is power distance index measuring the extent to which the members of a society accept the hierarchy of power and authority. This measure is a part of cultural

dimensions theory proposed by Hofstede (2001) as an attempt to quantify the differences in attitudes between cultures. We find that the power distance index negatively correlates with the research activity on systemic risk. Our finding meshes well with a recent study by Andries and Balutel (2022) who document that the countries characterized by high values of this index contribute less to systemic risk, as financial institutions in these jurisdictions tend to favor less risk-taking, adopting conservative business models and more stringent risk management controls. Hence, a less significant build-up of systemic risk in such countries may create fewer incentives to study it and publish corresponding research.

Overall, our paper does not only contribute to describing the current state of affairs in the research on systemic risk as a scientometric study, but also underscores the factors which influence the intensity of such research. From the scientometric perspective, it is important for researchers studying systemic risk to learn about the most prolific peers as well as key centers engaged in such research to benchmark their own scientific results and establish efficient collaborative networks. Besides, by knowing the journals which allocate a notable fraction of space to systemic risk research, they can better target proper outlets for their future publications. Since such data tend to change over time, bibliometric studies on systemic risk are useful, casting a panoramic and dynamic glance at this research field, thereby giving guidelines to the researchers. It is also important to pin down the factors stimulating research on systemic risk, as knowing such factors allows to elaborate incentives for scholars to enhance the productivity of research, which may lead to valuable insights. These may have both scientific and policy-making implications, eventually resulting in more efficient macroprudential policies and lower odds of a financial crisis. Such assertion is consistent with the literature emphasizing the primary role of evidence-based economic research in contemporary policy making, e.g. Hirschman and Berman (2014), Christensen (2018), Christensen and Mandelkern (2022). However, to the best of our knowledge, empirical studies pursuing such “research on research” are very scarce. The closest study to our paper is Caporin, Stolbov, and Shchepeleva (2022), which identifies the factors driving research on banking crises, but does not contain a wholesome bibliometric analysis.

The remainder of our study is structured as follows. Section 2 describes the bibliometric data on systemic risk. Section 3 presents the methodology employed both to conduct the bibliometric analysis and distil the drivers of research on systemic risk. Section 4 covers the corresponding findings, while Section 5 concludes.

## 2. Data

Our analysis builds on the articles bearing “systemic risk”<sup>1</sup> in the title and published in the Scopus-indexed journals during the period 2007–2021. We do not confine ourselves to any pre-specified subject area in Scopus, e.g. “Economics, Econometrics and Finance”, as papers on systemic risk can appear in mathematical, physics, computer science journals as well as in outlets representing other subject areas. Thus, we double-check our selection of papers by reading the abstracts to exclude the works which have nothing to do with the financial dimension of systemic risk, e.g. sociological and environmental studies. In addition, we filter out editorial articles, errata and retracted papers. For each author of a published article, we identify the university or research

center of affiliation and the country where this entity is situated. Then, each article is linked to the identified countries. Following Caporin et al. (2022), the publications co-authored by several researchers are assigned to all the countries to which they are related. Thus, we uncover a country-article association based on the location of researchers without focusing on the data analyzed in each paper.

Overall, there are 831 articles in our sample, which are first subject to the bibliometric analysis and are then used to distil the drivers of research on systemic risk in the sample of 67 countries. Fig. 1 describes the dynamics of published research on systemic risk during 2007–2021.<sup>2</sup>

The 2008 Global Financial Crisis and the European financial crisis trigger a surge in the number of such publications in 2009–2014. After a certain break in the years 2015–2017 this increase rebounds, with the annual number of publications exceeding one hundred papers in 2020–2021.

In order to identify the drivers of research on systemic risk, we compile a dataset of candidate indicators related to macroeconomic, financial, institutional and cultural characteristics of the countries in our sample. We also consider a set of global factors accounting for worldwide financial instability, uncertainty and risk aversion. Most of the variables are in line with the extant literature studying the determinants of systemic risk and financial crises. In our variable selection exercise, we examine whether they can help predict a country’s intensity of publications on systemic risk proxied by the number of Scopus-indexed publications on systemic risk divided by one mln population. All the indicators are averaged across five-year windows preceding the year of interest, thereby accounting for the business cycle and mitigating the endogeneity problem. Since there are multiple candidate indicators exposed to an open search, no hypotheses regarding their significance and the direction of impact are put forward *ex ante*.

We begin with a set of macroeconomic indicators: annual GDP growth rate (*GDPGR*), inflation rate (*CPI*), current account balance (*CURAC*) and the level of government debt (*GOVDEBT*). Besides, we use the global innovation index (*GII\_SCORE*), which describes multiple dimensions of education, infrastructure and knowledge creation in more than 130 countries. The set of macroeconomic indicators is extended by two measures capturing the a country’s economic openness, KOF Globalisation Index (*KOF*), as well as the Chinn-Ito index (*KAOPEN*) gauging a country’s degree of capital account openness.

We next include the key variables accounting for financial depth: the share of total bank assets, total bank credit and market capitalization to a country’s GDP (*BANK\_ASSET*, *BANK\_CREDIT* and *MARKETCAP*, correspondingly). Since systemic risk is primarily associated with the fragility of banks, we further look into the indicators of banking sector stability, namely Z-score measure, cost-to-income ratio, the level of NPL as a share of total bank credit and bank capital relative to assets (*Z\_SCORE*, *COST\_TO\_INC*, *NPL*, *CAP\_TO\_ASSET*). Our natural assumption underlying the extension of the financial depth indicators is that the less stable the system is with respect to individual banks, i.e. the higher are the cost-to-income ratio and the level of NPL, whereas the lower are the Z-score and capital to assets ratio, the more it stimulates researchers to study systemic financial risk. We also include the level of banking sector

<sup>1</sup> We also include the articles containing the following variants of the baseline term “systemic risk” in the title: “systemic financial risk”, “systemic financial stress”. However, we leave out the papers which are dedicated to standalone financial risks, e.g. credit, market risks, and those which focus on narrow aspects of financial instability, e.g. contagion, Too Big To Fail phenomenon, etc. They are often confused with genuine systemic risk, though the latter should be understood as a specific risk impairing the functioning of the whole financial system and typically having adverse consequences for the real economy.

<sup>2</sup> The dynamics of publications based on the Scopus data is compatible with that based on the series derived from the IDEAS RePEc. Although the overall number of publications selected from this alternative source using our criteria totals 912 items, their annual dynamics is strongly correlated with our series. The correlation ratio is equal to 0.98, suggesting that tracking the evolution of research on systemic risk via Scopus yields a representative result. Additionally, we correlate the dynamics of publications on systemic risk with the number of publications on some other related searches, namely, “financial stress”, “financial contagion” and “financial instability”. The corresponding correlation ratios are equal to 0.97, 0.74 and 0.59, respectively, thereby confirming that our series on systemic risk publications is representative not only across alternative databases, but also across alternative notions capturing the stance of financial stability.

concentration (*BANK\_CONCENTR*) in light of the long-standing debate whether concentration consolidates or undermines financial stability. In addition to these aggregate metrics of banking sector stability, we consider the country-level conditional capital shortfall measure, which is a widespread systemic risk indicator capturing the aggregate shortage of a country's financial institutions equity if a strong shock to the world stock market occurs (Brownlees & Engle, 2017). Positive bank-level *SRISK* values are aggregated into a nationwide measure which is then scaled to GDP to account for the size of a national economy (*SRISK\_GDP*).

Next comes the block of variables capturing a country's experience with financial crises in the past. We account for the total number of crises as well as the distance to the last crisis episode measured in years (*CRIS\_NUM* and *DIST\_TO\_CRIS*).

We also include the *IMaPP* index (*IMAPP*), which demonstrates how active the government is in implementing macroprudential policy instruments. We borrow the data from the IMF integrated macroprudential policy database (Alam, Alter, Eiseman, Gelos, Kang, Narita, & Wang, 2019) and construct an aggregate indicator summarizing seventeen dummy-type measures which denote if a certain macroprudential instrument applies in a particular country for a given year.

The two additional measures, a country's position in the Tilburg University Economics Ranking and the overall number of Scopus-indexed publications on economics and finance scaled to one mln of population (*TILB* and *SCI*), are used to proxy the excellence of the sample countries in economic research. They are further complemented by two more potential covariates of a country's intensity of research on systemic risk. The first of them is a dummy variable (*RES\_CENTER*) which takes on the value of one if there is a specialized research center on systemic financial risk established in a country, e.g. the V-Lab in the USA, the LSE systemic risk centre in the UK, the SAFE in Germany, etc., and zero otherwise. The other variable (*RePEc*) is the number of finance and financial economics departments in a country which belong in top-25 % of the best departments in the world, according to the IDEAS RePEc website. Since occupying top positions in the rankings above or launching a reputable research center require long term efforts aimed at attracting funding, recruiting talented researchers, elaborating career goals for them, etc., we consider this sub-group of indicators the proxies of social motivation to produce research on systemic risk.<sup>3</sup>

We also include six indices from the dataset for cultural dimensions, proposed by Hofstede (2001) as an attempt to quantify the differences in attitudes between cultures. The five indices comprise the power distance index (*PDI*), uncertainty avoidance index (*UAI*), individualism vs. collectivism measure (*IDV*), masculinity vs. femininity index (*MAS*), long-term orientation vs. short-term orientation index (*LTOWVS*), indulgence vs. restraint index (*IVR*).

Finally, we include a set of factors capturing worldwide uncertainty and financial turmoil. As for the uncertainty measures, we build on the global economic policy uncertainty index (*GEPU*), a GDP-weighted index of economic policy uncertainty in more than 20 major economies (Baker, Bloom, & Davis, 2016), and the world uncertainty index (*WUI*) based on the Economic Intelligence Unit data (Ahir & Bloom, 2022). To proxy global financial stress and related risk aversion, we employ the VIX index (*VIX*) and the Federal Reserve Office of Financial Research financial stress index (*OFR\_FSI*) proposed by Monin (2019). These variables are included to examine how potent country-specific

factors driving the research on systemic risk in comparison with the global drivers which may underlie a rise in the researchers' attention to systemic risk. Such global drivers may matter in terms of the interconnectedness of banking systems and financial markets across the globe, motivating researchers to study systemic risk when it is not necessarily on the rise in their home country or in the country of their affiliation.

Table 1 presents information on the acronyms of the candidate drivers of research on systemic risk, their brief definitions and sources.

### 3. Methodology

#### 3.1. Bibliometric analysis

The bibliometric part of our study is mainly based on the descriptive analysis of the data retrieved from the Scopus database.

We first analyze the intensity of research in a cross-country framework. Thus, we calculate the shares of each country in the worldwide production of research on systemic risk for the period 2007–2021. In addition, we construct Herfindahl-type concentration indices to figure out whether there are dominant countries in producing such research and how their shares evolve over time.<sup>4</sup>

We also build time series capturing publication dynamics in different economic journals and universities or other national financial institutions. We identify the Scopus-indexed journals, which concentrate the largest number of publications on systemic risk, the most prolific universities and scholars in this research program for the period 2007–2021.

Since we view the bibliometric analysis a standalone, yet preliminary exercise to underscore the drivers of research on systemic risk, a number of specific methods pertinent to bibliometric analyses, e.g. co-citation analysis, citation burstness analysis, etc., remain beyond the scope of our study.<sup>5</sup>

#### 3.2. Variable selection techniques to establish factors driving the research on systemic risk

In order to identify robust factors driving research on systemic risk, we apply a set of machine learning techniques which are customized for datasets with multiple explanatory variables and better resolve the problem of model uncertainty compared to traditional econometric approaches. The methods briefly described below apply to a sample of 67 countries where the dependent variable, the number of Scopus-indexed publications on systemic risk divided by one mln population, refers to each year within the period 2007–2021, while the independent variables are averages for five-year rolling windows preceding each year within the observation period, i.e. 2002–2006 in case of the dependent variable for the year 2007, 2003–2007 in case of dependent variable for the year 2008, etc.

##### 3.2.1. Bayesian model averaging (BMA)

Bayesian model averaging rests on the assumption that a combination of models performs better than a single model. This method allows to overcome model uncertainty by averaging across a set of models and selecting robust predictors based on posterior inclusion probability (Raftery, Madigan, & Hoeting, 1997).

<sup>3</sup> We acknowledge that this set of indicators cannot fully capture the motivation to publish on systemic risk related to funding, career goals and professional networks. Yet, we are unable to rely on funding data from the sample papers, as this information is not accurately disclosed in the papers published at the beginning of the observation period, i.e. during 2007–2010. Besides, in case of the multi-author papers it is not always clear from the funding statements whether all the authors are supported by the grant or not. Hence, assigning a grant to this or that country could create a bias.

<sup>4</sup> In industrial organization, the Herfindahl index (H-index) measures market concentration as a proxy of competition intensity. It is calculated as a sum of squared market shares of the firms operating in the industry. In our context, countries' shares as % of total publications on systemic risk are used for a given year.

<sup>5</sup> These methods are implemented in a purely bibliometric study on systemic risk by Zhou, Chen, and Meng (2022) as well as in similar studies on credit risk and macroprudential policy, e.g. Zhou and Chen (2019), Tang, Zhang, Liu, and Wu (2021).



**Table 1**  
List of variables.

Variable name	Definition	Source
PUB_SCALED	Number of publications on systemic risk scaled to 1 mln of people	Scopus
GDPGR	Annual GDP growth rate	World Bank
CPI	CPI	World Bank
CURAC	Current account balance as % of GDP	World Bank
GOVDEBT	Central government debt, total % of GDP	World Bank
GII	Global Innovation Index	World Intellectual Property Organisation
KAOPEN	The Chinn-Ito index measures a country's degree of capital account openness.	Chinn-Ito website <a href="https://web.pdx.edu/~ito/Chinn-Ito_website.htm">https://web.pdx.edu/~ito/Chinn-Ito_website.htm</a>
KOF	The KOF Globalisation Index	KOF Swiss Economic Institute <a href="https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html">https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html</a>
BANK_ASSET	Deposit money banks' assets to GDP (%)	World Bank
BANK_CREDIT	Domestic credit to private sector, % of GDP	World Bank
MARKETCAP_ZSCORE	Market capitalization, % of GDP Z-Score	World Bank
COST_TO_INC	Cost-to-income ratio	World Bank
NPL	Bank non-performing loans to total gross loans, %	World Bank
CAP_TO_ASSET	Bank capital to assets ratio (%)	World Bank
CONCENTR	5-bank asset concentration	World Bank
SRISK_GDP	Aggregate conditional capital shortfall related to GDP	V-Lab, <a href="#">Brownlees and Engle (2017)</a>
CRIS_NUM	Total number of crises	<a href="#">Laeven and Valencia (2020)</a>
DIST_TO_CRIS	Distance to last crisis episode (years)	<a href="#">Laeven and Valencia (2020)</a>
IMAPP	Macroprudential policy index	<a href="#">Alam et al. (2019)</a>
TILB	Country's position in Tilburg University Economics Ranking	Tilburg University Economics Ranking
SCI	Total number of publications, related to 1 mln of population	Scimago Journal and country rank
RES_CENTER	Dummy variable, which takes on the value 1, if there is a national research center for systemic risk study, and 0 otherwise	Authors' compilation
RePEc	The country's score in Ideas RePEc ranking "Top 25 % of finance and financial economics departments"	IDEAS RePEc website <a href="https://ideas.repec.org/top/">https://ideas.repec.org/top/</a>
PDI	Power distance index. The PDI measures the extent to which the members of a society accept the hierarchy of power and authority	Hofstede database on differences in cultural dimensions
IDV	Individualism vs. collectivism measure. The IDV measures how intensively integrated people are in different groups.	Hofstede database on differences in cultural dimensions
MAS	Masculinity vs. femininity index. The MAS shows, whether the society is more oriented on such traditional masculine values as success, heroism, assertiveness and material reward.	Hofstede database on differences in cultural dimensions
UAI	Uncertainty avoidance index. The UAI captures the attitude towards the lack of predictability in life and the ability to cope with anxiety.	Hofstede database on differences in cultural dimensions
LTOWVS	Long-term orientation vs. short-term orientation index. The LTOWVS index demonstrates the attitude of the population to link	Hofstede database on differences in cultural dimensions

**Table 1 (continued)**

Variable name	Definition	Source
IVR	past and current problems with future challenges. Indulgence vs. restraint index. The IVR demonstrates how strict are social norms related to fulfilment of different human desires.	Hofstede database on differences in cultural dimensions
VIX	CBOE Volatility Index	<a href="https://www.cboe.com/tradable_products/vix/">https://www.cboe.com/tradable_products/vix/</a>
GEPU	Global GDP-weighted index of national economic policy uncertainty indices based on 20 countries.	Economic Policy Uncertainty index website <a href="https://policyuncertainty.com/">https://policyuncertainty.com/</a>
WUI	Global uncertainty index measures the share of the word "uncertain" (or its variants) in the Economist Intelligence Unit country reports.	World Uncertainty Index website <a href="https://worlduncertaintyindex.com/">https://worlduncertaintyindex.com/</a>
OFR_FSI	OFR Financial Stress Index captures stress in global financial markets based on market information.	Office of Financial Research <a href="https://www.financialresearch.gov/financial-stress-index/">https://www.financialresearch.gov/financial-stress-index/</a>

Suppose we have a linear regression with  $k$  candidate variables

$$y_{it} = \beta_0 + \beta_1 x_{1,it} + \dots + \beta_k x_{k,it} + \varepsilon_{it}, \quad (1)$$

where  $t$  is a time subscript, which runs from  $t = 2007, \dots, 2021$  and  $i$  is a cross-sections subscript, running from  $i = 1, \dots, k$ .

Model uncertainty concerns the selection of regressors to be included into the right-hand side of the equation. When the true model is unknown, a conventional econometric approach suggests including all the variables into the regression and then sequentially deleting insignificant variables based on statistical tests.

On the contrary, the Bayesian model averaging takes into account all possible combinations of regressors and constructs a weighted average of the coefficients. Thus, if we have  $k$  potential regressors as in Eq. (1), BMA will consider the model space,  $M_j$ , consisting of all possible  $2^k$  regressor combinations.

The weights used for averaging the coefficients across the sub-models in the model space are called *posterior model probabilities* and are calculated as follows:

$$p(M_i|y, X) = \frac{p(M_i|X)p(M_i)}{p(y, X)} \quad (2)$$

where  $p(M_i|X)$  denotes the marginal likelihood of each sub-model (probability of the model  $M_i$  given the data),  $p(M_i)$  – the prior model probability,  $p(y, X)$  – integrated likelihood, which is usually omitted as it is considered constant over all sub-models. Thus, PMP formula can be rewritten as follows:

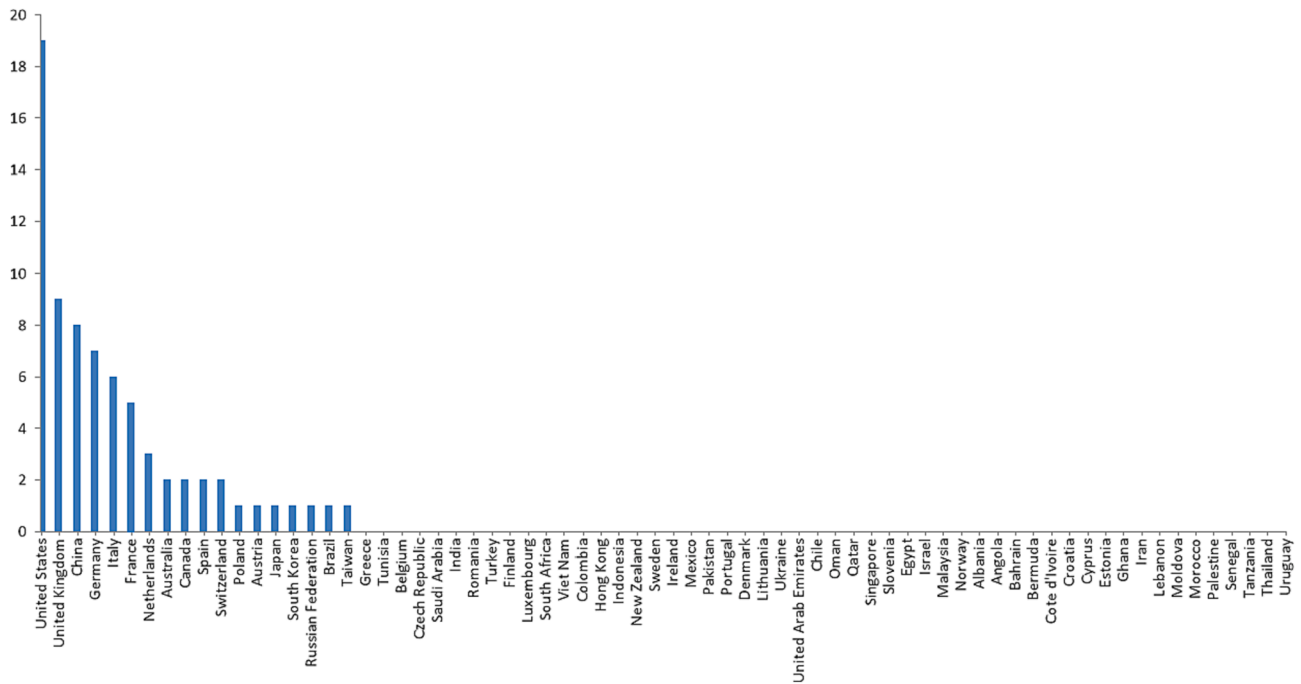
$$p(M_i|y, X) \propto p(M_i|X)p(M_i) \quad (3)$$

Before estimating the models we need to choose priors on the parameters of each model and on the models themselves,  $p(M_i)$ . PMPs are dependent on the choice of priors. In our case, we set a conditional prior for the coefficients of each of the sub-models to have zero mean and variance structure proposed by Zellner (1986). For the model prior we choose a uniform model prior to satisfy our assumption that all the models are equally possible.

The posterior distribution of the coefficients is defined according to the following equation:

$$p(\beta|y, X) = \sum_{i=1}^{2^k} p(\beta|M_i, y, X)p(M_i|y, X), \quad (4)$$

where  $p(\beta|M_i, y, X)$  is a posterior distribution of the coefficients under each sub-model. Based on this equation, one can also calculate posterior



**Fig. 2.** Country shares of publications on systemic risk, %, 2007–2021. *Note:* the bars are not visible for some countries as their shares of publications on systemic risk are too small (<1%).

means and standard deviations. Posterior inclusion probability (PIP) represents the probability that a particular regressor is to be included into all the sub-models considered. Based on the PIPs generated by the BMA, a researcher can identify relevant regressors to predict the dependent variable. Normally, a 50 % (0.5) threshold for the PIP values applies: the coefficients equal or exceeding it are found significant.

Thus, the BMA deals with the whole set of explanatory variables, but through the procedure some of them are revealed as insignificant based on the PIPs.

### 3.2.2. Adaptive least absolute shrinkage and selection operator (LASSO)

Adaptive LASSO is a regularization technique and an extension to the standard LASSO approach.

The conventional LASSO assumes that we use a special penalty term with a hyperparameter  $\lambda$  in the objective function when estimating coefficients:

$$\hat{\beta}_{\text{lasso}} = \underset{\beta}{\operatorname{argmin}} |y - \sum_{j=1}^p x_{ij}\beta_j|^2 + \lambda \sum_{j=1}^p |\beta_j| \quad (5)$$

where  $\hat{\beta}_{\text{lasso}}$  are coefficient estimates;  $\lambda$  is a nonnegative regularization parameter, which accounts for the degree of shrinkage. With the increase of  $\lambda$  an increasing number of coefficients is shrunk to zero. Consequently, the number of selected relevant variables decreases. This leads to lower variance error or lower odds of overfitting, while increasing the model bias error or the odds of underfitting the model. Thus, choosing  $\lambda$  implies finding the value which secures an optimal bias-variance trade-off.

Zuo (2006) shows that LASSO is consistent for variable selection only under some stringent conditions, proposing an alternative approach, adaptive LASSO, which exploits adaptive weights in the  $l_1$  penalty term for penalizing different coefficients. Thus, instead of using a common parameter  $\lambda$ , coefficients are penalized individually. Coefficient estimates in the adaptive LASSO are defined by the following equation:

$$\hat{\beta}_{\text{lasso}}^{*(n)} = \underset{\beta}{\operatorname{argmin}} |y - \sum_{j=1}^p x_{ij}\beta_j|^2 + \lambda_n \sum_{j=1}^p \hat{w}_j |\beta_j|, \quad (6)$$

where  $\hat{\beta}_{\text{lasso}}^{*(n)}$  – are adaptive LASSO estimates;  $\lambda$  is a nonnegative regularization parameter;  $\hat{w}_j$  – the vector of weights, defined as  $\hat{w} = 1/|\hat{\beta}|^2$ .

Adaptive LASSO also possesses better oracle properties compared to the standard LASSO technique, meaning that it performs as well as if the true underlying model were known.

### 3.2.3. Elastic net

Although adaptive LASSO is a suitable method for variable selection, it might provide biased estimates in case of highly correlated independent variables: the algorithm might randomly select one of the features and set all other relevant variable coefficients to zero.

Elastic net is a general type of regularized regression, which combines feature elimination from LASSO (L1 penalty term in the cost function) and coefficient reduction from ridge regression (L2 penalty term). Thus, coefficients are estimated according to the following equation:

$$\hat{\beta}_{\text{elasticnet}} = \underset{\beta}{\operatorname{argmin}} (|y - \chi\beta|^2 + \lambda_2 |\beta|^2 + \lambda_1 |\beta|_1) \quad (7)$$

where  $\hat{\beta}_{\text{elasticnet}}$  – are adaptive LASSO estimates;

$\lambda_1 |\beta|_1$  – LASSO (L1) penalty term equal to absolute sum of coefficients.

$\lambda_2 |\beta|^2$  – Ridge (L2) penalty term equal to the square of the coefficient.

### 3.2.4. Variable selection with second-generation p-values

Penalized regression with Second-Generation P-Values (ProSGPV) is a novel variable selection approach which possesses good predictive properties and performs well even in case of strong collinearity among features (Zuo, Stewart, & Blume, 2021). The method is based on the idea of excluding variables with small effects on the dependent variable and retaining the variables with effects, larger than a certain threshold, say  $\delta$ .

Let  $\theta$  be the parameter of interest and let  $I = \theta_l, \theta_u$  be an interval estimate of  $\theta$ , whose length is given by  $|I| = \theta_u - \theta_l$ . Let us define  $H_0 = -\delta, \delta$  as a pre-specified interval null, which would serve a buffer region between “null” and “non-null” effects.

If we denote the length of the interval null by  $|H_0|$ , then the SGPV  $p_\delta$

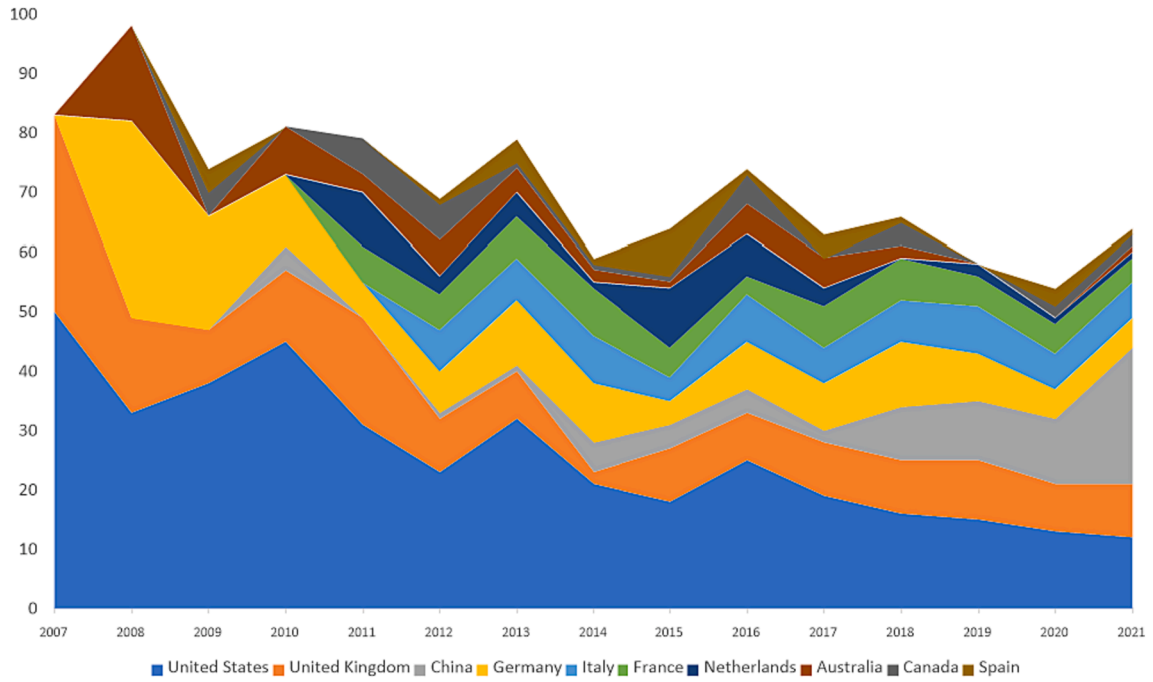


Fig. 3. Dynamics of the country shares of publications on systemic risk, %, top-10 countries, 2007–2021.

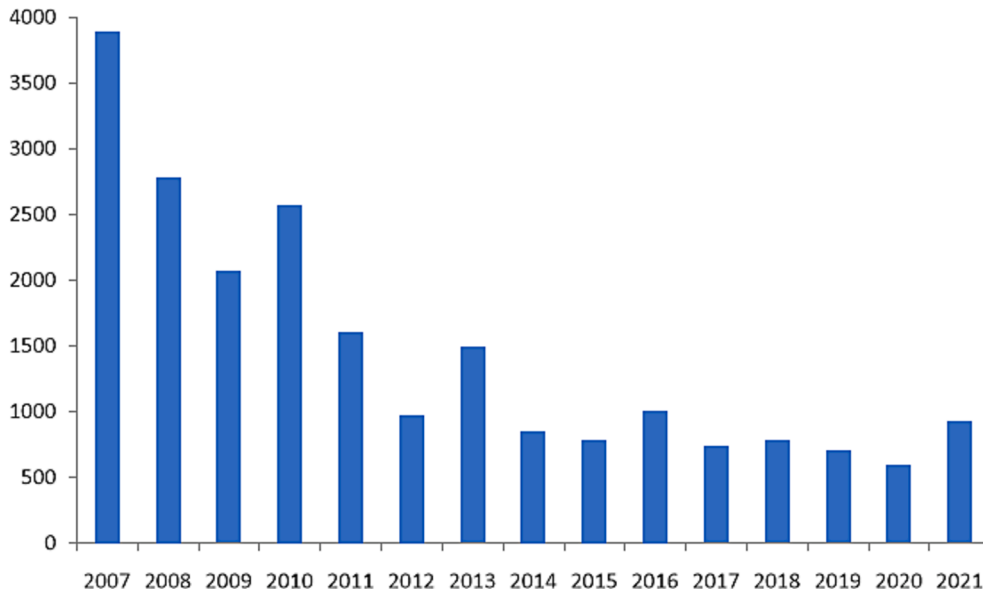


Fig. 4. Dynamics of the H-index capturing the concentration of publications on systemic risk, 2007–2021.

is calculated as:

$$p_\delta = \frac{|I \cap H_0|}{|I|} \times \max\left\{\frac{|I|}{2|H_0|}, 1\right\} \quad (8)$$

where  $I \cap H_0$  is the intersection of two intervals. The correction term  $\max\left\{\frac{|I|}{2|H_0|}, 1\right\}$  applies when the interval estimate is very wide, i.e., when  $|I| > 2|H_0|$ . In case  $p_\delta = 1$ , the data is compatible with null hypothesis, while when  $p_\delta = 0$  – the data is compatible with the alternative hypothesis. When  $0 < p_\delta < 1$ , the data is inconclusive.

ProSGPV is a two-stage selection algorithm. In the first stage, it standardizes the inputs, fits a LASSO regression and then, additionally, fits an OLS model on the set of variables, selected by LASSO. In the second stage, ProSGPV extracts confidence intervals for the variables included in the OLS-model, calculates the mean coefficient standard

error and keeps only the variables with the effects larger than a certain threshold. That is, coefficients are estimated in the following way:

$$\hat{\beta}_{pro} = \beta_S^{OLS} \in R^p, \text{ where}$$

$$S = \{k \in C : |\hat{\beta}_k^{OLS}| \lambda_k\}, \quad C = \{j \in \{1, 2, \dots, p\} : |\hat{\beta}_j^{lasso}| > 0\} \quad (9)$$

where  $\beta_S^{OLS}$  is a vector of length  $\rho$  with non-zero elements being the OLS coefficient estimates for the variables in the final selection set  $S$ .  $C$  is the candidate set from the first-stage screening.  $\hat{\beta}_j^{lasso}$  is the  $j$ th LASSO solution evaluated at  $\lambda_{gic}$  identified with the use of the general information criterion. In the second stage, SGPV for each variable  $k$  is calculated as  $I_k = \hat{\beta}_k \pm 1.96SE_k$ , while the interval null is defined as  $H_0 = -SE_k, SE_k$ .



**Table 2**

Peer-reviewed journals with the highest shares of publications on systemic risk, %, 2007–2021.

Journal	Share of publications
Journal of Banking and Finance	7
Journal of Financial Stability	7
Journal of Economic Dynamics and Control	3
Finance Research Letters	3
Economic Modelling	2
International Journal of Finance and Economics	2
Research in International Business and Finance	2
Journal of Economic Interaction and Coordination	2
Journal of Financial Intermediation	2
North American Journal of Economics and Finance	2

ProSGPV finally keeps only the variables with SGPV, equal to zero.<sup>6</sup>

## 4. Results and discussion

### 4.1. Results of the bibliometric analysis

Taking the stock of publications on systemic risk during 2007–2021, we document that major advanced economies contribute most to the expansion of this research field. The share of the publications linked to the US universities and research centers totals 19.2 %, twice as much as the share of the UK which ranks the second on the list (Fig. 2). Major EU countries (Germany, France, Italy) also belong in the top of the ranking, while the only emerging market economy present among the top-10 countries is China.

However, if one examines the changes in the shares of publications from year to year within the observation period, the positions maintained by the major advanced economies tend to weaken. The US share witnesses a decline from 50 % in 2007 to 12 % in 2021. Similarly, the share of the UK decreases from 33 to 10 %. This indicator dramatically shrinks in case of Germany, remaining largely stagnant in case of France and Italy (Fig. 3).

Conversely, the share of Chinese publications on systemic risk tends to increase. Moreover, its growth has become more pronounced recently. As a result, in 2021, China overtakes the global leadership, reaching the share equal to 23 %. On the one hand, this finding meshes well with the increasing contribution of China to global systemic risk. Based on the conditional capital shortfall measure (SRISK), the lack of capital in the Chinese financial system in case of an extreme shrinkage in the world stock market, increased from 29 to 2000 bln US dollars during January 2007–December 2021.<sup>7</sup> The contribution of Japan and the USA which follow China appears much more modest. The SRISK measure increased from 170 to 1063 bln US dollars for Japan and from 195 to 489 bln in case of the USA, respectively. On the other hand, the increasing share of Chinese publications on systemic risk is likely to stem from the general strengthening of this country's role in worldwide economic research.<sup>8</sup> According to SCImago, China ranks the second country in the Scopus subject area “Economics, Econometrics and Finance” for the year

2021, demonstrating steady progress in this ranking since 2007 when it occupied the 10th position. By narrowing down the subject area to “Finance” category only, we observe an even more striking surge: from the 18th position in 2007 to the 2nd in 2021.<sup>9</sup> These impressive results in the field of economics and finance comport with a more general trend suggesting that the successful Chinese performance in scientific competition is due to the sustained investment efforts in research which appear superior to those in traditional scientific countries. Courtioux, Métivier, and Reberioux (2022) document that although the USA and the UK tend to increase R&D investments at the national level in the long run, China outpaces them. As a result, the US and UK shares of public investment in the world scientific research diminish, so do their positions in various research rankings, especially if the the latter primarily rest on quantitative rather than qualitative indicators of research excellence.<sup>10</sup>

The erosion of the leading positions previously maintained by major advanced economies makes research on systemic risk a more competitive field. By computing a Herfindahl-type index which captures the concentration of publications on systemic risk across the sample countries in 2007–2021, we find a pronounced decline in this indicator since the year 2010 (Fig. 4).

Against this backdrop, other major emerging markets alongside China succeed in increasing their scientific output on systemic risk, e.g. Brazil, India, Russia. At first glance, their shares do not appear impressive, ranging between 2 and 3 %. However, these countries started virtually from zero in 2007. Besides the above-mentioned countries, other emerging markets have recently become more visible in this research field, e.g. Turkey, Vietnam.

As regards peer-reviewed journals which publish research on systemic risk, the most important outlets are the *Journal of Financial Stability* and *Journal of Banking and Finance*. Each of them accounts for 7 % of the articles released during the period 2007–2021. These journals significantly outperform their closest contenders, the *Journal of Economic Dynamics and Control* as well as *Finance Research Letters* whose shares are equal to 3 %. As expected, most of the leading outlets where research on systemic risk is published are field finance journals (Table 2).

Although the top outlets on the list are quite strong and reputable journals, they do not encapsulate all the influential papers in the research field. A number of highly cited papers which have enriched the literature on systemic risk come from the primer field sources like the *Review of Financial Studies* (RFS) and *Journal of Financial Economics* (JFE). Namely, the studies introducing the SRISK measure (Brownlees & Engle, 2017) as well as MES, the marginal expected shortfall (Acharya, Pedersen, Phillipon, & Richardson, 2017) were published by the RFS. Similarly, the JFE published a paper on the interconnectedness and systemic risk between the US finance and insurance sectors by Billio, Getmansky, Lo, and Pelizzon (2012), which by now has collected the biggest number of citations among all the papers on systemic risk indexed in Scopus. Besides, some seminal contributions to systemic risk research, e.g. the paper introducing conditional value-at-risk (CoVaR) by Adrian and Brunnermeier (2016) appeared in the leading general interest journals, e.g. the *American Economic Review* (AER). This journal also published a highly influential paper on systemic risk and the stability of financial networks by Acemoglu, Ozdaglar, and Tahbaz-Salehi

<sup>6</sup> To implement the described methods, we use the following R packages: **BMS** for Bayesian model averaging (<https://cran.r-project.org/web/packages/BMS/index.html>); **HDeconometrics** for adaptive lasso and elastic net (<https://rdrr.io/github/gabrielrvsc/HDeconometrics>); **ProSGPV** – for penalized regression with second-generation p-values (<https://cran.r-project.org/web/packages/ProSGPV/index.html>).

<sup>7</sup> See <https://vlab.stern.nyu.edu/srisk> for details.

<sup>8</sup> However, we do not assert that the current magnitude of systemic risk in China and its overall progress in economic research are the only factors fostering research on systemic risk. Other triggers, including those which are politically motivated may play a role, e.g. the particular attention to systemic risk during the 19th National Congress of the Communist Party of China in 2017. Nonetheless, their investigation is beyond the scope of the paper.

<sup>9</sup> See <https://www.scimagojr.com/countryrank.php?area=2000&year=2021> for details.

<sup>10</sup> However, the underlying bibliometric data cannot fully account for the differences in publication incentives and quality across countries. For example, Chinese researchers may be more oriented towards producing more papers on systemic risk, while their peers in the USA and the UK may have more incentives to target top-tier journals without paying too much attention to the overall number of articles published. We recognize the relevance of these issues, but leave them for future research.

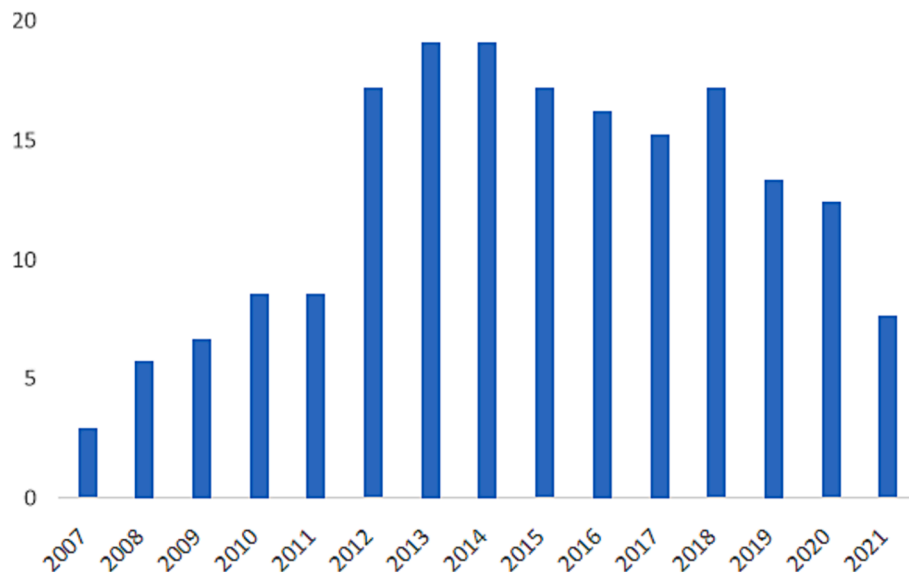


Fig. 5. Dynamics of the Hirsch index of publications published in each sample year.

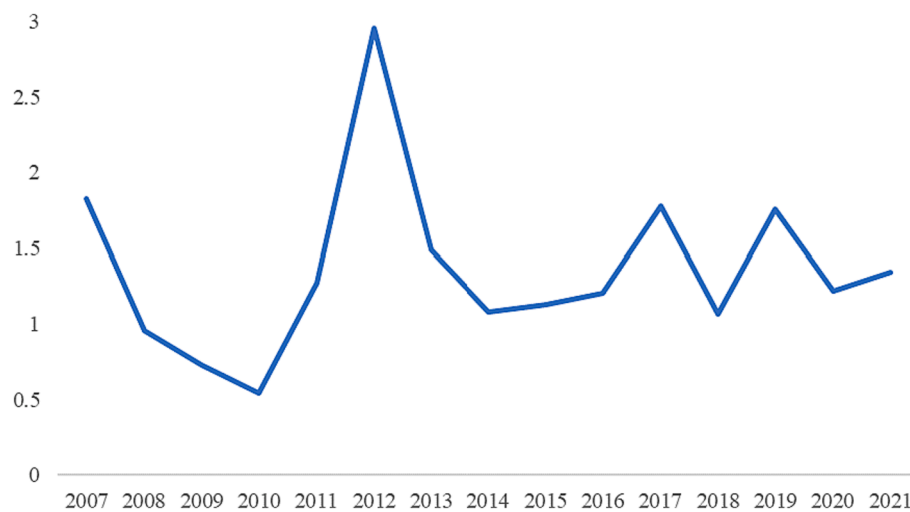


Fig. 6. Dynamics of weighted impact factor for publications on systemic risk.

(2015).

All in all, taking into account the publications for all years in our sample, we conclude that the most impactful research as of now dates back to the years 2013–2014. The stock of papers published on systemic risk in these years witnesses the highest Hirsch indices (Fig. 5). Meanwhile, the impact of the papers published right after the outbreak of the Global Financial Crisis somewhat surprisingly appears rather limited. Based on this finding and the annual dynamics of publications represented in Fig. 1, we conjecture that the research on systemic risk as a scientific field reached its maturity by the years 2013–2014. Naturally, the decreasing dynamics in the Hirsch index in the subsequent years should not be interpreted as a decay of the research field: it just reflects that there has not been enough time so far for the papers published in 2015 and onwards to fully collect the citation “harvest”.

For the whole observation period the weighted average impact factor of the journals which published research on systemic risk totals 1.36, with a relatively moderate standard deviation of 0.57 (Fig. 6).<sup>11</sup> The maximum value of the impact factor is for the year 2012 (2.96), while

the minimum dates back to the year 2010 (0.54). Overall, these findings suggest that the quality of research on systemic risk was largely maintained over time.

Table 3 reveals the most prolific authors in the research field during the whole period between 2007 and 2021. Some of them, e.g. R. Engle, V. Acharya, G.N.F. Weiß, regularly published on systemic risk during the observation period, while, for instance, M. Frittelli is included into the ranking thanks to the articles published mainly in 2019–2021. This also supports the assertion that the research on systemic risk is competitive since new contributors to the field can rapidly achieve visibility. As regards the affiliations of the authors, most of the scholars unsurprisingly represent US universities and research centers.

Against this backdrop, it appears natural that US universities and research centers are the key producers of research on systemic risk (Table 4).

The most important US institutions in the field are Stern School of Business, New York University, Santa Fe Institute, the MIT Sloan School of Management. A lot of research is also done by the researchers from the Federal Reserve System. The most important European players are Université d’Orleans (France), which is a relatively small, but influential research center specialized in systemic risk modeling, Deutsche Bundesbank (Germany), Goethe-Universität (Frankfurt am Main),

<sup>11</sup> The impact factors are SJR (SCImago Journal Rank) values, i.e. impact factors which additionally account for the quality of citing publications.

**Table 3**

Top-10 prolific authors in the systemic risk research, 2007–2021.

Name	Country of affiliation	Number of published articles
V.V. Acharya	USA	8
S. Thurner	USA/Austria	8
S. Poledna	Austria	7
M. Richardson	USA	7
G.N.F. Weiß	Germany	7
P. McConnell	USA	6
R. Engle	USA	5
M. Frittelli	Italy	5
P. Gai	Australia	5
X. Huang	USA	5

**Table 4**

Top-10 universities and research centers studying systemic risk, % of all Scopus-indexed publications, 2007–2021.

University/research center	Country	Share
Leonard N. Stern School of Business	USA	2
International Monetary Fund	N/A	1.9
New York University	USA	1.9
Federal Reserve System	USA	1.9
Santa Fe Institute	USA	1.4
MIT Sloan School of Management	USA	1.3
Universite d'Orleans	France	1.3
Deutsche Bundesbank	Germany	1.3
Tinbergen Institute - TI	Netherlands	1.1
Goethe-Universität Frankfurt am Main	Germany	1.1

Tinbergen Institute (Netherlands). Research on systemic risk is also extensively conducted by the IMF researchers.

Our bibliometric findings partly overlap with the study by [Zhou and Chen \(2022\)](#) based on the Web of Science (WoS) data for the period 1990–2020. They largely concur in identifying the main journals publishing research on systemic risk: 7 out of top-10 outlets in the rankings coincide. However, there is less commonality in the results as regards the most prolific authors and institutions. In case of the author and institutional rankings, there are only four coincident items. Besides the objective differences in the observation periods and databases, the discrepancy in the results is likely to emerge from a different understanding of the notion “systemic risk”. [Zhou and Chen \(2022\)](#) consider it a wider category, embracing, for example, volatility analysis and credit risk, while we adhere to a narrower understanding, which implies a standalone and system-wide type of risk which does not boil down to conventional (credit, market, operational, etc.) risks.

#### 4.2. Identification of factors driving the research on systemic risk

The variable selection exercise based on a combination of techniques described in [Section 3.2](#) complements the bibliometric analysis, uncovering the driving forces of research on systemic risk in the sample of countries. The results are generalized in [Table 5](#) below, while the comprehensive output of the variable selection algorithms is reported in [Tables A1–A4](#) in the [Appendix](#).

Overall, our analysis reveals four indicators consistently driving such research out of 33 candidate variables. They are grouped into two tiers, conditional on the number of variable selection techniques which find these indicators statistically significant.

The first tier consists of two variables, cost-to-income ratio in the banking sector (*COST\_TO\_INC*) and the number of publications in Scopus-indexed journals in the subject area “Economics, Econometrics and Finance” scaled to one million of population (*SCI*). Both of them are found significant by all the four algorithms. The cost-to-income ratio is a proxy of bank profitability. It positively relates to the number of articles published on systemic risk by the authors affiliated with a university/research center of a given country, i.e. lower profitability spurs research on systemic risk. Based on the literature examining the link between

bank profitability and financial stability, lower profitability is often considered an attribute of riskier business models involving an over-reliance on wholesale funding and non-interest income,<sup>12</sup> and eventually a higher exposure to systemic risk ([Bostandzic & Weiß, 2018](#); [Brunnermeier et al., 2020](#); [Xu et al., 2019](#)). Since bank business models tend to exhibit inertia, the persistence of high cost-to-income ratios in a country over several years can force policymakers and scholars to draw attention to the increasing systemic risk. Therefore, growing public concerns about financial stability may shape researchers’ focus on this matter. Interestingly, the cost-to-income ratio appears more salient than lagged values of SRISK to GDP and Z-score.

In addition to the cost-to-income ratio, general excellence in a country’s economic research lays ground for the increased output in research on systemic risk. This excellence is proxied by the number of publications in Scopus-indexed journals in the subject area “Economics, Econometrics and Finance” scaled to one million of population (*SCI*). This indicator outperforms more subtle measures, e.g. the launch of a research center specialized in systemic risk studies or the reputation of a country’s economics and finance departments.

The second tier also comprises two indicators identified by two out of the four techniques. The first of them is global innovation index (*GII*), a composite measure characterizing multiple dimensions of education, infrastructure and knowledge creation. In line with intuition, a higher country’s score of the *GII* index is related to more publications on systemic risk, as a more advanced level of science and innovation in a country in general creates a strong premise for an elevated productivity of research, especially if it is data-intensive and involves sophisticated quantitative methodologies, as is the case of systemic risk analysis. Additionally, we draw attention to a variable accounting for cultural values - the power distance index (*PDI*). This measure is an ingredient of cultural dimensions theory proposed by [Hofstede \(2001\)](#) as an attempt to quantify the differences in attitudes between cultures. The *PDI* measures the extent to which the members of a society accept the hierarchy of power and authority. The *PDI* negatively influences the research activity on systemic risk. This finding complies with a recent study by [Andries and Balutel \(2022\)](#). They find that the countries characterized by higher *PDI* values contribute less to systemic risk, as financial institutions in these jurisdictions favor less risk-taking, adopting conservative business models and tougher risk management controls. Hence, a less significant build-up of systemic risk in such countries may create fewer incentives to study it and publish corresponding research. Other studies support the mitigating effect of power distance (hierarchy) on risk-taking in banking, though they do not focus explicitly on systemic risk, e.g. [Ashraf, Zheng, and Arshad \(2016\)](#), [Mourouzidou-Damtsa, Milidonis, and Stathopoulos \(2019\)](#). Besides, [Boubakri, Mirzaei, and Samet \(2017\)](#) find that banks from the countries with higher power distance appeared more resilient during the Global Financial Crisis.

Overall, our results indicate that country-specific factors appear more important drivers of research on systemic risk compared to the global ones. Notably, increases in global financial stress and global volatility do not translate into a rise in the researchers’ attention to systemic risk. Similar evidence is found for global economic uncertainty.

We next run a pooled OLS regression with the independent variables from the two tiers. [Table 6](#) reports its results, accounting for heteroskedasticity through the Newey-West standard errors. All the four

<sup>12</sup> There are also studies which argue that higher profitability can undermine financial stability, as banks may become less rather than more risk averse. As a result, they may increase risk-taking and ultimately, leverage. This effect is demonstrated theoretically, e.g. [Martynova, Ratnovski, and Vlahu \(2020\)](#), and empirically, mainly in case of European banks, e.g. [Pessarossi, Thevenon, and Weill \(2020\)](#). Our explanation of the effect of cost to income ratio on the intensity of research on systemic risk, however, complies with the conventional relationship between bank profitability and financial stability, which is confirmed, for example, by [Poghosyan and Cihak \(2011\)](#) and [Lapteacru \(2022\)](#).

**Table 5**

Results of the variable selection procedures to identify the drivers of research on systemic risk.

Significance confirmed by 4 algorithms	Significance confirmed by 3 algorithms	Significance confirmed by 2 algorithms	Significance confirmed by 1 algorithm	Found insignificant by all the algorithms
COST_TO_INC		PDI	RES_CENTER	CURAC
SCI		GII	ZSCORE	NPL
			CPI	CRIS_NUM
			GOVDEBT	DIST_TO_CRIS
			BANK_ASSET	IMAPP
			UAI	TILB
			BANK_CREDIT	LTOWVS
			MARKETCAP	IVR
			MAS	SRISK_GDP
			IDV	CAP_TO_ASSET
			CONCENTR	RePec
			GEPU	VIX
				KAOPEN
				KOF
				OFR_FSI
				GDPGR
				WUI

**Table 6**

Results of a pooled OLS regression with Newey-West standard errors with the first- and second-tier indicators.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
COST_TO_INC	0.001514	0.000224	6.750570	0.0000
SCI	0.001280	0.000173	7.416846	0.0000
GII	0.000446	0.000169	2.646161	0.0088
PDI	−0.000424	0.000213	−1.990110	0.0479
C	−0.065497	0.020179	−3.245761	0.0014
No of obs.	1216			
DW-statistic	2.07			
Adjusted R-squared	0.56			

indicators are found statistically significant at least at the 5 % level. Besides, these results indicate a sufficiently large share of the variance of the dependent variable, as adjusted R-squared totals 0.56. Thus, we confirm the robustness of the variables selected by the above techniques in the regression analysis framework. Based on the Darbin-Watson (DW) statistic, there are no signs of autocorrelation in the model. The coefficients' importance metrics, i.e. scaled regression coefficients multiplied by their respective partial correlations with the dependent variable, reveal that the SCI (0.32), COST\_TO\_INC (0.13) exert most of the impact on the research output in the field of systemic risk, followed by PDI (0.06) and GII (0.04).

**Table A1**

BMA results.

	PIP	Mean	Standard Deviation
<b>COST_TO_INC</b>	<b>1.000</b>	<b>0.002</b>	<b>0.000</b>
<b>SCI</b>	<b>1.000</b>	<b>0.001</b>	<b>0.000</b>
PDI	0.763	−0.001	0.000
SRISK_GDP	0.669	−0.175	0.150
GII	0.585	0.000	0.000
GDPGR	0.584	0.003	0.003
VIX	0.447	0.001	0.001
MAS	0.301	0.000	0.000
ZSCORE	0.281	0.000	0.000
WUI	0.280	0.000	0.000
KOF	0.257	0.000	0.001
GEPU	0.238	0.000	0.000
KAOPEN	0.208	−0.002	0.004
CONCENTR	0.130	0.000	0.000
CAP_TO_ASSET	0.127	0.000	0.000
NPL	0.113	0.000	0.000
IVR	0.112	0.000	0.000
BANK_CREDIT	0.102	0.000	0.000
IMAPP	0.098	−0.002	0.016
RES_CENTER	0.097	0.001	0.006
GOVDEBT	0.093	0.000	0.000
CRIS_NUM	0.084	0.000	0.001
CURAC	0.083	0.000	0.000
RePec	0.083	0.000	0.000
CPI	0.066	0.000	0.000
OFR_FSI	0.064	0.000	0.000
UAI	0.063	0.000	0.000
LTOWVS	0.062	0.000	0.000
TILB	0.061	0.000	0.000
BANK_ASSET	0.060	0.000	0.000
IDV	0.055	0.000	0.000
MARKETCAP	0.054	0.000	0.000
DIST_TO_CRIS	0.034	0.000	0.000

Note: significant indicators are in bold.

**Table A2**

Adaptive LASSO results.

(INTERCEPT)	−0.05362
<b>PDI</b>	<b>−0.0001</b>
<b>GII</b>	<b>0.00016</b>
<b>COST_TO_INC</b>	<b>0.001086</b>
<b>SCI</b>	<b>0.001251</b>
<b>RES_CENTER</b>	<b>0.005027</b>
IDV	0
MAS	0
UAI	0
LTOWVS	0
IVR	0
BANK_CREDIT	0
CONCENTR	0
ZSCORE	0
CRIS_NUM	0
DIST_TO_CRIS	0
GOVDEBT	0
GDPGR	0
CURAC	0
CPI	0
MARKETCAP	0
TILB	0
NPL	0
IMAPP	0
BANK_ASSET	0
SRISK_GDP	0
CAP_TO_ASSET	0
RePec	0
VIX	0
GEPU	0
WUI	0
KAOPEN	0
KOF	0
OFR_FSI	0

Note: significant indicators are in bold.

**Table A3**  
Elastic net results.

<b>PDI</b>	<b>−0.00055</b>
<b>ZSCORE</b>	<b>−0.00050</b>
<b>CPI</b>	<b>−0.00019</b>
<b>GOVDEBT</b>	<b>−0.00011</b>
<b>BANK_ASSET</b>	<b>−0.00010</b>
<b>UAI</b>	<b>−0.00005</b>
<b>BANK_CREDIT</b>	<b>−0.00003</b>
<b>MARKETCAP</b>	<b>0.00013</b>
<b>MAS</b>	<b>0.00014</b>
<b>IDV</b>	<b>0.00015</b>
<b>CONCENTR</b>	<b>0.00019</b>
<b>GII</b>	<b>0.00040</b>
<b>GEPU</b>	<b>0.00043</b>
<b>SCI</b>	<b>0.00099</b>
<b>COST_TO_INC</b>	<b>0.00132</b>
CURAC	0.00000
NPL	0.00000
CRIS_NUM	0.00000
DIST_TO_CRIS	0.00000
IMAPP	0.00000
TILB	0.00000
LTOWVS	0.00000
IVR	0.00000
SRISK_GDP	0.00000
CAP_TO_ASSET	0.00000
RES_CENTER	0.00000
RePEc	0.00000
VIX	0.00000
KAOPEN	0.00000
KOF	0.00000
OFR_FSI	0.00000
GDPGR	0.00000
WUI	0.00000

Note: significant indicators are in bold.

**Table A4**  
ProSGPV results.

	Estimate	Std. Error	t value	Pr(> t )	
(Intercept)	−0.08619	0.012952	−6.655	0.00	***
<b>COST_TO_INC</b>	<b>0.001503</b>	<b>0.000227</b>	<b>6.612</b>	<b>0.00</b>	<b>***</b>
<b>SCI</b>	<b>0.001597</b>	<b>0.000126</b>	<b>12.69</b>	<b>0.00</b>	<b>***</b>

Overall, our variable selection exercise has certain policy implications. While the *PDI* is hard to alter over a reasonable time span, countries can consolidate their positions in the research on systemic risk by promoting high-quality economic research and also by investing in science and education in general, thereby increasing their *GII* scores. In the long run, this policy creates positive externalities which can enhance the theoretical and practical dimensions of macroprudential policy and ultimately increase the country's resilience to a financial crisis. In the short run, a country's visibility in the research on systemic risk may rise due to the increasing fragility of its banking system, as more studies within this research field are published as a response to low bank profitability, a precursor of systemic risk build-up.

## 5. Conclusion

The paper investigates the evolution of research on systemic risk during the period 2007–2021, which is peculiar for at least three major episodes of global financial turmoil: the GFC, European financial crisis and the outbreak of COVID-19 pandemic. The study builds on two complementary methodological approaches.

First, we conduct a bibliometric analysis which highlights the decreasing role of advanced countries in the research field over time alongside the advancement of emerging markets, primarily, China. It reveals the leading positions of such field finance journals as the *Journal of Financial Stability* and *Journal of Banking and Finance* in accumulating the highest shares of publications on systemic risk during the

observation period. The bibliometric analysis also allows to identify the most impactful institutions and scholars in the field, in both cases representing the USA. Based on the results of the bibliometric analysis, we conjecture that this research field reached its maturity and current scientific landscape around the years 2013–2014.

The second approach involves the identification of factors which incentivize systemic risk research on the national level in a vast sample of countries. We apply four advanced variable selection techniques to 33 candidate factors and find that there are only four indicators which are consistently found statistically significant. A lower level of bank profitability proxied by cost-to-income ratio coupled with the general productivity in economic research measured by the number of publications in Scopus-indexed journals in the subject area “Economics, Econometrics and Finance” scaled to one million of population (*SCI*) appear the most robust drivers of research on systemic risk. They are found significant by all the four algorithms. A higher country's score in the Global innovation index (*GII*) leads to a higher research intensity on systemic risk. Cultural values also matter for the expansion of research on systemic risk. Such studies are less likely to appear in the societies with a higher power distance (*PDI*), i.e. favoring hierarchy rather than individualism. We attribute this result to less risk-taking by banks in such countries due to more conservative business models and more stringent risk management controls. The *GII* and *PDI* indices are found significant by a half of the algorithms and constitute the second tier of variables predicting the intensity of research on systemic risk.

The bibliometric part of our study provides valuable insights for researchers investigating systemic risk with respect to building collaborative networks and targeting proper journals. In its turn, the identification of factors promoting publishing on systemic risk allows to design specific measures to incentivize scholars and thereby consolidate the scientific underpinning of macroprudential policy measures.

The study has a natural limitation since we are unable to exploit a number of potentially relevant factors stimulating research on system risk. Most of these factors deal with such issues as research funding, career goals, the role of professional networks, etc. Unlike the indicators based on statistical data, these factors build on “soft” data. Thus, it is reasonably hard to find appropriate proxies for them. Overcoming this obstacle is a promising area for future studies involving new methods, e. g. cross-country researchers' surveys, thereby allowing to refine our tentative evidence of the drivers promoting research on systemic risk.

## CRedit authorship contribution statement

**Mikhail Stolbov:** Conceptualization, Writing – original draft, Methodology, Writing – review & editing, Data curation, Formal analysis. **Maria Shchepeleva:** Methodology, Writing – review & editing, Visualization, Data curation, Formal analysis.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A

See [Tables A1–A4](#).



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