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Research report

Evolution and determinants of firm-level systemic risk in local production networks

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Abstract

Recent crises like the COVID-19 pandemic and geopolitical tensions have exposed vulnerabilities and caused disruptions of supply chains, leading to product shortages, increased costs, and economic instability. This has prompted growing efforts to assess systemic risk, namely the effects of firm disruptions on entire economies. However, the ability of firms to react to crises by rewiring their supply links has been largely overlooked, limiting our understanding of production networks resilience. Here, we study dynamics and determinants of firm-level systemic risk in the Hungarian economy from 2015 to 2022. We benchmark our results to a heuristic maximum entropy null model that generates randomized production networks while preserving the total input (demand) and output (supply) of each firm at the sector level. We show that the fairly stable set of firms with highest systemic risk undergoes a structural change during COVID-19, as those enabling economic exchanges become key players in the economy—a pattern not reproduced by the null model. Although empirical systemic risk closely matches the null value prior to the pandemic, it becomes significantly lower afterwards, reflecting the emergence of a more resilient economy driven by firms' adaptive behavior. Furthermore, firms' international trade volume (being itself a channel of potential disruption) becomes a significant predictor of their systemic risk. However, international linkages alone cannot fully explain the observed trends, as imports and exports exert opposing effects on local systemic risk through the supply and demand channels.

Keywords production networks, systemic risk, null network models, COVID-19

Significance statement:

Production networks underpin modern economies, yet their adaptive response to major disruptions remains poorly understood. By analyzing firm-level data from the Hungarian economy over 2015–2022, we reveal how production networks dynamically reconfigured in response to the COVID-19 pandemic shock. The resulting rewiring of supply connections ultimately led to a more resilient economy, both in absolute terms and relative to configurations generated by a maximum-entropy network model with firm-level productivity constraints. Firms facilitating economic exchanges became key players of the economy, while international trade volume turned into a significant predictor of systemic risk. Our findings provide new insights into the determinants of firm-level systemic risk, with potential implications for the assessments of economic resilience at the firm and system level.

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Introduction

Production networks arise as firms exchange goods and services that are needed for their own production (1, 2). The resulting interdependencies between suppliers, manufacturers, and consumers across industries and geographic regions foster economic and technological progress and are essential to the functioning of modern economies (3–5). However, production networks have become increasingly vulnerable (6), as a consequence of the growing globalization, interconnectedness, and complexity of supply chains (7–11) as well as the constant drive toward efficiency (12, 13). Interconnectedness, in particular, implies that disruptions affecting firms in one region or sector can ripple across the entire network, with large-scale economic consequences (14–16). The propagation of shocks through global supply chains has occurred repeatedly in recent years. For example, natural disasters such as Hurricane Katrina and the Fukushima earthquake had economic impacts far beyond the area directly affected (17–19). Similarly, geopolitical events, such as the Russian invasion of Ukraine, disrupted global grain supplies for importing nations (20, 21). In the paramount case of the COVID-19 pandemic, lockdown measures and the subsequent factory shutdowns had a disruptive effect on global production networks, affecting entire economies that struggled to supply basic goods to the population (22–25). These events have stimulated growing interest in assessing systemic risk—specifically, understanding how disruptions propagate through production networks and generate large-scale economic effects, and how local networks face external shocks through their export and import connections.

Although the propagation of economic shocks has been traditionally studied using industry-level Input-Output tables (26–30), recent research has highlighted the role of granular network effects (31–33). As a consequence, attention has increasingly shifted towards production networks at the firm level (16, 34–47), also thanks to the growing availability of large-scale datasets of inter-firm relationships (48–50). Notably, the use of firm-level data allows to overcome the aggregation bias inherent in Input-Output tables (51), thereby enabling more reliable estimates of systemic risk (52). The supply chain management literature studied several aspects of disruption propagation along supply chains, such as the *supply chain resilience* (53), the *snowball effect* (54), the *ripple effect* (55–57) and the *nexus suppliers* index (58, 59), recognizing the importance of considering variability (60) and topological features (61) of the underlying network. Furthermore, how supplier and customer disruptions affect firms depends on both their production process and network position. The recently proposed *Economic Systemic Risk Index* (ESRI) (34) builds on these insights to quantify the risk associated with a firm in terms of the total reduction in economic output caused by its failure.

Measuring systemic risk typically relies on a static network assumption, where firms and their relationships within the production network are fixed as shocks propagate. However, when a crisis occurs, firms actively respond by adapting their supply chains (62–66). These adaptations may include finding alternative suppliers, changing logistics pathways, reallocating production, or exploiting new market opportunities that arise during the crisis (67–70). Such adaptive responses are not merely temporary fixes, but can lead to long-term modifications in the structure of the production network (71, 72). These structural changes can then either mitigate systemic risk, by making the network more resilient and diversified, or exacerbate it, by creating new dependencies and bottlenecks. As a result, systemic risk can no longer be regarded as a static property that is solely determined by the pre-crisis network structure.

In this work, we study the evolution and determinants of firm-level systemic risk using a subset of the Hungarian production network (see Methods), which contains all firms (above a minimum size) located in Budapest and all their value-added tax (VAT) transactions (exceeding a minimum threshold), during years from 2015 to 2022—thus including the outbreak of the COVID-19 pandemic. We compute and track the ESRI value for each firm in the network (see Methods) to draw a detailed portrait of the evolution of systemic risk at both the individual firm and sector level over an extended time span. This enables us to investigate how resilience evolves over time, providing a comprehensive analysis of system-level adaptation to the COVID-19 shock and identifying new key players of the economy.

To focus on how firms' specific position in the evolving production network determines their systemic risk properties, beyond what their supply and demand levels would imply, we benchmark empirical findings to a null network model that randomizes the supply links of the network but preserves the sector-specific input and output trade volumes of each firm. We construct this null model using the *stripe-corrected gravity model* (s-GM) (73), a heuristic maximum entropy formulation tailored to production networks (see Methods). We employ the s-GM to generate an ensemble of synthetic networks on which we compute ESRI scores, serving as null values against which we compare empirical observations. Importantly, these null ESRI depend solely on the sector-specific trade volumes of firms, and are therefore independent on the particular topology of the production network (74, 75). Figure 1 illustrates our working pipeline.

By constraining the supply and demand of each firm by sector, the s-GM is consistent with the assumption of fixed production function and input portfolio (here proxied by sectors) commonly used to study shock propagation during crises (25). Indeed, previous research has shown that the s-GM can faithfully reproduce systemic risk levels observed in empirical production networks (76). However, we expect null model estimates to deviate from the empirical ESRI measured during the COVID-19 shock, due both to extreme fluctuations experienced by the system and to firm-level adaptive responses that the random network model cannot capture. We are also particularly interested in understanding the role of firms' international trade activities, which can transmit global shocks into domestic markets (18, 77), but can also alter firms' importance within local production networks. Importers, for example, can redistribute foreign products locally (78), or replace local sources with international suppliers (79), while exporters can attract and coordinate local suppliers (77). In the context of the COVID-19 shock, we expect disruptions in global supply chains (23) to affect local systemic risks through both the propagation of external shocks and the adaptation of domestic networks to changing international trade relationships (80).

Our results reveal that, at the onset of the COVID-19 pandemic, the set of firms bearing the highest systemic risk undergoes a substantial shift, with firms facilitating economic exchanges emerging as central players in the network—a structural

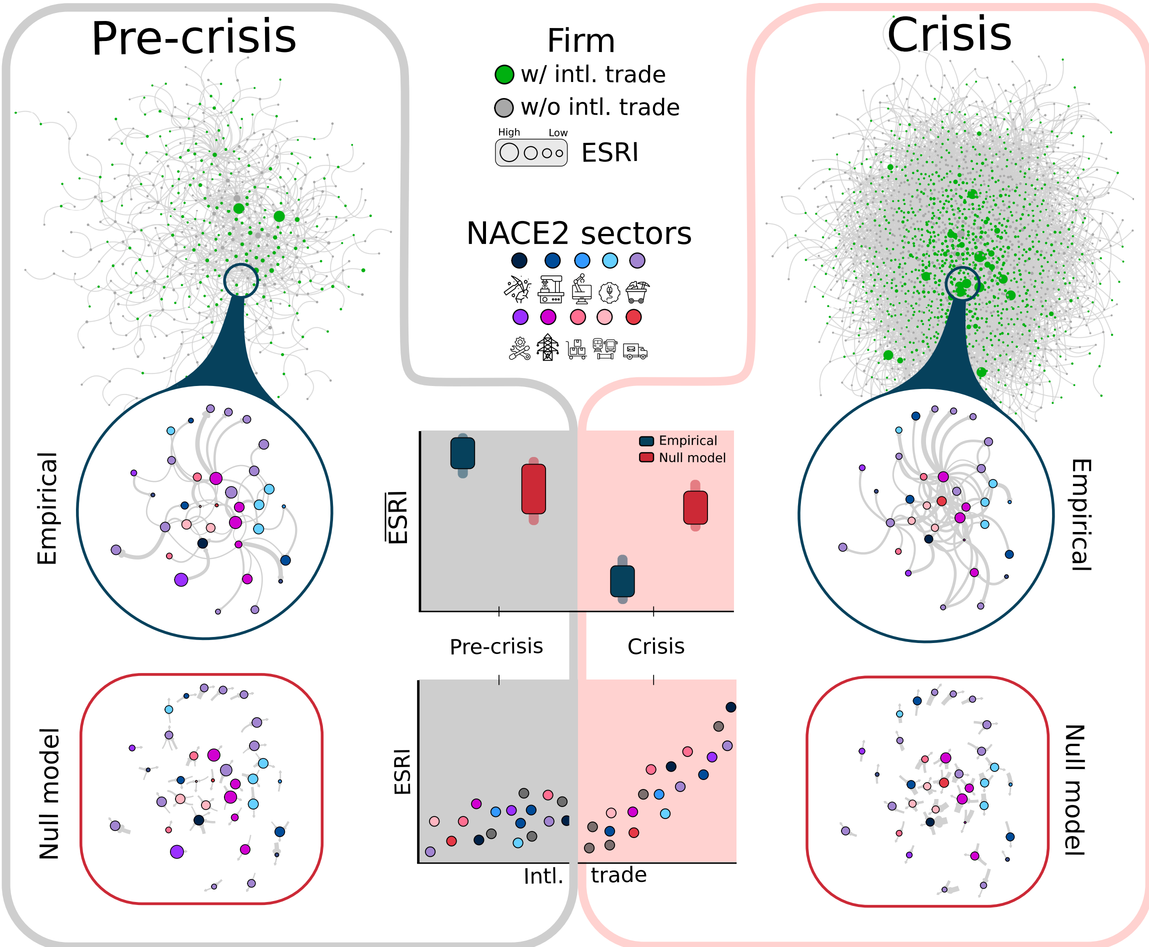

Figure 1 Empirical and null model networks are compared before and during the COVID-19 crisis, to study the evolution of economic systemic risk and understand the role of international trade. We start with temporal snapshots of the empirical production network. The top of the figure shows a sample sub-network of 1,000 nodes, before and during the crisis. Firms are colored according to the presence (green) or absence (gray) of international trade ties, while nodes' size is proportional to firms' ESRI value. We then focus on the firms with the highest systemic risk values, highlighted with a circular magnification from the empirical networks, where nodes' color represents firms' industrial (NACE2) sector. Finally, the squares in the third row represent the null models for the same set of risky firms, where we show only the constrained quantities (for each firm, its supply volumes from different sectors and total sales). Our framework thus allows studying the temporal evolution of systemic risk, how it deviates from the predictions of the null model, and which characteristics of the firms, such as the presence of international trade, are linked to their risk value (as shown by the sample analysis plots in the middle of the figure).

transformation that is absent in the null model. While systemic risk closely follows null expectations before the pandemic, it diverges significantly afterward, reflecting an adaptive reconfiguration of economic interactions that enhances resilience both in absolute terms and relative to benchmark predictions. Using regression analysis (see Methods), we find that international trade volume becomes a key predictor of firms' systemic risk dynamics during the crisis, although global linkages alone cannot fully explain the observed patterns. Imports and exports exert opposing influences on local systemic risk through distinct supply and demand mechanisms, underscoring the complexity of risk propagation in globally interconnected economies.

Results

The Hungarian production network

Supplier-customer relations in the Hungarian economy are obtained from firm-level value added tax (VAT) transaction data (34, 49) (see Methods). Since data contain no information on the type of product exchanged, but only the industrial classification of firms, we follow the typical assumption in related studies that every firm produces only one out of m different products (goods or services) (34), which is determined by the firm's industry classification. Therefore, we assume that each firm i produces product p_i corresponding to its NACE (Statistical Classification of Economic Activities in the European Community (81)) classification scheme on the 4-digit level, with a total of $m = 615$ product categories.

The data is then represented as a directed weighted network, where nodes correspond to firms and a link from supplier firm i to buyer firm j is established when data report a purchase transaction from j to i, with value $w_{i\to j}$ corresponding to the volume of product type p_i delivered from i to j. We aggregate transactions between firms on a yearly basis to build production networks for the time range 2015–2022. These networks are extremely large, with hundreds of thousands of firms and millions of transactions. Moreover they are not coherent in time, as the VAT reporting threshold (the minimum value for a transaction to appear in the data) was lowered in 2018 and completely removed in 2020 (see Supplementary Materials S1 for forfordetails on the various thresholds are how they affect our data). To make these networks computationally manageable and at the same time to remove threshold effects, we apply the highest reporting threshold of 2015 to all networks. Further, we only consider firms whose headquarters are based in Budapest (the region with the highest firm concentration and economic activity) and remove the smallest firms (in terms of number of employees and customers)—see Methods and Supplementary Materials S1 and S3 for further details. In this way, we decrease the size of the networks by a factor ten and obtain yearly coherent snapshots of the *local* production network of Budapest (see Methods).

The number of firms and transactions in these yearly networks grows substantially over time (Figure 2A). Links grow more than the number of nodes N but slower than N^2, hence the network density declines. A big jump is observed in 2018, likely due to the use of online cash registers imposed by the government in 2017[a] and the introduction of the Real-Time Invoice Reporting (RTIR) for all domestic invoices above 100,000 HUF in 2018[b]. Thus, from 2018 onward data start to include many small-medium enterprises, which mainly have a few connections, causing the drastic drop of link density. Concerning node-level statistics for each time snapshot, the trading volume of each firm i is described by its out-strength (total sales) $s_i^{\text{out}} = \sum_j w_{i\to j}$ and in-strength (total purchases) $s_i^{\text{in}} = \sum_j w_{j\to i}$, whereas, the firm's connectivity is described by its out-degree (number of customers) $k_i^{\text{out}} = \sum_j a_{i\to j}$ and in-degree (number of suppliers) $k_i^{\text{in}} = \sum_j a_{j\to i}$, where $a_{i\to j} = 1$ if $w_{i\to j} > 0$ (and 0 otherwise). Similarly to previous research in other production networks (48), we find power-law tails (without cut-off (82)) in the distribution of these quantities (Figure 2B-C-E-F), and that the total sales/number of customers is typically much larger than the total supply/number of suppliers, respectively. As observed for the density, the degree distributions change mostly because of the introduction of the RTIR, which brought to surface a part of the economy that was hidden beforehand, thus increasing the average degree of firms (see Supplementary Materials S4). Strength distributions are instead rather stable in time.

Evolution of economic systemic risk of firms

To assess how firm-level systemic risk evolves throughout the years, we compute the ESRI (34) of all firms in each yearly network. In a nutshell, the systemic risk of a firm is computed by removing it from the network and iteratively propagating the upstream (demand) and downstream (supply) shock to connected firms in the production network, which respectively occur when a customer reduces purchases and a supplier reduces provision for a product. The ESRI of the firm, then, corresponds to the overall output reduction of the economy due to its failure (see Methods for more details on the ESRI methodology, Supplementary Materials S26 for details on how the simulations were carried out, and Supplementary Materials S5 and S6 for how ESRI relates to firm's degree and strength values).

We first consider the time series of average and total ESRI values of all firms, for each year (Figure 2D). The decreasing trend of the average ESRI is tied to the decreasing network density, which implies relatively less connections and thus fewer shock propagation channels. On the other hand, the growing trend of the total ESRI sum mirrors the growth in number of nodes of the yearly networks. We then focus on the evolution of single-firm ESRI values, to understand whether they are stable or vary over years—despite firms frequently rewiring their connections (35). By computing the Pearson correlation coefficient of firm-level values for each pair of years, we find strong consistency of ESRI over time (Figure 2G), even when the network structure changes considerably from 2017 to 2018. However, the drop in correlation observed from 2019 to 2020 indicates that the COVID-19 pandemic brought about deep network changes that influenced firms' potential impact on the economy (for further insights into yearly ESRI correlations for upstream and downstream values separately, refer to Supplementary Materials S7; for correlation matrices of node centrality measures, see Supplementary Materials S8—interestingly, none of them reproduce the structural breaks of ESRI correlations).

As highlighted in previous research (34, 36, 76), plotting ESRI values versus ESRI rankings reveals a plateau composed of the most risky firms, followed by a steep decrease for higher rankings (see Figure 2H for 2015, Figure 2I for 2021 and Supplementary Materials S9 for the other years). Plateau firms represent the biggest threat to the network: according to ESRI, their failure would result in the loss of about 10% to 15% of the total output of the local Budapest economy. We observe that the shape of the plateau, together with the downstream and upstream values, remains consistent in time until 2019, while starting from 2020 the upstream ESRI shows large positive variations that are responsible for the emergence of a step-like structure of the plateau. In particular, the growth in upstream ESRI scores for the plateau firms can be associated with an increase in the firms' in-strength (see the slightly longer tail of the CCDF in Figure 3F). A possible explanation (supported by the increase in fraction of essential links during the pandemic, see Supplementary Materials S20) is that firms increased their connections with local firms to replace those with foreign countries, restricted due to COVID.

Empirical vs. null model values of ESRI

To benchmark empirical values of ESRI to the null model, using the s-GM method we construct an ensemble of 100 networks for each year in our data (see Methods for the s-GM description, Supplementary Materials S10 showing how the model is able to reproduce the degree and strength statistics of the empirical network and Supplementary Materials S11 for more insight into how link weights are reproduced). We compute the ESRI values of all firms for each of these networks and then average over the ensemble to obtain null yearly values of ESRI for each firm.

Similarly to the empirical network, ESRI values in the null model are stable across subsequent years, as revealed by high Pearson correlation coefficients (Figure 3A). However, while for empirical values the highest change is observed between 2019 and 2020 (the onset of COVID), for the null model changes are more pronounced in going from 2017 to 2018, when the real network experienced a considerable growth in nodes and links. This result points out that the null model is not able to fully capture the underlying dynamics of ESRI when the system is affected by exogenous shocks. Nonetheless, as shown in Figure 3B for year 2019 (see Supplementary Materials S12 for the other years),

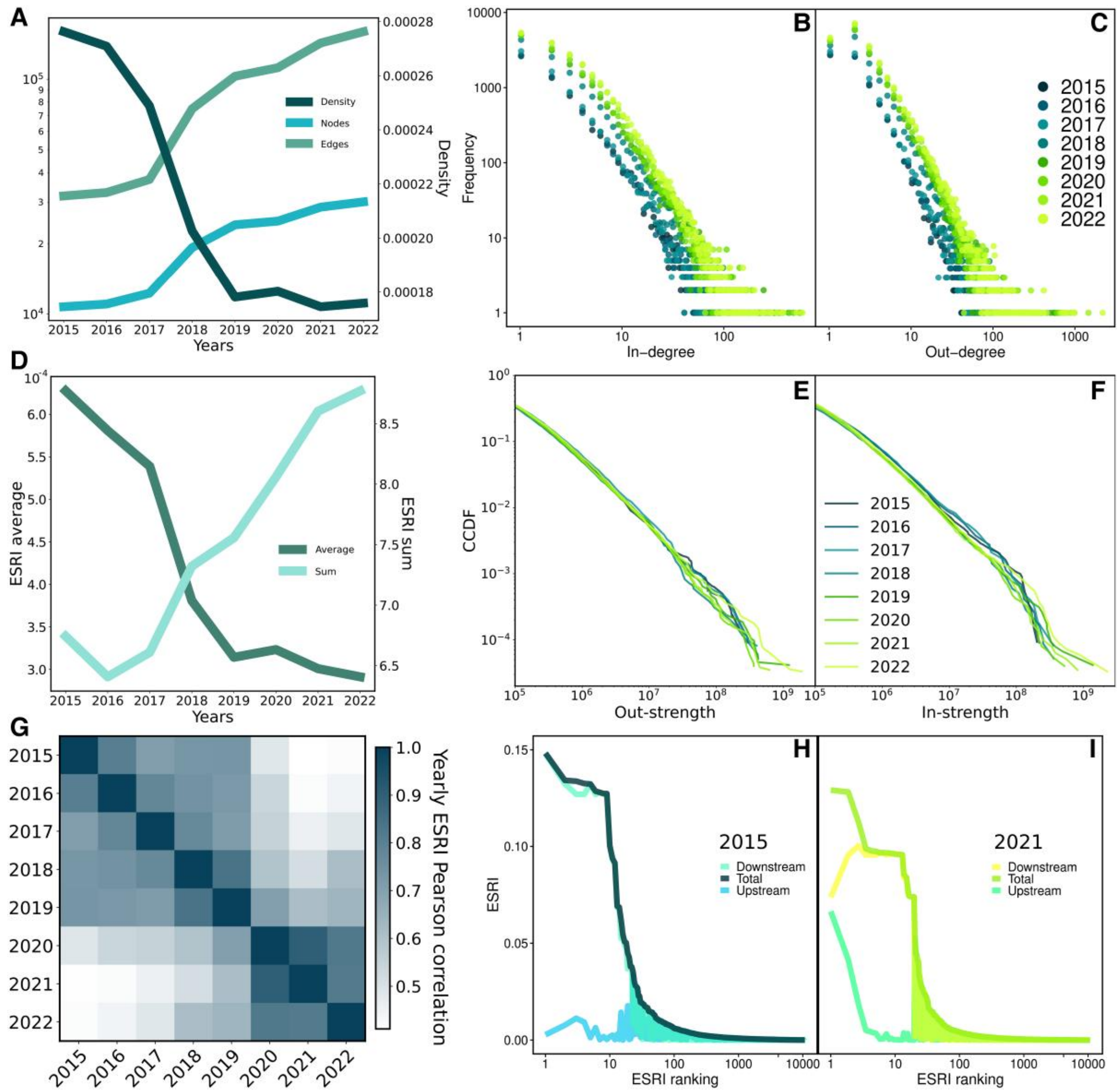

Figure 2 Time evolution of topological properties and systemic risk of the empirical production networks. A) Number of nodes (firms), links (transactions) and density of the local Budapest production network in the considered time range. B,C) Frequency distributions of firms' in-degree (number of suppliers) and out-degree (number of customers) for all yearly production networks. D) Average and total ESRI of firms in the yearly networks. E,F) Tail of the survival distribution of out-strength values (total sales of firms) and in-strength values (total supply of firms) of yearly production networks. G) Matrix of Pearson correlation coefficients for ESRI values of firms among different years. H,I) ESRI values vs. rankings for the total, upstream and downstream components for 2015 and for 2021.

there seems to be a good agreement between real and model ESRI values for individual firms (76), that is yet not able to reproduce the long-term correlations. In fact we can observe a shift of high-ESRI firms above and of low-ESRI firms below the identity line. These discrepancies arise as the model slightly overestimates ESRI of the most risky firms (top right corner), while underestimating that of the least risky ones (bottom left corner). This is mainly due to the sampling method at the basis of the s-GM, for which small firms may happen to get disconnected from the network in some model samples (83). Consequently, these firms have very small ESRI, as they cannot propagate shocks to others. At the same time, since the link density is preserved, bigger firms may then receive slightly more connections, increasing their impact with respect to the empirical case.

Considering global statistics, the average values of empirical and null model ESRI across all firms are statistically compatible from 2015 to 2017 (Figure 3C). However, from 2018 onward, the model ESRI becomes significantly higher than the real one, possibly because the new firms entering the network in this period follow different market dynamics that are not captured by the null model. Notably the deviation increases in 2020–2022, when we witness opposite trends of empirical and null values. Furthermore, the Pearson correlation coefficient between real and model ESRI scores drops in 2020–2021, during the flare-up of COVID (Figure 3D). These results reveal that the null model, which works well both in reconstructing the empirical networks (73) and reproducing the ESRI dynamics (76) during normal times, becomes unable to faithfully do so during times of crisis, as the real networks deviate from their null configurations. This deviation may be the result of additional network formation mechanisms at work during that period, which are not included in the null hypothesis underlying the s-GM.

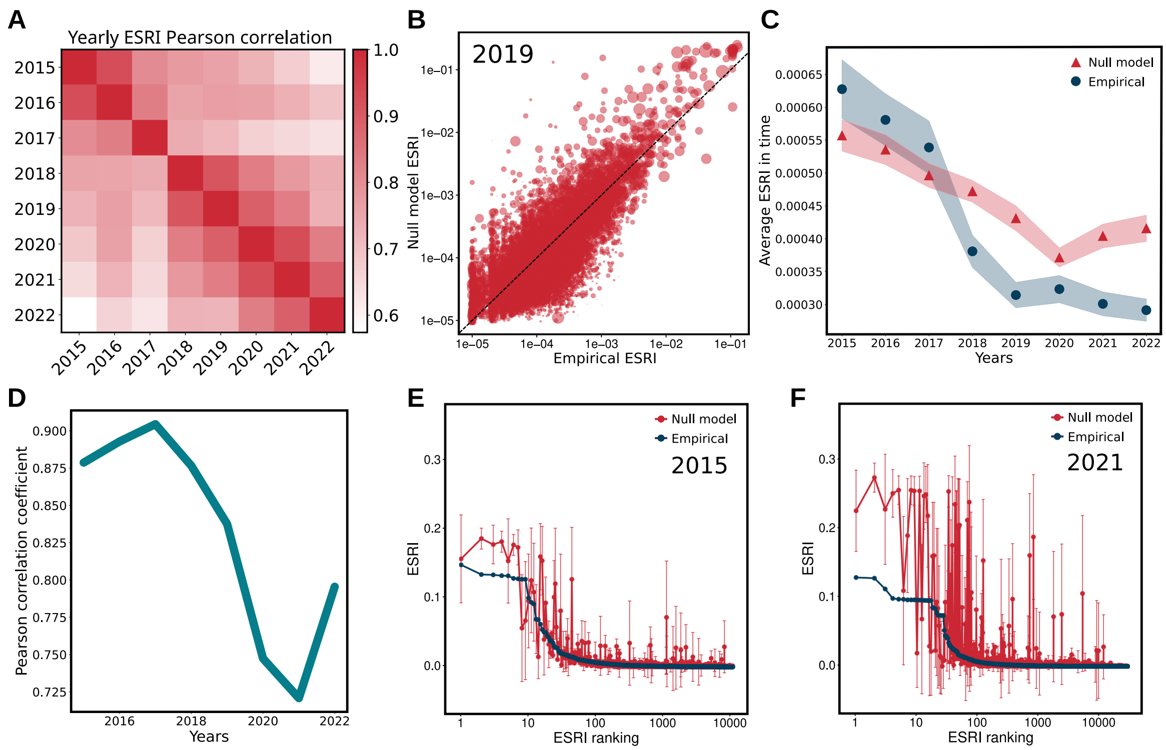

Figure 3 Empirical vs. null model ESRI values. A) Matrix of Pearson correlation coefficients for null ESRI values of firms among different years. B) Empirical vs. null ESRI values of individual firms for 2019. The size of each point corresponds to the firm's number of employees, here taken as proxy for size. C) Mean value of ESRI for empirical and null networks. Shaded area refers to standard deviations (which are larger for the model due to the sampling procedure). D) Pearson correlation coefficient of empirical vs. null ESRI values of individual firms, for each year. E,F) Empirical and null ESRI ranking for years 2015 and 2021. Error bars represent standard deviations of ensemble values. Model values are ordered according to their empirical ranking.

To further corroborate this statement, we compare empirical and model rankings of ESRI for individual firms (Figure 3E,F). The overestimation of null ESRI for highly risky firms, discussed above, leads to a higher plateau for model values. Overall we observe a good agreement between the empirical and model curves for 2015, with deviations between 0.05 and 0.1 only for a handful of ten firms and much lower for the others—again confirming that, in normal times, the s-GM provides accurate estimates of single-firm ESRI values (76). However, this is not the case for 2021, as the model rankings become more disordered and unable to correctly reproduce not only the plateau, but most of the ranking as well. Indeed we observe deviations above 0.05 (and up to 0.2) for about 40 firms. The mismatch between empirical and model values grows steadily starting from 2018, with 2021 and 2022 yielding the largest deviations (refer to Supplementary Materials S13 for ranking plots of all years, to Supplementary Materials S14 for plots of the deviations between real and null model values, and to Supplementary Materials S15 for distributions of empirical and null model ESRI values).

Sector composition of ESRI plateaux

We now focus on the most risky firms, namely those that belong to the ESRI ranking plateaux. For each year, we select plateau firms as the top 0.1% of the corresponding ESRI ranking (see Supplementary Materials S16 for the full list of NACE4 sectors of these companies). Figure 4A provides a graphical illustration of the time evolution of the empirical network composed of only the plateau firms, colored by NACE2 sector and sized according to their ESRI values. Figure 4B shows the empirical and null model trends of ESRI only for the plateau firms. Notably, these trends are not affected by the 2018 drop that we see for the full networks, and the null model ESRI is always significantly above the empirical value, with the gap between the two widening during COVID. This supports our previous results, as plateau firms are mostly large companies as well as suppliers of essential goods (see Supplementary Materials S7) that are likely present in the network even before the introduction of RTIR in 2018.

Figure 4C further shows that the set of plateau firms changes throughout the years, with a Jaccard index between consecutive years of about 0.5 in ordinary times (meaning that about half of the firms remain in the plateau from one year to the next one) and of 0.7 for the COVID years 2020–2022 (pointing to a rather stable composition of the plateaux). Among the top firms, a few remain in the plateau for the entire period analyzed. They correspond to NACE2 code 35 (electricity, gas, steam and air conditioning supply) and 28 (manufacture of machinery and equipment). In addition, all plateau firms belong to only a handful of industrial sectors (see Supplementary Materials S17 for more details).

We then compare the plateau composition in empirical and null model networks of the same year, where model plateau firms are selected using the corresponding null ESRI rankings. The overlap between the sets of firms in the empirical and model plateaux is high in most years, but decreases noticeably during the pandemic (Figure 4D), when the null model cannot identify

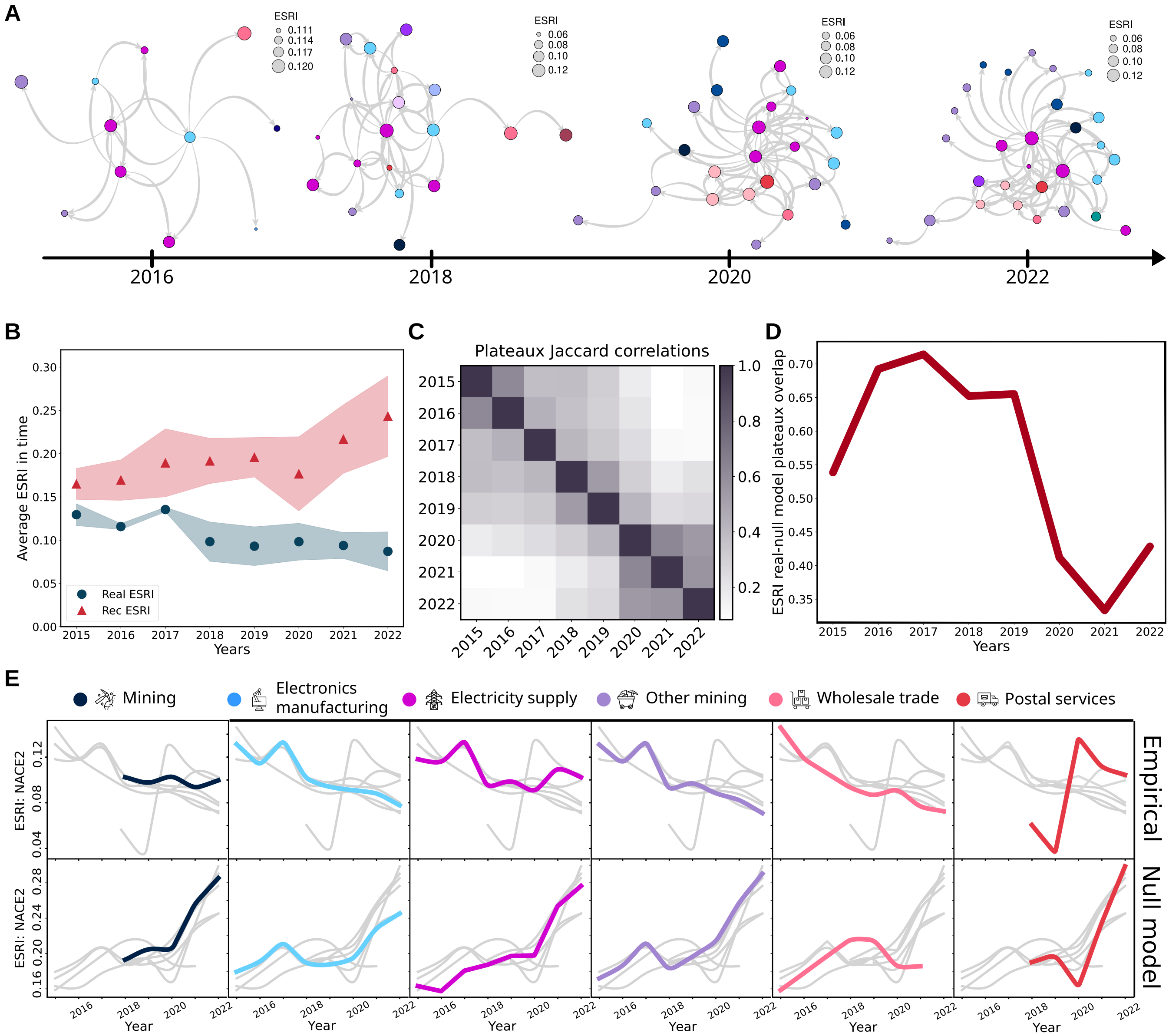

Figure 4 ESRI plateaux analysis. A) Representation of the empirical network among plateau firms, with node size proportional to ESRI values and color identifying the NACE2 sector. B) Average ESRI for plateaux firms, displaying the same trend observed for the whole networks. C) Matrix of Jaccard indices quantifying the overlap among the sets of empirical plateaux firms between different years. D) Time evolution of the Jaccard coefficient of plateau firms sets between empirical vs. model networks in the same year. E) Evolution of empirical (top panels) and null (bottom panels) ESRI values, for firms appearing more than 3 years in the plateaux, grouped by NACE2 sectors. Each panel highlights the evolution of a single sector (the other sectors are displayed in gray).

most of the most risky firms: in line with the previous result, the model becomes less compatible with the empirical network during COVID-19. To better analyze the time evolution of the sector composition of the plateau we focus on a stable set of top firms, as those that appear in the empirical plateaux for more than three years. Figure 4E shows the temporal evolution of ESRI for all these firms, summed over NACE2 sectors, for both empirical and null model networks. Concerning empirical values, we observe a decreasing trend of ESRI for the majority of these sectors, while there is a steep increase in ESRI for the postal activity sector, which represents an emblematic example of the impact of COVID on the production network: due to mobility restrictions, postal services became crucial for the entire system, by allowing trade transactions and maintaining the economy running (84). The ESRI values for the null model, instead, grow steadily in time, even during COVID years.

We may argue this occurs because the null model is simply driven by the increase in degrees and strengths of the largest firms in the empirical networks in time (see the increasing tail in the distributions of Figures 2B-C-E-F), which results in more interconnections and thus higher systemic-ness for these firms. The growth of these statistics could be partly caused by import bans that forced companies to search for products in the domestic economy, thus increasing the connections we see in the data. Since the s-GM directly constrains the strength values, it is already taking into account this increase in local trade, therefore null model ESRI values of large firms become higher during COVID. On the other hand, in the empirical case, the increase in connections and strengths does not result in increasing ESRI for large firms which, apart from the postal services, display a decreasing trend. In fact, while the postal services represented the only available alternative to bypass lockdown measures, resulting inevitably in an increase of its ESRI value, other firms could decide how to eventually rewire their links (for example to cope with import bans). Notably, this optimization process at the level of individual firms also led to a more resilient network configuration at the global level. Of course, these mechanisms at work during times of crises are not captured by the null model (see Supplementary Materials S20 for further analyses).

Determinants of firm-level systemic risk

To understand the drivers of firm-level systemic risk in the local production network, we estimate the ESRI value of firms in each year *t* using a multivariate regression, in which explanatory variables include the systemic risk indicator of the s-GM null model ($ESRI_{model}$). To explain the variance in empirical ESRI that null values cannot describe, we add as regressor further company characteristics that are important in the ESRI computation, such as firm size measured by number of employees (Employment), its importance in the local trade network measured by in-strength and out-strength of trade flows ($Strength_{in}$, $Strength_{out}$) and Essentiality—the number of customers for which the firm's input is essential, computed according to the essentiality matrix of (25). In addition, we include volume of international trade (Import, Export) that, even if not directly used in the ESRI computation, we expect to be non-trivially related to systemic risk in the local economy—by generating spillovers from international product flows through local links in the production network. The regression includes company fixed-effects that capture further unobserved firm characteristics and year dummies that control for yearly fluctuations (see Methods for a more detailed presentation of the regression model and the variables included, and Supplementary Materials S18 for the correlation table of firm features).

Table 1 shows a series of regressions, in which models including either *Import* (Models 1–4) or Export (Models 5–8) are separated due to the high correlation of these variables. Regressions (1) and (5) allow to understand the influence each variable has on the value of the empirical ESRI for a given firm. As expected from the previous analyses, we find a strong correlation between empirical ESRI and null model values. Growing intensity of local trade is associated with increasing ESRI, especially if the company's supply is essential for the customers' businesses. Size effects are stronger for out-strength than in-strength, because the former is related to downstream shocks, which propagate with a generalized Leontief production function, while upstream shocks propagate linearly. Essentiality has a strong positive correlation with ESRI, signaling that systemic risk is higher for those firms that provide essential inputs for many other firms in the local economy. Overall, the contributions of these variables containing information of the local trade network are in line with expectations and also seem to capture the scale effects, since Employment has no significant relationship with ESRI (not reported in Table 1).

The positive and significant coefficients of Import (1) and Export (5) signal that international trade can also increase systemic risk of firms in national economies. This result is non-trivial, but paired with local links, increasing international trade can ripple through to local economic systems. To disentangle these mechanisms, we add the interaction terms between international trade and local trade variables and find that the impact of international trade on local systemic risk through domestic links (represented by in—and out-strengths) shows a mixed picture. On the one hand, the negative interaction term in (2) and (4) between Import and $Strenght_{out}$ as well as Essentiality signals that import does not have a spillover impact on systemic risk in the local economy of Budapest. Due to the dominance of multinational companies in manufacturing sectors that are more embedded in global value chains than in local economies (85, 86), importing companies probably sell their products predominantly on export markets, instead of distributing imported goods through local links. As a result, we see a negative association of $Import \times Strength_{out}$ with ESRI. However, the positive interaction term between Import and $Strength_{in}$ in Models (2) and (4) signals that firms can also complement domestic supplies and thus increase the firm-level ESRI altogether. On the other hand, the interaction of Export with $Strength_{out}$ and Essentiality is negatively correlated with ESRI (6), suggesting that increasing exports can decrease systemic risk in the domestic economy, in case they substitute local revenues. Yet, the interaction of Export with $Strength_{in}$ has a positive relationship with ESRI, indicating that growing export can increase systemic risk of firms if entering international markets is paired with growing local supplies. We further find that a firm's market share is never significant, a surprising result only at first glace, since the market share of firms is reproduced by the null model, thus its effect is already incorporated in the coefficient of $ESRI_{model}$.

Splitting the period into pre-COVID years (3,7) and COVID years (4,8) reveals that both Import and Export become significantly correlated with ESRI only during COVID. This can be explained considering that during the COVID-19 pandemic there was an overall drop in trade due to import and export difficulties all over the globe. Thus, only the most important firms were able to maintain trade with foreign countries, and these firms get the highest ESRI values (see Supplementary Materials S19 for a correlation of ESRI, essentiality and size, proxied by the firm's out-strength, Supplementary Materials S20 for the yearly evolution of fraction of essential links, and Supplementary Materials S21 and S25 for results obtained with a weighted version of the essentiality score).

Consequently, the above reported impact of import on national systemic risk through local production networks is only apparent during the COVID period in our case (4). However, we find that the effect of export is slightly different with respect to COVID. While exports as supplements for domestic revenues only decrease ESRI during COVID, they only substitute essential links in the pre-COVID period. We find a stable positive and significant joint effect between Export and $Strength_{in}$ in both pre- and COVID years. This signals that increasing export may increase systemic risk in national production networks if it increases the demand for local inputs.

We run a series of robustness checks that provide further support for the above results. Pooled OLS regressions with year fixed-effects and cross-sectional linear regressions run by years are reported in Supplementary Materials S22, S23 and S24.

Table 1. Fixed-effects panel regressions with empirical ESRI as the dependent variable.

	ESRI							
	(1)	(2)	(3) (2015–2019)	(4) (2020–2022)	(5)	(6)	(7) (2015–2019)	(8) (2020–2022)
$ESRI_{model}$	0.319***	0.319***	0.287***	0.243***	0.319***	0.318***	0.286***	0.242***
	(0.004)	(0.004)	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)	(0.007)
Import	0.003***	0.008***	0.005	0.020***				
	(0.000)	(0.002)	(0.003)	(0.004)				
Export					0.003***	0.006*	−0.003	0.021***
					(0.001)	(0.003)	(0.004)	(0.006)
$Strength_{out}$	0.058***	0.061***	0.063***	0.103***	0.058***	0.061***	0.063***	0.102***
	(0.003)	(0.003)	(0.005)	(0.006)	(0.003)	(0.003)	(0.005)	(0.006)
$Strength_{in}$	0.039***	0.038***	0.041***	0.032***	0.039***	0.038***	0.040***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Essentiality	0.469***	0.480***	0.480***	0.491***	0.470***	0.474***	0.480***	0.480***
	(0.005)	(0.005)	(0.009)	(0.009)	(0.005)	(0.005)	(0.008)	(0.008)
market share	−0.034	−0.024	−0.039	0.056	−0.033	−0.023	−0.045	0.057
	(0.042)	(0.042)	(0.060)	(0.093)	(0.042)	(0.042)	(0.060)	(0.093)
Import × $Strength_{out}$		−0.001***	−0.001	−0.004***				
		(0.001)	(0.001)	(0.001)				
Import × $Strength_{in}$		0.001***	−0.000	0.001***				
		(0.000)	(0.000)	(0.000)				
Import × Essentiality		−0.004***	−0.003*	−0.004**				
		(0.001)	(0.002)	(0.002)				
Export × $Strength_{out}$						−0.002***	0.000	−0.006***
						(0.001)	(0.001)	(0.001)
Export × $Strength_{in}$						0.002***	0.001***	0.002***
						(0.000)	(0.000)	(0.001)
Export × Essentiality						−0.004***	−0.007***	0.002
						(0.001)	(0.002)	(0.002)
N	137,956	137,956	65,639	72,317	137,956	137,956	65,639	72,317
R^2	0.388	0.389	0.357	0.310	0.388	0.389	0.357	0.310
F Statistic	4,085.666***	3,369.078***	1,408.953***	1,349.365***	4,084.467***	3,370.141***	1,410.481***	1,347.189***

Given the high correlation between Import and Export, the two variables have been taken into consideration separately. Unreported control variables include Employment. ***, **, * denote significance at the 1%, 5%, 10% level. Standard errors in parentheses.

Conclusions

Understanding how firm-level systemic risk evolves and reacts to external disruptions is key to explaining shock propagation in economic networks. We analyzed the temporal evolution of the Economic Systemic Risk Index (ESRI) (34) for firms in the Budapest VAT transaction network (2015–2022) and compared empirical patterns with the stripe-corrected gravity model (73), a null model that constrains the input by sector and output volumes of each firm in the economy. In normal times, ESRI is highly persistent, reflecting stable structural regularities. This persistence breaks sharply during COVID-19 (2020–2022), when systemic risk declines both absolutely and relative to the null benchmark. This decorrelation shows that systemic importance is not a fixed firm attribute but an emergent, context-dependent property of the production network.

We interpret the observed ESRI reduction during the pandemic as evidence of an adaptive behavior: when faced with factory closures, mobility restrictions, and disruptions to international trade, firms actively rewire their supply-chain connections, leading to a global network configuration that is more resilient than predicted by the null model. This result suggests that decentralized firm-level optimization, even in the absence of coordination or planning, can give rise to collective resilience. More broadly, our findings support a view of the economy as a complex adaptive network rather than a system that fluctuates around a fixed equilibrium. Sectoral heterogeneity further supports this dynamic view. While most initially high-risk firms experienced declining ESRI, the postal sector became increasingly systemically relevant during the pandemic, acting as a connectivity enabler. This shift, not captured by the null model, highlights the need for crisis policies that protect network coordinators and logistics providers, not only large producers.

Regression results reveal that international trade is strongly associated with ESRI, but only during the COVID-19 pandemic. This finding signals an effect of trade links on systemic risk in local production networks during crises. However, our evidence on mechanisms remain asymmetric. On the one hand, we find that export increases systemic risks more if companies develop their local supply connections as well, suggesting a link between global value chains and local systemic risk. On the other hand, we find no evidence for the propagation of international effects in the local system. However, imports increase systemic risks more for those companies that also increase their local inputs, suggesting that combining imported and local intermediary inputs can generate channels of shock propagation on the local level.

Overall, this work paves the way for a broader temporal analysis of systemic risk and shock propagation in economic networks, emphasizing the importance of adaptive behavior and contextual systemic relevance. Maximum-entropy models provide a useful normal-times benchmark (76), but persistent deviations during crises signal they cannot reproduce endogenous adjustments (87–89). In particular, the s-GM we use resembles a thermodynamic construction of networks at the Walrasian economic equilibrium (90, 91), according to which agents in an exchange economy care only about final allocations and are indifferent with respect to various market configurations (i.e. network structures) that realize the same allocations.[c] Therefore, comparison with the null model allows us to assess how far the empirical networks are from their thermodynamic equilibrium configurations induced by the production structure of each firm, and whether significant deviations appear in the presence of exogenous macroeconomic shocks (for a detailed discussion see Supplementary Materials S2).

We stress that the time span of our analysis covers years with different values of the reporting threshold. Our systematic filtering procedure (see Methods) is specifically meant to remove effects of the changing threshold and highlight other structural changes—in particular, the introduction of RTIR in 2017/2018 and the adaptive reconfigurations due to the COVID-19 pandemic in 2020. Of course, there could be confounding factors affecting our results, since the threshold change and these events both took place during the same years. Therefore, it may be possible that the filtering procedure cannot offset all the changes in network topology the threshold change is causing. Further analyses (see Supplementary Materials S1, S8 and S20 support the robustness of our filters and point to a changing link formation mechanism taking place during COVID. Nevertheless, a robust comparative analysis would ideally require a dataset that is homogeneous from the outset, with consistent reporting criteria throughout the selected time frame.

Another key limitation of our study is the computational intensity of ESRI, which restricted the analysis to Budapest and a limited null-model ensemble. Additionally, although Hungary faced lockdown restrictions similar to those of other European countries, a wider generalization of our results to other nations is not trivial. Given data availability, future work may extend the framework to broader contexts and incorporate measures of firm resilience and spatial exposure to better understand shock absorption and recovery. Further research is needed to get actionable insights on what the firms and economic policies could do to reduce systemic risk.

Methods

Data description and filtering

The Hungarian production network is obtained from VAT transaction data as follows. For every sales transaction between a supplier i and buyer j, we have the monetary value of the goods and services sold, V_{ji} in forints (HUF), and the tax amount paid T_{ji}. We use V_{ji} as an estimate for the volume w_{ij} of product type p_i delivered from i to j. We aggregate all transactions on a yearly basis by summing all exchanges between two firms that take place in a given year.

Transactions for years 2015 to 2017 appear in the dataset only if they exceed a reporting VAT threshold of $t = 1{,}000{,}000$ HUF (about 2,500 EUR), which was lowered in 2018 and completely removed in 2020. In order to make the whole dataset homogeneous we apply the same threshold of 2015 for all other years, thus removing transactions with value less than t. We also implement two additional filters. To build a local production network and remove possible geographical effects or biases, we only consider firms whose headquarters are based in Budapest (which represent 29% of the total firms in Hungary). Furthermore, in order to make the yearly networks easier to handle, for each snapshot we also remove the smallest firms, selected as those having a number of employees ≤ 11 and also a number of customers $k^{\text{out}} \leq 2$. See Table 2 for number of nodes and edges, and Supplementary Materials S1 and S3 for further information on the goodness of the filters.

Table 2 Number of firms and transactions for all yearly networks, before and after the filtering procedure.

Year	Pre-filtering		Post-filtering	
	Firms	Transactions	Firms	Transactions
2015	88,992	221,200	10,745	31,893
2016	93,258	225,165	11,032	32,967
2017	101,590	254,940	12,267	37,456
2018	272,410	1,373,207	19,224	74,866
2019	305,492	2,059,287	24,039	102,928
2020	440,715	12,457,336	24,921	111,953
2021	448,750	18,147,540	28,580	159,308
2022	457,239	19,050,904	30,098	159,308

The economic systemic risk index

The *Economic Systemic Risk Index* (ESRI) quantifies the systemicness of a firm by evaluating the output reduction experienced by the whole production network due to its failure. More in detail, the removal of a firm from the network (meaning that it stops buying from its suppliers and supplying to its customers) generates an upstream and a downstream shock, which are propagated to all other firms by recursively updating their production levels. The downstream shock propagates according to a generalized Leontief *production function* (34). Inputs from *essential* sectors set a Leontief-kind of constraint on the output of firms, while the inputs from *non-essential* sectors are treated in a linear way. The identification of essential products, according to their NACE4 industry classification, is provided by expert based surveys (25, 92), while the technical coefficients of the production function are calibrated on the empirical network. The shock propagation dynamics is iterated until convergence, when the final production level of every firm is used to compute the ESRI of the initially defaulted company. We remand the reader to (34) for full details of the method, and Supplementary S26 for the description of the specific setting we employ. Below is a brief description of the algorithm.

To represent the initial default of firm j, while other firms remain unaffected, the initial shock is set as $\psi_j = 0$ and $\psi_i = 1$ $\forall i \neq j$. Then, ESRI dynamics is based on: (i) the downstream impact matrix, whose element $\Lambda^{\mathrm{d}}_{ji}$ determines the fraction of production firm i loses if firm j stops supplying to it: $\Lambda^{\mathrm{d}}_{ji} = w_{j\to i}/s_{g_j\to i}$ if $g_j \in \mathrm{Ess}_i$ and $\Lambda^{\mathrm{d}}_{ji} = w_{j\to i}/\sum_{g'} s_{g'\to i}$ otherwise, where Ess_i is the set of products that are essential for firm i; (ii) the upstream impact matrix, whose element $\Lambda^{\mathrm{u}}_{ji} = w_{i\to j}/s^{\mathrm{out}}_i$ determines the fraction of production firm i loses if firm j stops buying from it.

After applying the initial shock, downstream and upstream shocks are propagated to any firm i through two iterative equations:

$$h^{\mathrm{d}}_i(n+1) = \min\left[\min_{g\in \mathrm{Ess}_i}\left(\tilde{\Pi}_{ig}(n)\right), \tilde{\Pi}_i(n), \psi_i\right] \tag{1}$$

$$h^{u}_i(n+1) = \min\left[\sum_j \Lambda^{\mathrm{u}}_{ji} h^{\mathrm{u}}_j(n), \psi_i\right] \tag{2}$$

Here n indicates the time step of the propagation, while $h^d_i(n)$ and $h^u_i(n)$ are the residual fraction of production of firm i at step n following the propagation of the downstream and upstream shock, respectively, with initial values $h^d_i(0) = h^u_i(0) = \psi_i$. In the equations above, the relative amount of essential inputs in sector $p \in \mathrm{Ess}_i$ available for firm g is $\tilde{\Pi}_{ig}(n) = 1 - \sum_{j\in g}\sigma_j(n)\Lambda^d_{ji}(1 - h^{\mathrm{d}}_j(n))$, the relative share of all non-essential inputs is $\tilde{\Pi}_i(n) = 1 - \sum_{g\notin \mathrm{Ess}_i}\sum_{j\in g}\sigma_j(n)\Lambda^d_{ji}(1 - h^{\mathrm{d}}_j(n))$, while the firms' market share, used as a proxy for how replaceable it is for its customers, reads $\sigma_j(n) = \min\left[1, s^{\mathrm{out}}_j / \left(\sum_{l\in g_j} s^{\mathrm{out}}_l h^d_l(n)\right)\right]$. After the two, independent shocks of Eqs. 1 and 2 have converged at $n = n^*$, the residual fraction of output of firm i is computed as $h_i(n^*) = \min\{h^d_i(n^*), h^u_i(n^*)\}$. Finally, the ESRI of firm i is computed by summing the output reduction of each firm in the network, stemming from its initial default:

$$\mathrm{ESRI}_i = \sum_j \frac{s^{\mathrm{out}}_j}{\sum_l s^{\mathrm{out}}_l}\left[1 - h_j(n^*)\right] \tag{3}$$

The stripe-corrected gravity model

Unbiased null models of networks can be constructed using constrained entropy maximization, which generates an ensemble of networks that are maximally random but preserve (constrain) selected features of the empirical system (93). In physics jargon, these networks are in "thermodynamic equilibrium" with the imposed constraints. This construction thus defines a rigorous null hypothesis that the constrained features can explain any observation on the network (74, 75). This validation approach is widely used in economic and financial network studies (87–89, 94–96).

In order to define unbiased null models of sparse weighted networks (which is the case of production networks), the typical recipe is to constrain node strengths (the total weight of incident connections) as well as node degrees (the number of connections per node) (97, 98). This can be done using a heuristic two-step procedure, known as *density-corrected gravity model* (d-GM), assessing first whether two nodes are connected and then the value of the link weights (99, 100). The first step is based on the canonical *configuration model* (101), where model parameters controlling the degrees can be replaced by node strengths using a *fitness ansatz* that connectivity is proportional to size (102, 103). The *stripe-corrected Gravity Model* (s-GM) (73) improves the d-GM recipe by constraining the sector-specific strength of each node (rather than the overall strength), preserving in this way the input-output productive structure of each firm. Specifically the model preserves, for each firm j, the total output $s^{\mathrm{out}}_j = \sum_i w_{j\to i}$ as well as the list of input quantities by industry g, namely $s_{g\to j} = \sum_{i\in g} w_{i\to j}$, which is a good proxy for the amount of products by industry that the firm uses to produce its output.

Quantitatively, the two-step procedure of the s-GM consists in first estimating the probability of a connection from supplier i to customer j:

$$p_{i\to j} = \frac{z_{g_i} s^{\mathrm{out}}_i s_{g_i\to j}}{1 + z_{g_i} s^{\mathrm{out}}_i s_{g_i\to j}}, \quad \forall\, i \neq j \tag{4}$$

where g_i is the industrial sector of the supplier i, and then assigning the link weight according to:

$$w_{i\to j} = \frac{s_i^{out} s_{g_i\to j}}{w_{g_i}^{tot} p_{i\to j}}, \quad \forall\, i \neq j \tag{5}$$

where $w_{g_i}^{tot} = \sum_{k\in g_i}\sum_j w_{k\to j} = \sum_{k\in g_i} s_k^{out} = \sum_j s_{g_i\to j}$ is the total outgoing strength of sector g_i. We employ the multi-z variant of the s-GM, thus we have a different parameter z_{g_i} for each industrial sector, which can be determined by solving the equations $\sum_{k\in g_i}\sum_{j\neq k} p_{k\to j} = L_{g_i}$ where $L_{g_i} = \sum_{k\in g_i}\sum_j a_{k\to j}$ is the number of outgoing links from sector g_i. Thus by construction the model preserves, on average, the total number of links as well as the out-strength and the in-strength by sector of each firm, reproducing the production structure of the empirical network:

$$\begin{aligned}\langle s_i^{out}\rangle &= \sum_j \langle w_{i\to j}\rangle = s_i^{out}\frac{\sum_j s_{g_i\to j}}{w_{g_i}^{tot}} = s_i^{out}, \quad \forall\, i,\\ \langle s_{g_i\to j}\rangle &= \sum_{k\in g_i}\langle w_{k\to j}\rangle = s_{g_i\to j}\frac{\sum_{k\in g_i} s_k^{out}}{w_{g_i}^{tot}} = s_{g_i\to j}, \quad \forall\, j, g_i\end{aligned} \tag{6}$$

Regression framework

To analyze the dynamics of firms' systemic risk, we estimate *ESRI* values of firm j at year t in a multivariate fixed-effect panel regression, following the formula:

$$\begin{aligned}\mathrm{ESRI}_{j,t} = \alpha + \beta_1(\mathrm{ESRI}_{\mathrm{model}})_{j,t} + \beta_2 E_{j,t} + \beta_3 LT_{j,t}\\ + \beta_4 IT_{j,t} + \beta_5(LT_{j,t}\times IT_{j,t}) + \mu_j + \epsilon_{j,t},\end{aligned} \tag{7}$$

where $\mathrm{ESRI}_{\mathrm{model}}$ denotes the average of ESRI values from the null model, E_j stands for firm size (number of employees), LT_j is the characteristics of local trade measured in the production network (out-strength, in-strength, essentiality score), IT_j denotes the value of international trade (import and export), μ_j is the firm fixed-effect and ϵ is the error term. This framework allows for assessing the determinants that can explain firms' systemic risk, beyond the null model expectations. The interaction term between LT and IT enables us investigate how international trade is related to local systemic risk, mediated by local trade channels.

Notes

[a]https://www.vatcalc.com/hungary/hungary-online-real-time-vat-cash-registers/
[b]https://www.storecove.com/blog/en/e-invoicing-in-hungary/?unbounce_brid=1699967181_5491104_e17e0a18c82a49f0b68fce7880aba2eb
[c]This parallel holds by assuming that constraints are imposed, not solved for (as endogenous outcomes emerging from technologies, preferences, and market clearing), that there are no agents, prices, supply and demand, nor conditions on costs, profits, efficiency.

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Supplementary material

Supplementary material is available at *PNAS Nexus* online.

Competing interest

The authors declare no competing interests.

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Author contributions

Study conception and design: BL, RDC, GC. Data analysis: AM, BL. Contributed methods: AM, GC. Discussion and interpretation of results: AM, BL, RDC, GC. Manuscript preparation: AM, BL, RDC, GC.

Preprints

A preprint of this article can be found at https://arxiv.org/abs/2506.21426.

Data availability

This manuscript was prepared using the datasets of the Hungarian Central Statistical Office. These datasets are not publicly available and can only be accessed after authorization by the institution and after signing a declaration to ensure data protection. They are available in-loco at the DataBank of KRTK-KTI, 1097 Budapest, Tóth Kálmán utca 4. Access to the data is organized through the Head of the Data Bank, Melinda Tir (ELTE Center for Economic and Regional Studies; tir.melinda@krtk.hu), who also provides the necessary infrastructure; however, the legal decision on granting access rests with the Hungarian Central Statistical Office.

Sample codes and datasets used to produce our results are available at https://github.com/mnlknt/Evolution-and-reconstruction-of-firm-level-systemic-risk.

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