The Architecture of Power: Patterns of Disruption and Stability in the Global Ownership Network

Article *in* SSRN Electronic Journal · January 2019

DOI: 10.2139/ssrn.3314648

James B Glattfelder
MQ Learning Academy

The architecture of power: Patterns of disruption and stability in the global ownership network

James B. Glattfelder[1], Stefano Battiston[1]

[1] *Department of Banking and Finance, University of Zurich, Andreasstrasse 15, 8050 Zurich, Switzerland*

It is today widely understood that the global economy is a densely interconnected network[1–6] that affects the everyday lives of billions of people. In particular, the network structure can amplify financial instability[7–9], exacerbate wealth and income inequality[10,11], and hamper investments in climate change mitigation[12]. However, little is known about how the global economic network evolves over time and specifically how a major disruptive event, such as the 2008 financial crisis, may have reshaped its structure. Here we show that, although many actors gain or lose their position of influence over time, overall, economic power structures are remarkably robust to shocks and that power remains extremely concentrated in the hands of a few individuals and organisations. While previous works have been restricted by limitations, our analysis represents the first comprehensive analysis of the entire global ownership network over time. Our results provide an explanation for how a global economic shock, while negatively affecting many individuals, can have only a marginal impact on the existing power structures.

Understanding the evolution of the global economic network is crucial for building a sustainable society. However, previous research has been restricted by data and computational limitations[4,13–17]. Here we address this gap in the literature by analysing[*] the emerging power structures in the global ownership network, their evolution in time, and the meaning for inequality. While economic networks comprise several types of relations, such as credit lending or supply of goods and services, the network of ownership[13,14,16–20] best reflects the relations of power[21,22] among economic actors. The importance of shareholder power has only seen little attention in the mainstream economic literature so far[22]. However, in the last decades, the prominent role played in financial markets by institutional shareholders, such as pension funds and asset managers, has been widely documented[4,16,23–25]. The view that institutional shareholders do not influence the management of owned firms is being challenged by mounting evidence[15,16,26]. Currently, schol-

[*] To aid understanding, an FAQ can be found at `http://tiny.uzh.ch/LA` and source code implementing the methodology at `https://github.com/jbglattfelder/influenceindex`.

ars from corporate law, management science, and corporate finance are debating the implications of shareholder empowerment, not only for corporate governance matters[27], but also in terms of macro-economic growth and financial stability[22]. In particular, the potential systemic importance of large assets managers on the economy is the object of a global policy debate[†]. Some scholars[22] also foresee a continued increase in shareholder activism (i.e., the level of engagement of shareholders in exercising their rights as owners) even for asset managers traditionally thought to be inactive shareholders, such as passive investment funds (i.e., with strategies that track the market) (see also Supplementary Information). Prominent examples are recent cases of institutional shareholders, such as BlackRock, demanding energy companies, such as ExonMobil, to assess their risk in relation to global climate policies[‡]. Sociologists and political economists have long investigated ownership in the context of shareholder power[13,26,28,29], because ownership is associated with varying levels of corporate control via voting rights at shareholder meetings[3,30–32]. However, through chains of ownership, shareholders have a means to influence, intentionally or not, the activities of firms owned directly and indirectly. As a result, the structure of ownership networks has implications not only for individual firms, but also for the economy at wide[3,4,13,14,33–35]. We contribute to the debate on shareholder power by developing two measures of shareholder influence in terms of the monetary value of the portfolio of firms owned directly and indirectly. Next to the ability to rank individual shareholders by economic influence, our methodology can be crucially applied to groups of shareholders, allowing for the identification of power structures in the network. All previously unresolved theoretical and conceptual issues related to the existence of cycles in the network have been resolved. Specifically, we applied our methodology to the entire global corporate ownership network and tracked its evolution in time.

Analysing its topology, we find that, despite the diversity of firms in the dataset in terms of geography, economic sector, and size, the *largest connected component* (LCC) in the network always contains most of the economic value of firms ($87.5\% \pm 1.5\%$) (see Table S7 in Supplementary Information), while the other connected components (OCC) are economically irrelevant

[†] *The Economist*: *The monolith and the markets*, (2013) http://www.economist.com/node/21591164; *The rise of BlackRock* (2013), http://www.economist.com/node/21591174; *Stealth socialism*, (2016) http://www.economist.com/node/21707191.

[‡] *The Washington Post*, May 31 2017, https://www.washingtonpost.com/news/energy-environment/wp/2017/05/31/exxonmobil-is-trying-to-fend-off-a-shareholder-rebellion-over-climate-change; similarly, *Bloomberg*, May 12 2017, https://www.bloomberg.com/news/articles/2017-05-12/blackrock-to-back-climate-shareholder-proposal-at-occidental.

and fragmented. Furthermore, the LCC has a *bow-tie* structure (Fig. 1c, 1d). This is a prevalent architecture in the complex network literature, found in many natural and engineered systems[§], containing four main components: a *core* or *strongly connected component* (SCC, in which nodes are all directly or indirectly connected to each other), an IN component (where shareholders own firms in the SCC, directly or indirectly, but not vice versa), an OUT component (in which firms are owned directly or indirectly by shareholders in the SCC, but not vice versa), and the remaining tubes and tendrils (TT). A distinct feature of the global ownership network is that the SCC and the IN are very small compared to the OUT and TT (see Table S6 in Supplementary Text Information). Since the SCC and IN are the components where economic value tends to flow to, these proportions have implications in terms of the concentration of influence. With respect to the evolution of the network topology, we find that, over time, the main network structure, the LCC, remains stable in size (i.e., $6,72 \pm 0,78$ million nodes) (see Table S6 in Supplementary Information), despite an increase in the total number of nodes (from 16.6 million in 2007 to 35.8 million in 2012). Within the LCC, we however do see a structural change from 2008 to 2009. The SCC and the IN components shrink significantly in node number (by 26.37% and 40.26%, respectively, see Tables S8 and S9 in Supplementary Information). However, their size remains approximately stable in the years following 2009, as seen in Fig. 2a. The loss of nodes by the IN and SCC is due, to a large extent, to nodes that have migrated to the TT and OUT components, respectively, implying that they have lost their indirect ownership links with the SCC.

In order to quantify and identify the power structures within the network, we first compute the Influence Index values for all individual economic actors. Then we analyse the location of the most influential actors in the various bow-tie components. This inquiry points to the SCC and the IN as being the most relevant power structures in the network (see Table S10—S15 in Supplementary Information). By computing the cumulative Influence Index of each network component within the bow-tie, we can, for the first time, quantify their group influence in monetary terms. We find that, although most of the nodes are located in the OUT and the TT (over 99.6% of LCC nodes), the components with the largest cumulative Influence Index value are the IN and the SCC. On average $\langle \xi^{\text{IN}} \rangle = 23.63\% \pm 2.03\%$ of the yearly total operating revenue in the network, and $\langle \xi^{\text{Core}} \rangle = 18.34\% \pm 1.93\%$ (see Table S19 in Supplementary Information). In other words, the IN and SCC, acting as a group, can potentially influence a total economic value, in terms of operating

[§]E.g., metabolic networks, gene networks, the immune system, the World Wide Web, Wikipedia, computer networks, networks of online communities, interaction structures in social networks, and production networks, next to economic networks.

revenue, respectively ranging from 19.1 to 31.3 trillion USD and from 17.1 to 23.0 trillion USD. In contrast, the cumulative Influence Index for the TT is $\langle \xi^{\mathrm{TT}} \rangle = 11.17\% \pm 0.56\%$, while for the OUT $\xi^{\mathrm{OUT}} = 0$ (by construction, since all the actors in the OUT, as a group, are at the end of the ownership chain).

Furthermore, we find that even within the SCC the distribution of the individual Influence Index values is very skewed (see Fig. S18 in Supplementary Information), i.e., a few top actors accumulate most of the economic influence. We thus select the set of actors in the SCC with a value of ξ_i in the top 5% quantile of the SCCs individual Influence Index distribution. This set corresponds to a handful of exceptionally influential actors, who, since they are all part of the SCC, are also highly interconnected and strategically positioned in the network. In line with previous studies that hinted at a similar quintessential power structure [4,15], we denote this set of actors as the *super-entity* (SE). Its yearly size ranges from 101 to 150 nodes (see Table S21 in Supplementary Information) and its cumulative Influence Index value is $\langle \xi^{\mathrm{SE}} \rangle = 16.74\% \pm 2.98\%$ or approximately 16.2 to 20.3 trillion USD (see Table S22 in Supplementary Information). Put in perspective, less than 0.0009% of the actors in the entire global ownership network have the potential to influence slightly more than one sixth of the operating revenue of firms worldwide. In terms of the network evolution, we find a subset of 70 nodes remaining in the SE across all years. Out of the whole global ownership network, comprised of dozens of millions of nodes, this group represents the ultimate distillate of shareholder power (see Table S23 in Supplementary Information). See Fig. 3a and 3b for an illustration of all the power structures and some of their major economic actors. In Fig. 4 a graph layout of a selection of the nodes in the LCC is shown. Before the crisis in 2007, $\xi^{\mathrm{IN}} \approx \xi^{\mathrm{Core}} \approx \xi^{\mathrm{SE}} \approx 20.5\% \pm 1.1\%$. In 2008, both the SCC and the SE lose influence, while the IN gained: $\xi^{\mathrm{Core}} = 17.80\%$, $\xi^{\mathrm{SE}} = 16.18\%$, and $\xi^{\mathrm{IN}} = 24.77\%$. After this initial shock, the Influence Index values remain stable for the following years (Fig. 2b).

Our work provides a way to quantify, in monetary terms, the influence over the economic value of both individuals and groups of actors. We find that the individual Influence Index values are distributed extremely unequally across economic actors in the world and it is furthermore concentrated in specific power structures. While the fate of individual actors is uncertain as they may gain or lose their influence over time, the power structures have not only survived the shock of the 2008 financial crisis but have been remarkably stable ever since. There are several market and policy issues on which the actors within the power structures (i.e., SCC, IN, and SE) may have aligned interests that, in contrast, are not fully aligned with the economy and society as a whole (see Supplementary Information). Examples include: climate action[12], considered by many policy makers as one of the greatest examples of market failure in human history*; corporate tax avoidance [35,36], anti-competitiveness [37]; and collective moral hazard in financial stability[38]. As a result, while structural robustness is usually regarded as a feature of successful ecosystems in nature[39,40], here, the robustness of structures associated with extreme concentration of power suggests the need for more innovation in order for the global economy to embrace a more sustainable and inclusive path.

1 Methods

Data We analysed a dataset derived from the Orbis database (see Methods in Supplementary Information), containing information on companies and their shareholders (e.g., other companies, natural persons, foundations, or governments) worldwide. From the raw data we constructed six yearly snapshots (2007–2012) of the global ownership network. For instance, for the year 2012 these efforts yielded a network comprised of 35,839,090 nodes and 27,307,642 shareholding links (see Table S1 in Supplementary Information).

The Influence Index An ownership relation refers to an economic actor holding equity shares in a firm. Shareholding relationships are described by an ownership matrix W, where the component $W_{ij} \in [0, 1]$ reflects the percentage of ownership that shareholder i holds in firm j. We further extend this notion to include indirect ownership. If firm j, in turn, owns W_{jk} shares in company k, there is an indirect ownership path from i to k via j. In terms of ownership percentages this can be expressed as $W_{ik} := W_{ij}W_{jk}$ (Fig. 1a). However, ownership alone does not take the economic value of companies into account. A frequently utilised proxy for such value is the operating revenue of company j, denoted as v_j (see Tables S2 and S3 in Supplementary Information). The product $W_{ij}v_j$ reflects the value associated with shareholder i, derived from its ownership in j. As a result, $p_i := \sum_j W_{ij}v_j$ yields the direct portfolio value of i. Similarly, we compute the indirect portfolio value, $\hat{p}_i$, along all indirect ownership paths (see Methods in Supplementary Information). The total portfolio value is defined as the sum of the direct and indirect values, $\chi_i := p_i + \hat{p}_i$. In the absence of cycles in the network (i.e., closed chains of ownership), the total portfolio value of each economic actor is easily computed using the adjacency matrix. However, the presence of cycles leads to theoretical and conceptual challenges that have previously remained unresolved[4,20].

*See e.g. Bank of England governor's famous speech on the "Tragedy of the Horizons" https://www.bis.org/review/r151009a.pdf

Here we present a novel methodology that, for the first time, allows the computation of the monetary value ξ_i of each shareholder's direct and indirect portfolio value, regardless of the complexity of the network structure. We refer to ξ_i as the Influence Index value. Its economic interpretation is the amount of value that shareholder i can directly or indirectly influence through its chains of ownership. In other words, the higher this number is for shareholder i (e.g., in USD), the greater the economic value that i is in the position to influence. What this index naturally does not capture is whether actor i decides to actually exert its influence and how (i.e., covertly or overtly). Intuitively, one can envision the economic value of owned companies flowing upstream through the weighted links and accumulating at each shareholder by traversing only the trails in the network (i.e., unique paths along which each node is only visited once). Our procedure preserve all links in the network but resolves the problem of double counting economic value by preventing it to flow through cycles (see Methods in Supplementary Information). In the absence of cycles, the total portfolio values and the Influence Index values coincide, i.e., $\xi_i = \chi_i$. However, they differ significantly in most cases. An example of the computation is shown in Fig. 1b. Without cycles: $\xi_1 = W_{12}v_2 + W_{13}v_3 = 2.0$. With a cycle: $\xi_1 = W_{12}v_2 + W_{13}v_3 + W_{12}W_{13}v_3 + W_{13}W_{32}v_2 = 1.5$. In summary, our methodology is a recursive algorithm that can be efficiently implemented on large networks and overcomes all previously reported problems (see Supplementary Information).

The cumulative Influence Index One crucial question relates to the collective influence of specific groups of shareholders. When such actors also own shares in other members of the same group, the Influence Index of this group cannot be simply computed by summing up the individual member's influence due to double counting issues. We extend the methodology to groups of nodes in the network by excluding the ownership links among the actors within the group under consideration, as seen in Fig. 1e. If $\mathcal{A}$ denotes a set of nodes in the network, $\xi^{\mathcal{A}}$ reflects the Influence Index value computed for the entire set of nodes. This quantity measures the economic value that the group as a whole can influence (see Methods in Supplementary Information) and it allows for the identification of power structures in the network.

1. Hidalgo, C. A., Klinger, B., Barabasi, A. L. & Hausmann, R. The product space conditions the development of nations. *Science* **317**, 482 (2007).

2. Schweitzer, F. *et al.* Economic networks: the new challenges. *Science* **325**, 422–5 (2009). URL `http://www.sciencemag.org/content/325/5939/422.abstract`.

3. Glattfelder, J. B. & Battiston, S. Backbone of complex networks of corporations: The flow of control. *Physical Review E* **80**, 36104 (2009). URL `http://arxiv.org/abs/0902.0878`. `0902.0878`.

4. Vitali, S., Glattfelder, J. B. & Battiston, S. The network of Global corporate control. *PLoS ONE* **6**, e25995 (2011). URL `http://arxiv.org/abs/1107.5728`. `1107.5728`.

5. Battiston, S. *et al.* Complexity theory and financial regulation. *Science* **351**, 818–819 (2016).

6. Battiston, S., Caldarelli, G., May, R., Roukny, T. & Stiglitz, J. E. The price of complexity in financial networks. *PNAS* **113**, 10031–10036 (2016).

7. Haldane, A. G. & May, R. M. Systemic risk in banking ecosystems. *Nature* **469**, 351–5 (2011). URL `http://dx.doi.org/10.1038/nature09659`.

8. May, R. M., Levin, S. A. & Sugihara, G. Complex systems: ecology for bankers. *Nature* **451**, 893–5 (2008). URL `http://dx.doi.org/10.1038/451893a`.

9. Bardoscia, M., Battiston, S., Caccioli, F. & Caldarelli, G. Pathways towards instability in financial networks. *Nature Communications* **8**, 14416 (2016). URL `http://arxiv.org/abs/1602.05883`. `1602.05883`.

10. Chin, G. & Culotta, E. What the numbers tell us. *Science* **344**, 818–821 (2014). URL `http://science.sciencemag.org/content/344/6186/818`.

11. Piketty, T. & Saez, E. Inequality in the long run. *Science* **344**, 838–843 (2014).

12. Battiston, S., Mandel, Antoine Monasterolo, I., Schuetze, F. & Visentin, G. A Climate stress-test of the financial system. *Nature Climate Change - published online* **7**, 283–288 (2017).

13. Kogut, B. & Walker, G. The small world of Germany and the durability of national networks. *American Sociological Review* **66**, 317–335 (2001).

14. Corrado, R. & Zollo, M. Small worlds evolving: governance reforms, privatizations, and ownership networks in Italy. *Industrial and Corporate Change* **15**, 319–352 (2006).

15. Haberly, D. & Wójcik, D. Earth incorporated: Centralization and variegation in the global company network. *Economic Geography* **93**, 241–266 (2017). URL `http://papers.ssrn.com/sol3/papers.cfm?abstract{\_}id=2699326`.

16. Fichtner, J., Heemskerk, E. M. & Garcia-Bernardo, J. Hidden power of the Big Three? Passive index funds, re-concentration of corporate ownership, and new financial risk. *Business and Politics* **19**, 298–326 (2017). URL `http://papers.ssrn.com/sol3/papers.cfm?abstract{\_}id=2798653`.

17. Brancaccio, E., Giammetti, R., Lopreite, M. & Puliga, M. Centralization of capital and financial crisis: a global network analysis of corporate control. *Structural Change and Economic Dynamics* **45**, 94–104 (2018).

18. Scott, J. Networks of corporate power: A comparative assessment. *Annual Review of Sociology* **17**, 181–203 (1991).

19. Garlaschelli, D., Battiston, S., Castri, M., Servedio, V. D. & Caldarelli, G. The scale-free topology of market investments. *Physica A: Statistical Mechanics and its Applications* **350**, 491–499 (2005).

20. Glattfelder, J. B. *Decoding Complexity: Uncovering Patterns in Economic Networks* (Springer, Heidelberg, 2013).

21. Weber, M. *Economy and Society: An Outline of Interpretive Sociology* (University of California Press, Berkeley, 1978).

22. Hill, J. G. & Thomas, R. S. *Research Handbook on Shareholder Power* (Edward Elgar Publishing Limited, Cheltenham, 2015).

23. Drucker, P. F. *The Unseen Revolution: How Pension Fund Socialism Came to America* (Heinemann, London, 1976).

24. Davis, G. F. A new finance Capitalism? Mutual funds and ownership re-concentration in the United States. *European Management Review* **5**, 11–21 (2008).

25. Davis, G. F. After the corporation. *Politics & Society* **41**, 283–308 (2013).

26. Peetz, D. & Murray, G. The financialization of global corporate ownership. In Murray, G. & Scott, J. (eds.) *Financial Elites and Transnational Business* (Edward Elgar Publishing Limited, Cheltenham, 2012).

27. Friel, N., Rastelli, R., Wyse, J. & Raftery, A. E. Interlocking directorates in irish companies using a latent space model for bipartite networks. *Proceedings of the National Academy of Sciences* **113**, 6629–6634 (2016).

28. Domhoff, G. W. *Who Rules America?* (Englewood Cliffs, New Jersey, 1967).

29. Nitzan, J. & Bichler, S. *Capital as Power: A Study of Order and Creorder* (Routledge, New York, 2009).

30. La Porta, R., Lopez-de Silanes, F. & Shleifer, A. Corporate ownership around the world. *Journal of Finance* **54**, 471–517 (1999).

31. Goergen, M., Martynova, M. & Renneboog, L. Corporate governance convergence: Evidence from takeover regulation reforms in {E}urope. *Oxford Review of Economic Policy* **21**, 243–268 (2005).

32. Chapelle, A. & Szafarz, A. Controlling firms through the majority voting rule. *Physica A* **355**, 509–529 (2005).

33. Aguilera, R. V. & Jackson, G. The cross-national diversity of corporate governance: Dimensions and determinants. *Academy of Management Review* **28**, 447–465 (2003).

34. Wheeler, D., Colbert, B. & Freeman, R. E. Focusing on value: Reconciling corporate social responsibility, sustainability and a stakeholder approach in a network world. *Journal of General Management* **28**, 1–28 (2003).

35. Garcia-Bernardo, J., Fichtner, J., Heemskerk, E. M. & Takes, F. W. Uncovering offshore financial centers: Conduits and sinks in the global corporate ownership network. *Scientific Reports* **7**, 6246 (2017). URL `https://arxiv.org/abs/1703.03016`.

36. Brown, J. L. & Drake, K. D. Network ties among low-tax firms. *The Accounting Review* **89**, 483–510 (2013).

37. Azar, J. & Schmalz, M. C. Common ownership of competitors raises antitrust concerns. *Journal of European Competition Law & Practice* **8**, 329–332 (2017).

38. Farhi, E. & Tirole, J. Collective moral hazard, maturity mismatch and systemic bailouts. *American Economic Review* **102**, 60–93 (2012).

39. Bascompte, J. Structure and dynamics of ecological networks. *Science* **329**, 765–766 (2010).

40. Yuan, X., Hu, Y., Stanley, H. E. & Havlin, S. Eradicating catastrophic collapse in interdependent networks via reinforced nodes. *Proceedings of the National Academy of Sciences* 201621369 (2017).

Acknowledgements We thank J.E. Stiglitz, M. D'Errico, D. Wójcik, and E.M. Heemskerk for fruitful discussions and feedback on this work. We acknowledge support from the European Commission's FP7 Program through the grant SIMPOL 610704 and the H2020 Program through the grants DOLFINS 640772 and SEI METRICS 649982. S.B. acknowledges the financial support from the Swiss National Fund Professorship grant no. PP00P1-144689.

Competing Interests The authors declare that they have no competing financial interests.

Correspondence Correspondence and requests for materials should be addressed to james.glattfelder@uzh.ch.

Supplementary Information This file contains Supplementary Methods, Supplementary Text, Supplementary Figures S1-S19, Supplementary Tables S1-S23, and Supplementary References.

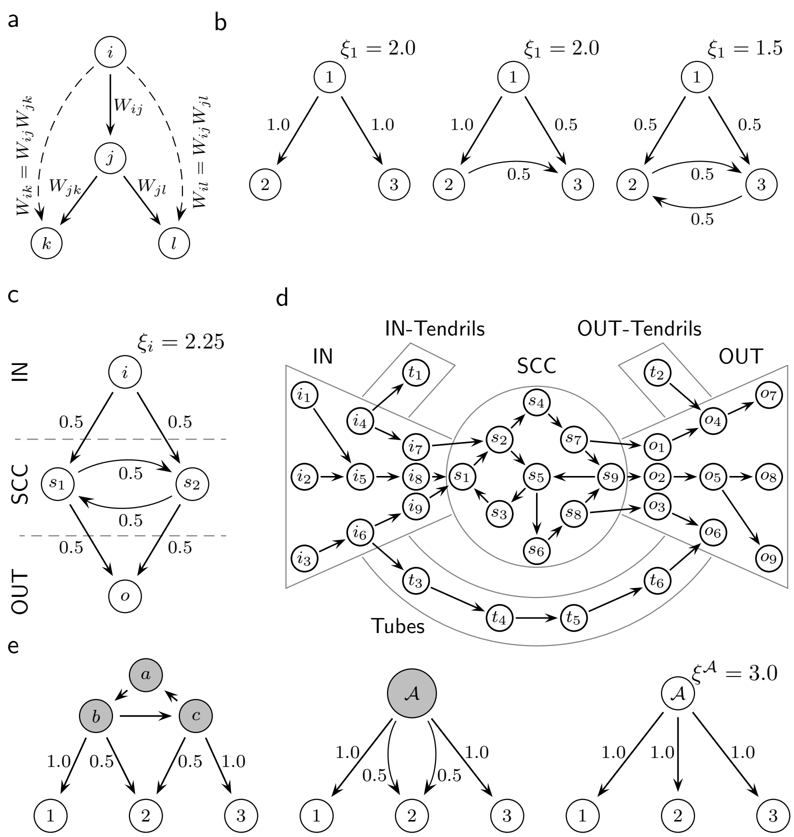

Fig. 1: **Ownership, the Influence Index, and the bow-tie topology. a**, Company i has W_{ij} percent of direct ownership in company j. Via j, it also has an indirect ownership in k and l. **b**, Assuming a unit value for all nodes ($v_j = 1$), shareholder 1 has an Influence Index value ξ_1 computed by traversing all trails and summing the weighted value of the firms it has direct and indirect ownership in. **c**, **d**, A bow-tie consists of an in-section (IN), out-section (OUT), and a strongly connected component (SCC) or core. Additionally, tubes and tendrils (TT) can be present. The largest connected component (LCC) of the global ownership network displays a bow-tie topology and is the focus of the empirical analysis. **e** Nodes a, b, and c are understood as a cohesive group and aggregated into a single node $\mathcal{A}$. After rewiring, the Influence Index value $\xi^{\mathcal{A}}$ represents the group's cumulative Influence Index.

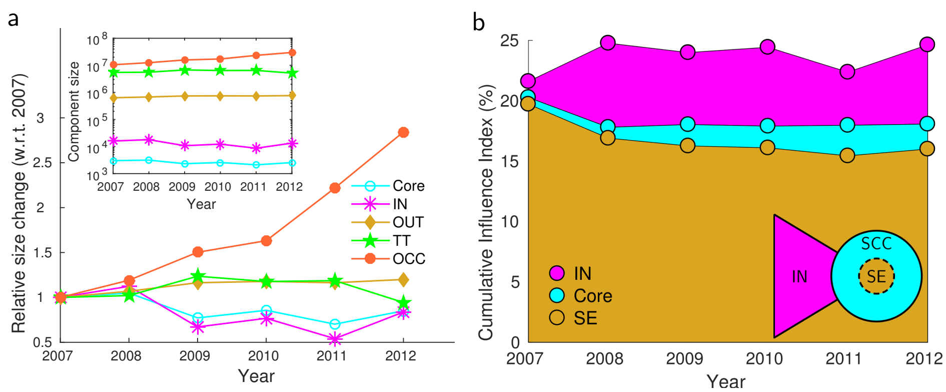

Fig. 2: **Evolution of the network and power structures.** . **a**, Number of nodes in the various sections of the network. Relative changes are shown. The inset depicts the absolute numbers. **b**, The effects of the global financial crisis on the power-structures in the network. Initial disruption in the super-entity (SE) and hence the core (SCC) followed by consolidation. Resilient behavior in the IN after the sovereign debt crisis.

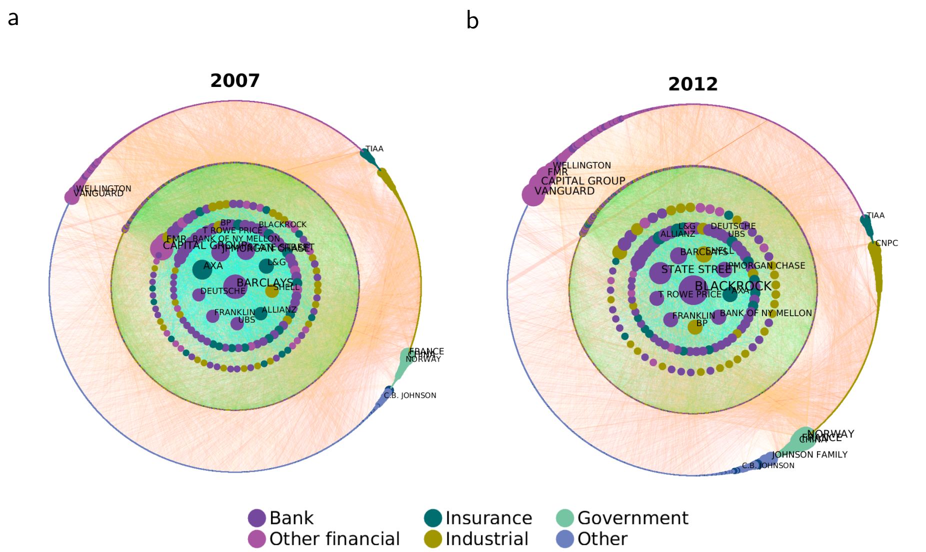

Fig. 3: **The power structures.** Network layout of the IN-section (outermost concentric layer) and the core (all the nodes in the four inner layers and the center). The core nodes are grouped as follows: the center is occupied by the actor with the highest Influence Index value. Then the next nine influencers by rank are placed in the innermost layer. Adding the next concentric layer completes the set of 70 nodes present in the super-entity of all the analyzed years. The next layer is given by the remaining nodes in the super-entity. Finally, the second-outer layer is given by the remaining nodes in the core. Nodes are scaled by Influence Index value and colored by type (see legend). All the nodes in the concentric layers are ordered clockwise by Influence Index value, starting in the 2nd quadrant. The nodes of the IN-section are first partitioned by type then ordered by influence. Links are shown for ownership stakes above 0.5%. The colors are defined as follows. Cyan: links between nodes in the super-entity. Green: all the remaining links in the core. Orange: links originating from a source node in the IN and a destination node in the core or the IN. For the yearly individual rankings, consult (see Supplementary Information). **a**, 2007 snapshot. **b**, 2012 snapshot

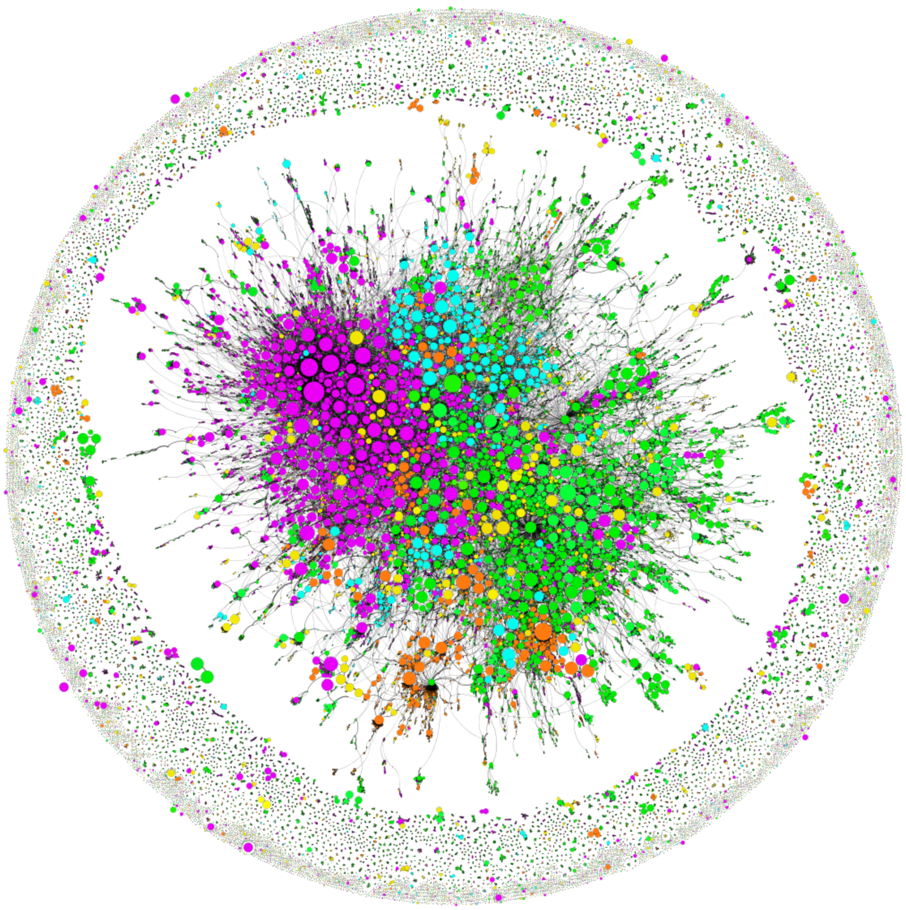

Fig. 4: **Zooming into the main network structure.** The layout of the top 1.2% of influential actors (i.e., 70,952) in the largest connected component (LCC) in 2012, with only their ownership links above 5% shown (i.e., 66'990), resulting in the halo of apparently isolated nodes, mostly from the tubes and tendrils (see Figure S13 in Supplementary Information). Nodes are scaled by influence and colored by country (pink: Anglo-Saxon; green: EU-28 plus CH and NO without GB and IE; cyan: Asia, orange BRICS; yellow: all others).

Supporting Information for

The Architecture of Power: Patterns of Disruption and Stability in the Global Ownership Network

James B. Glattfelder* and Stefano Battiston

*Corresponding author. E-mail: james.glattfelder@uzh.ch

This PDF file includes:

Methods
Supplementary Text
Figures S1 to S19
Tables S1 to S23
References

Contents

1 Methods

1.1 Data Description

Orbis[1] is a database from Bureau van Dijk (BvD) comprising detailed information on companies and their shareholders worldwide. For our analysis, we purchased historical data consisting of yearly snapshots from 2007 until 2012.

For a set of 109,841,682 economic actors (including companies, natural persons, families, foundations, research institutes, public authorities, states, and government agencies), located in 196 countries, the raw data contained many million ownership relations for each covered year. From these links, we select the directed and weighted ownership links (equity relations) corresponding to the BvD relationship type "single shareholders of first level" (Bureau van Dijk, 2014).

Such a relation means that BvD has received the information that a link exists between two entities. However, as a technical detail, such a link could be direct or indirect. Indirect ownership can occur for multiple reasons. For instance, when the information source indicates that entity i has a total stake in company j without specifying the path through which the ownership is held. Examples are major investment managers holding shares "via their funds". As a result, BvD lists two kinds of ownership percentages, denoted as "direct" and "total", where "total" represents the sum of the direct and indirect ownership percentages.

We addressed this technicality by employing the following simple procedure: whenever a direct ownership percentage is given we use that number, otherwise we utilize the total percentage, if available. We then treated these resulting numbers as the percentages of direct ownership relations in the yearly networks we constructed. Additional information assessing the quality of the links we extracted can be found in Section 1.3.

For the association of ownership with voting rights, see Section 2.2.2.

1.2 Constructing the Yearly Network Snapshots

From the raw data, after extensive data cleaning (e.g., by removing non-unique entities like "Unnamed private shareholders, aggregated"), the yearly global ownership networks can be constructed. In detail, for each year and for every usable ownership relation $i \rightarrow j$ the corresponding economic actors i and j are extracted from the pool of 109,841,682 entities and added as linked nodes to the yearly network. Hence these yearly network snapshots are directed and weighted graphs, as detailed in Table S1. This unique and exhaustive global ownership network, seen evolving in time, has never been analyzed before. Previous studies have focussed on subsections of limited scope, for instance, constructed around a set of 43,060 transnational corporations in 2007 (Vitali et al., 2011).

1.3 Link Data Quality and Completeness

It is important to note that the yearly network snapshots contain a distinct largest connected component (LCC, see Section 2.3), containing the most valuable nodes in the network (for more details on the economic value of nodes, see Section 1.5). This network structure further has a bow-tie pattern, detailed in Section 2.3. Hence, for our analysis, it suffices to focus only on this largest connected component for each year.

To assess the quality of the extracted ownership data, a straightforward test is to sum up all the incoming shareholding relations for all companies. In other words, for each company j

[1] `http://www.bvdinfo.com/en-gb/our-products/company-information/international-products/orbis`

	Raw data	Networks	
	Relations	Usable links	Matching nodes
2007	87,974,712	14,724,489	16,636,351
2008	102,049,208	16,261,139	18,807,808
2009	123,910,632	20,022,388	23,312,973
2010	141,309,243	20,594,177	24,356,469
2011	170,993,197	24,545,148	30,563,099
2012	213,578,698	27,307,642	35,839,090

Table S1. Constructing the yearly networks. Based on the raw data of historical ownership relations, the usable links are extracted and the corresponding nodes drawn from a set of 109,841,682 economic actors.

its incoming ownership coverage is summed as

$$\Theta_j := \sum_{i=1}^{k_j^{\text{in}}} W_{ij}, \tag{1}$$

where W_{ij} is the adjacency matrix and k_j^{in} the in-degree. For 100% ownership coverage, $\Theta_j = 1$.

In cases where $\Theta_j > 1$ we simply rescaled the corresponding ownership weights W_{ij} to regain $\Theta_j = 1$. This affected less than 0.6% of all the nodes in each yearly network snapshot.

A value $\Theta_j < 1$ indicates incomplete data. In such cases there is unfortunately no remedy at hand. Luckily, the data coverage for the ownership links is very good, as seen in Figure S1. For most nodes, the sum of incoming link weights Θ_j is indeed 100% and there is only a minor second peak around 50%.

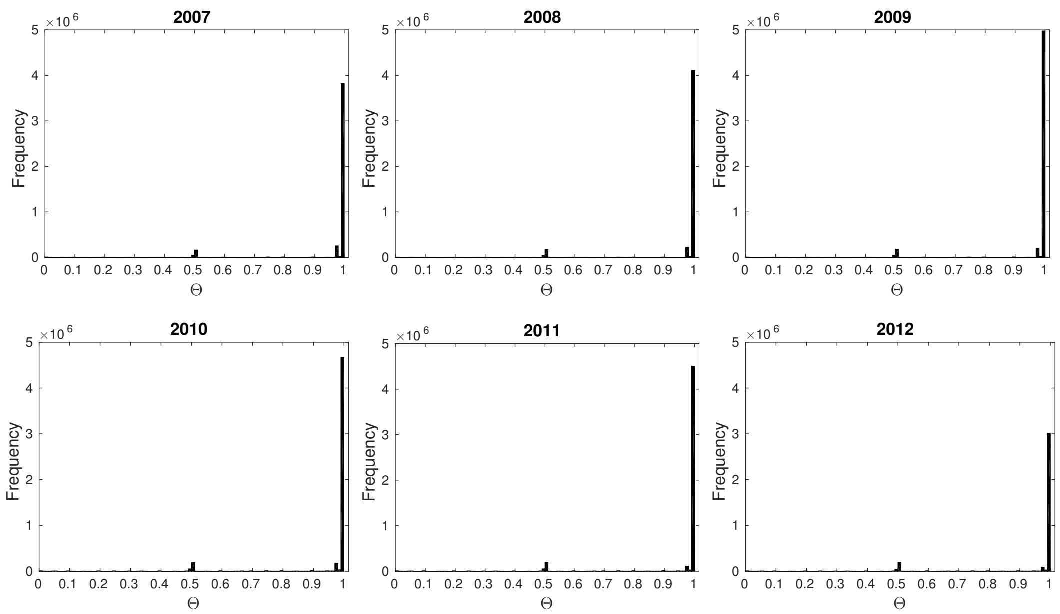

Figure S1. Ownership data coverage. Histogram of the sum of incoming weights Θ_j in the largest connected component after rescaling, shown for each year. Most nodes have complete ownership coverage.

In any case, the true problem associated with $\Theta_j < 1$ comes from the resulting loss of operating revenue v_j not able to "flow" through the missing links. The notion of the flow of value in an ownership network is related to our main methodology, the Influence Index $\{\xi_j\}$ associated with a node j, described in Section 1.6. As a consequence of incomplete link data, the Influence Index we compute will be underestimated due to these missing channels of propagation. We asses the potential loss of value due to incomplete coverage as follows. For a company j with an operating value v_j (in USD) the incurred loss is given by

$$\Phi_j := (1 - \Theta_j)v_j. \tag{2}$$

The corresponding total loss of operating revenue is captured by

$$\mathcal{L} := \sum_j \Phi_j. \tag{3}$$

We find this loss, expressed as a percentage of the total operating revenue in the yearly network snapshots, to be the following:

$$\begin{aligned} &\mathcal{L}_{2007} = 17.90\%; \qquad \mathcal{L}_{2008} = 18.72\%; \qquad \mathcal{L}_{2009} = 17.92\%; \\ &\mathcal{L}_{2010} = 18.32\%; \qquad \mathcal{L}_{2011} = 18.20\%; \qquad \mathcal{L}_{2012} = 17.19\%. \end{aligned} \tag{4}$$

However, this loss of operating revenue potentially results in the Influence Index being underestimated.

1.4 Degree Distribution

An analysis of the connectivity of the network for the nodes in the largest connected component is shown in Figure S2. The result for 2007 is very similar to what was reported in a previous, more restricted study (Vitali et al., 2011), a further indication that the data quality is consistent. See Section 2.7 for a comparison of this work to the 2011 study.

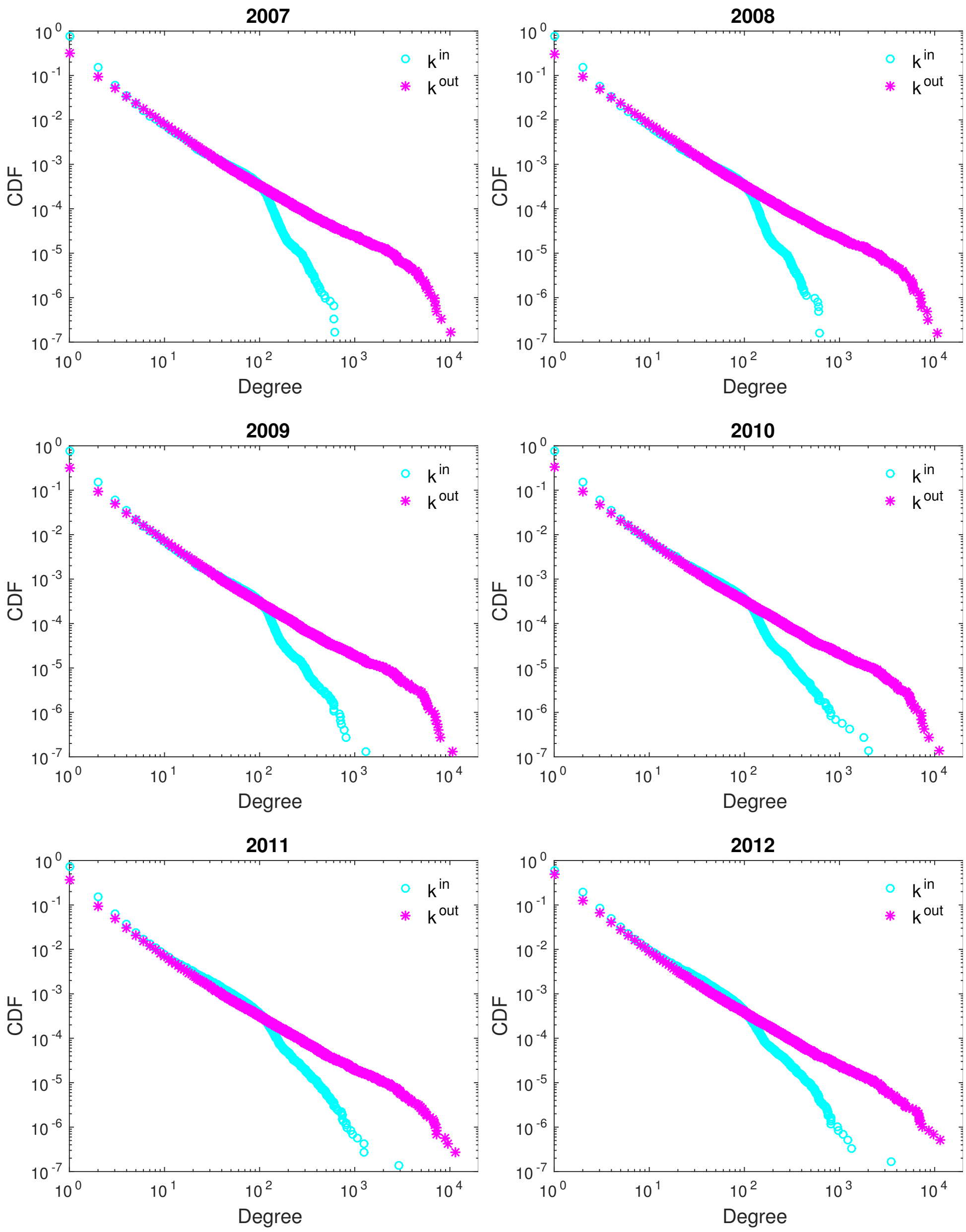

Figure S2. Degree distributions. CDF of k_i^{in} and k_i^{out} for the largest connected component in the network, shown for each year.

1.5 Incorporating Economic Value

Next to the ownership relations, Orbis also contains specific company data: financial information, industry classifications, and geographical locations. The relevant financial data is comprised of operating revenue v, total assets v^{ta}, and market capitalizations v^{mc}. In effect, these are three proxies for the economic value of companies. This additional layer of information adds to the heterogeneous nature of the data, increasing the challenge of processing and evaluating such an extensive set. The coverage of these value proxies is reported in Table S2. While market capitalization is only available for a limited set of listed companies, total assets introduces a bias in favor of financial institutions. In contrast, operating revenue is readily available and comparable across sectors. Therefore, we employ the consolidated operating revenue as the proxy for the companies' value in our analysis. As the historical dataset we analyzed was obtained in the fall of 2014, the three measures of value are expressed as USD at 2014 prices. In Table S3 the total value in the network for all three measures is shown.

In order to assess the coverage of the value we find in the yearly network snapshots, corresponding global aggregated figures need to be employed. The value of market capitalization can be trivially compared to the global market capitalization of all listed companies, as reported by the World Bank. The total of the operating revenue has no direct obvious global aggregate. Measures like the Gross Operating Surplus or the Industrial Production only make up a fraction of the total value of operating revenue retrieved and analyzed here. Nonetheless, the global Gross Domestic Product (GDP) can be utilized as a benchmark. This, and the global market capitalization, is reported in Table S3. In summary, the yearly network snapshots capture between 80% to 92% of the total global market capitalization: the minimal coverage occurred in 2009 with 80.36% and the maximal one in 2012 with 91.69%.

It should be noted that the operating revenue is a straightforward measure that quantifies business activities. In contrast, market capitalization incorporates future expectations in the valuation of companies. Figure S3 reveals that the only measure of value to suffer from the global financial crisis is market capitalization. Indeed, still in 2012 the pre-crisis levels of 2007 could not be recovered. In comparison, the global GDP took a small dip in 2009, only to recover the following year. The remaining measures of value are surprisingly unaffected by the dramatic and destructive turmoil of the crisis.

The distribution and evolution of the operating revenue in the bow-tie components of the network is seen in Section 2.3. Furthermore, the probability distributions of the three value measures found in the network are shown in Figure S4, restricted to the largest connected component. Finally, the proxy of value the Influence Index is based on is operating revenue.

	Number of firms with		
	v	v^{ta}	v^{mc}
2007	2,242,010	2,168,529	21,640
2008	2,733,421	2,639,398	24,247
2009	3,704,436	3,577,137	27,343
2010	3,981,925	3,837,234	30,653
2011	4,256,246	4,114,330	32,628
2012	4,004,331	3,912,161	33,645

Table S2. Value coverage in the network. Total number of firms with operating revenue v, total assets v^{ta}, and market capitalization v^{mc}.

	Operating revenue v	**Total assets** v^{ta}	**Market cap.** v^{mc}
2007	88,361,164,954,000	322,103,938,294,000	57,553,882,000,000
2008	95,706,385,061,000	349,540,761,777,000	28,480,059,000,000
2009	101,034,481,861,000	364,975,234,410,000	38,079,082,000,000
2010	118,354,452,745,000	405,720,541,733,000	44,544,674,000,000
2011	127,666,501,567,000	427,735,449,973,000	42,549,811,000,000
2012	127,134,546,757,000	437,871,011,115,000	48,750,477,000,000

Table S3. Value in the network. The total of the three measures of value in USD (2014 prices), shown for each year.

	Global market cap.	**Global GDP**
2007	64,471,812,116,978	56,868,119,606,496
2008	34,871,853,194,186	62,338,896,821,397
2009	47,380,718,189,093	59,043,815,701,262
2010	54,164,793,555,894	64,650,351,677,651
2011	46,499,122,204,875	71,521,442,021,877
2012	53,163,893,848,165	72,804,671,607,528

Table S4. Global measures of economic values. Global market capitalization of all listed companies and the global GDP are shown. All values in USD (2015 prices). Source World Bank.

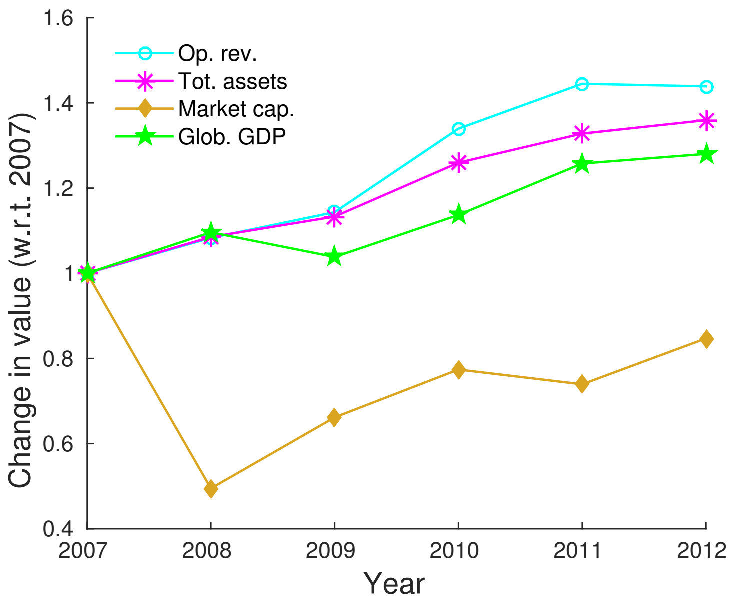

Figure S3. Change in value. The tree measures of value in the yearly network snapshots (operating revenue, total assets, and market capitalization, see Table S3) are analyzed, next to the global GDP (see Table S4). The changes in value, with respect to the value in 2007, are shown.

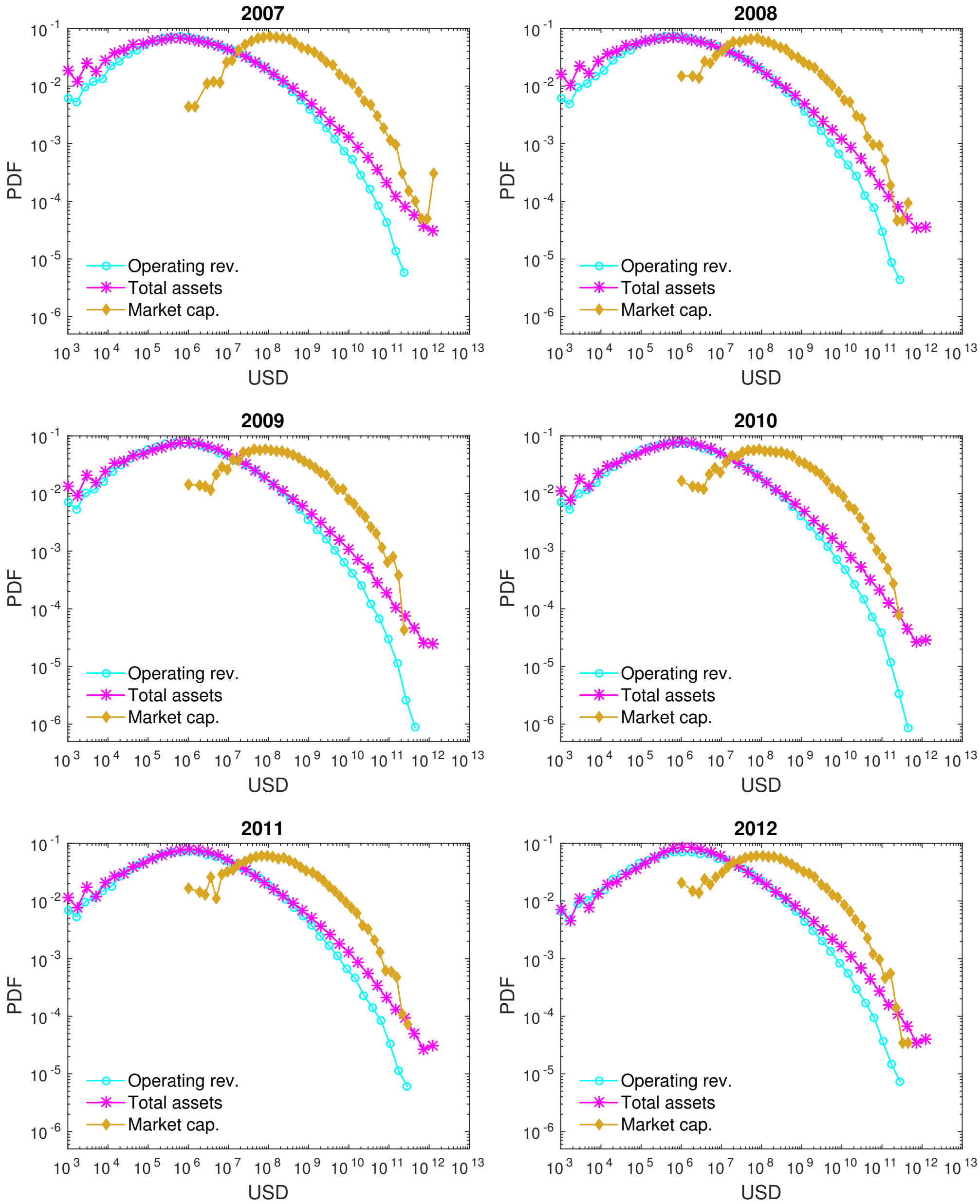

Figure S4. Value distribution. Probability density function of the three proxies of value in the largest connected component of the network, shown for each year.

1.6 Computing the Influence Index ξ_i

In graph theory, a graph G is defined as a pair $G = (V, E)$, consisting of a set of vertices (nodes) V and a set of edges (links or relations) E. If two vertices i and j in V are adjacent, then $e_{ij} \in E$. The adjacency matrix $A = A(G)$ of a graph is a matrix with rows and columns labeled by the graph vertices. The entry $A_{ij} = 1$ denotes the existence of the edge e_{ij}, otherwise $A_{ij} = 0$. For an undirected graph, A is always symmetric. If the graph is weighted, the entry W_{ij} of the adjacency matrix represents the edge from i to j with weight $W_{ij} \in [0, 1]$. See, for instance (West, 2001).

The study of real-world complex networks can be performed at three levels of analysis. Level 1 is a purely topological approach where the links A_{ij} either exists or not, yielding a binary adjacency matrix. Allowing the links to encode additional information, i.e., direction and weight, defines Level 2. At the highest level of detail, the nodes themselves are assigned an intrinsic degree of freedom, in the guise of non-topological state variables that can shape the network. These variables are sometimes also called fitness. However, for a 3-level analysis to be successful, it is essential that the methods utilized in the analysis of the complex network are appropriately adapted to the specific nature and domain of the network under investigation. See (Glattfelder, 2013).

The computation of the Influence Index represents the main methodology. Its definition is motivated by an extension of the notion of the portfolio value to a network. Hence, it is based on the economic value of the nodes (see Section1.5). We employ the operating revenue of companies as the proxy for value for the calculation of the Influence Index. The index holds a generic meaning as a centrality measure in directed and weighted networks, where the nodes are assigned some intrinsic quantity. Hence it is a measure considering all three levels of analysis. The crux of the matter, relating to cycles in the network, is solved in Section 1.6.3.

1.6.1 Step 1: The Total Portfolio Value

To summarize, an ownership relation $W_{ij} \in [0, 1]$ refers to the percentage of ownership shareholder i holds in company j. Hence the ownership (adjacency) matrix W represent the weighted and directed network. Furthermore, some nodes in the network are associated with an economic value. Due to this intrinsic, non-topological value, the network analysis performed here is at Level 3.

We utilize the operating revenue in USD (in 2014 prices), denoted by v_i, as the proxy for the economic value of companies. This allows the *direct portfolio value* of a shareholder i to be computed as

$$p_i = \sum_{j \in \Gamma(i)} W_{ij} v_j, \tag{5}$$

where $\Gamma(i)$ is the set of indices of the neighbors of i, denoting all the companies in the portfolio. However, in the presence of a network, this notion can be naturally extended to incorporate indirect ownership, thus defining the *indirect portfolio value*, by traversing all downstream paths reachable from i

$$\begin{aligned}\hat{p}_i = &\sum_{j \in \Gamma(i)} \sum_{k \in \Gamma(j)} W_{ij} W_{jk} v_k + \cdots + \\ &\sum_{j_1 \in \Gamma(i)} \sum_{j_2 \in \Gamma(j_1)} \cdots \sum_{j_{m-1} \in \Gamma(j_m)} W_{ij_1} W_{j_1 j_2} \cdots W_{j_{m-1} j_m} v_{j_m} + \cdots .\end{aligned} \tag{6}$$

As a result, one can assign the sum of the direct and indirect portfolio value in USD to each shareholder, retrieving the *total portfolio value*

$$\chi_i := p_i + \hat{p}_i. \tag{7}$$

In matrix notation, this can be re-expressed as

$$\chi = \sum_{l=1}^{\infty} W^l v, \tag{8}$$

where W^l encodes all paths of length l in the network. Thus Equation (8) considers all paths of all lengths in the network, retrieving the vector χ of the resulting total portfolio values. However, there is an alternative interpretation which is more generic in the sense that it applies to any complex network with weighted and directed edges, where the nodes are assigned an intrinsic, non-topological value.

1.6.2 Step 2: Centrality and Influence in Networks

The notion of centrality refers to a structural attribute of the nodes in a network which depends on their position in the network (Katz, 1953; Hubbell, 1965; Bonacich, 1972). In general, centrality refers to the extent to which a network is organized around a single nodes.

A popular family of centrality measures is called eigenvector centrality and quantifies the relevance of a node in a network. These are a feedback-type centrality measures, where a node is more central the more central its neighbors are themselves. Google's PageRank is an example of such a centrality measure (Page et al., 1999). A particular variant is the $c(\alpha, \beta)$-centrality introduced in (Bonacich, 1987), refining (Katz, 1953) and (Hubbell, 1965), defined as

$$c_i(\alpha, \beta) = \sum_j (\alpha + \beta c_j) A_{ij}, \tag{9}$$

where A is the adjacency matrix, c_i denotes the centrality score of node i, and α, β are scalar parameters. The solution is given by

$$c(\alpha, \beta) = \alpha(\mathbb{1} - \beta A)^{-1} A e, \tag{10}$$

e being the column vector of ones and $\mathbb{1}$ the identity matrix.

Similar to this expression, another centrality measure applied to ownership networks has been introduced (Glattfelder and Battiston, 2009; Vitali et al., 2011; Glattfelder, 2013). It is a recursive equation defining the centrality $\hat{\chi}$ as

$$\hat{\chi} = W \hat{\chi} + W v, \tag{11}$$

where W is the weighted adjacency matrix and v is a vector representing the values of the nodes. Equation (11) can be interpreted as follows: A node's centrality score is given by its neighbors' centrality scores plus the neighbors intrinsic value. The solution is given by

$$\hat{\chi} = (\mathbb{1} - W)^{-1} W v =: \widetilde{W} v. \tag{12}$$

By observing that

$$\widetilde{W} = \sum_{n=1}^{\infty} W^n, \tag{13}$$

it is revealed that

$$\hat{\chi} = \chi, \tag{14}$$

showing that the total portfolio value is an eigenvector centrality variant. In summary, the total portfolio value χ_i is comprised of the direct and indirect portfolio components p_i and $\hat{p}_i$, as seen in Equation (7). The computation of $\hat{p}_i$ requires the knowledge of all paths emanating from i. Alternatively, χ_i can also be derived using only local knowledge of the direct neighbors. As seen in Equation (11), it suffices to know the intrinsic value and the total portfolio value of all neighbors to compute a node's own total portfolio value.

In the absence of cycles, the *Influence Index value* ξ_i is simply defined as

$$\xi_i = \chi_i, \tag{15}$$

a centrality measure reflecting the influence of a node in the network. As it is also the value of the total portfolio measured in USD, there is a straightforward interpretation in economic terms as shareholder power, see Section 2.2.

The convergence criteria of the sum in Equation (13) is tied to the matrix $(\mathbb{1} - W)$ being non-negative and non-singular. A sufficient condition is that the Frobenius root is smaller than one, $\lambda(W) < 1$. This is ensured by the requirement that in each strongly connected component $\mathcal{S}$ there exists at least one node j such that $\sum_{i \in \mathcal{S}} W_{ij} < 1$. In an economic setting, this means that there exists no subsets of k firms ($k = 1, \ldots, n$) that are entirely owned by the k firms themselves. This is a condition which is fulfilled in ownership networks. See (Glattfelder and Battiston, 2009).

Finally, Equation (11) can be interpreted in terms of a physical system in which a quantity is flowing along the links of the network. In this picture, the value v_i associated with the nodes represents a physical quantity produced by them. Now χ_i is the inflow of the value node i registers from all nodes downstream. See (Glattfelder and Battiston, 2009; Vitali et al., 2011; Glattfelder, 2013) for details. In this new perspective, if v_i corresponds to an intrinsic economic value of the nodes, then the total portfolio value χ_i corresponds to the total inflow of value entering node i via its subnetwork of direct and indirect ownership relations. Colloquially, the flow of value in the network accumulates in certain nodes, bestowing them with influence, measured in monetary terms.

1.6.3 Step 3: Cycles

In ownership networks, cycles represent inter-firm cross-shareholdings. It has been realized that when the number of cycles in the network is large, for example in the core of the bow-tie (see Section 2.3), the measure χ_i is overestimated, due to the economic value flowing multiple times through the cycles (Baldone et al., 1998). Previous attempts at remedying this issue have themselves been plagued by additional problems (Baldone et al., 1998; Rohwer and Pötter, 2005; Vitali et al., 2011). See Section 1.6.7 for details.

Here we present a novel methodology that overcomes all previously reported problems. It is a simple recursive algorithm computing the Influence Index ξ_i, which can be implemented efficiently for large networks. In the absence of cycles, the algorithm simply retrieves the total portfolio value

$$\xi_i = \chi_i. \tag{16}$$

However, in the presence of cycles, the algorithm gives a lower bound

$$\xi_i < \chi_i, \tag{17}$$

thus circumventing the problem of overestimation.

The algorithm computes the direct and indirect portfolio values similarly to Equation (7)

$$\xi_i = p_i + \tilde{p}_i. \tag{18}$$

Crucially, $\tilde{p}_i$ does not take paths of all lengths in the network into account, like $\hat{p}_i$, seen in Equation (6). For the computation of $\tilde{p}_i$, only the *trails* in the network are traversed. These are unique paths where each node is only visited once, thus terminating any further flow through cycles. In the following, two examples are provided. See Section 1.6.6 for a summary and discussion of our methodology for networks with cycles. The algorithm is described in Sections 1.6.8 and 1.6.9. Finally, Section 1.8 concludes the methods description.

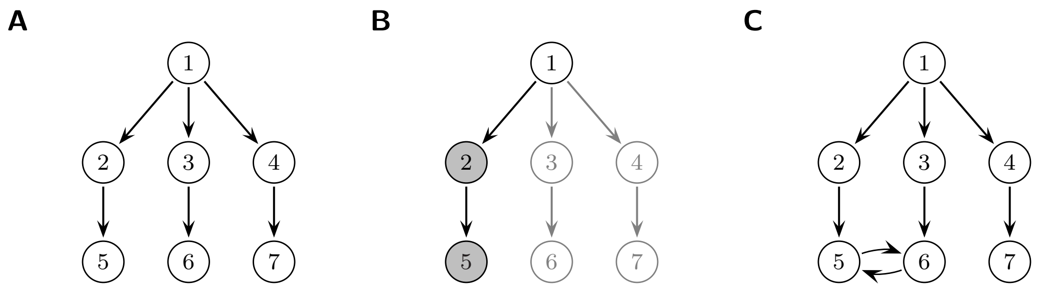

Figure S5. Computing the Influence Index for shareholder 1. (**A**) A simple network with a tree topology, comprised of three individual trails. Each trail is a downstream path, originating in node 1, where the nodes get visited only once. (**B**) The left-hand side trail is highlighted, yielding the direct portfolio value contribution $p_1^{\mathrm{L}} = W_{12}v_2$ and the indirect contribution $\tilde{p}_1^{\mathrm{L}} = \hat{p}_1^{\mathrm{L}} = W_{12}W_{25}v_5$. (**C**) Modifying the original network to contain loops.

1.6.4 A Simple Example

To illustrate, consider the simple network seen in Figure S5A. This network is comprised of three trails originating from node 1, one of which is highlighted in Figure S5B. The direct portfolio value has contributions from the left-hand, middle, and right-hand trails and is given by

$$\begin{aligned} p_1 &= p_1^{\mathrm{L}} + p_1^{\mathrm{M}} + p_1^{\mathrm{R}} \\ &= W_{12}v_2 + W_{13}v_3 + W_{14}v_4. \end{aligned} \tag{19}$$

Each one of the three trails is associated with an indirect portfolio, comprising the nodes 5 (Figure S5B), 6, and 7. The indirect portfolio value has again three contributions

$$\begin{aligned} \tilde{p}_1 &= \tilde{p}_1^{\mathrm{L}} + \tilde{p}_1^{\mathrm{M}} + \tilde{p}_1^{\mathrm{R}} \\ &= W_{12}W_{25}v_5 + W_{13}W_{36}v_6 + W_{14}W_{47}v_7. \end{aligned} \tag{20}$$

Because the network does not contain any cycles, $\hat{p}_1 = \tilde{p}_1$. Putting everything together yields the Influence Index value

$$\begin{aligned} \xi_1 &= p_1 + \tilde{p}_1 = p_1 + \hat{p}_1 = \chi_i \\ &= W_{12}v_2 + W_{13}v_3 + W_{14}v_4 + W_{12}W_{25}v_5 + W_{13}W_{36}v_6 + W_{14}W_{47}v_7. \end{aligned} \tag{21}$$

This value can also be computed by utilizing the adjacency matrix and taking the first component of the solution to Equation (12).

In Figure S5C this simple example is augmented by adding a loop. If we employ Equation (12), there is value flowing from node 5 to node 6 and vice versa. Indeed, there are now two infinitely long paths in the network

$$\begin{aligned} &1 \to 2 \to 5 \to 6 \to 5 \to 6 \to \cdots \\ &1 \to 3 \to 6 \to 5 \to 6 \to 5 \to \cdots \end{aligned} \tag{22}$$

The novel algorithm we propose, however, only takes the trails into account, namely

$$\begin{aligned} &1 \to 2 \to 5 \to 6 \\ &1 \to 3 \to 6 \to 5 \end{aligned} \tag{23}$$

In other words, if a previously visited node in a path is revisited, the algorithm terminates the computation. This procedure yields the following Influence Index value

$$\begin{aligned} \xi_1 = \quad & W_{12}v_2 + W_{13}v_3 + W_{14}v_4 \\ & + W_{12}W_{25}v_5 + W_{13}W_{36}v_6 + W_{14}W_{47}v_7 \\ & + W_{12}W_{25}W_{56}v_6 + W_{13}W_{36}W_{65}v_5, \end{aligned} \tag{24}$$

where the last line contains the contribution from the loop.

Simply by focussing on trails and hence not allowing the economic value to flow multiple times through the cycles, a straightforward and easily implementable algorithm is found that improves on previous calculations. Indeed, this computation can now also be generalized to arbitrary directed and weighted networks where the nodes are assigned an intrinsic, non-topological value. Again, see Sections 1.6.8 and 1.6.9 for details.

1.6.5 A Numerical Bow-Tie Example

In Figure S6A a generic bow-tie is shown, comprised of 27 nodes and 33 links. Under the following assumptions, the Influence Index ξ_i is computed for its nodes. The value of each node is one: $v_i = 1, \forall i$. Moreover, all incoming links are assumed to add up to 100% ownership, i.e., $\sum_j W_{ij} = 1, \forall i$. Finally, all incoming links have the same weight. In other words

$$\begin{aligned} W_{i_1 i_5} = W_{i_2 i_5} = W_{i_7 s_2} = W_{s_1 s_2} = W_{s_2 s_5} = W_{s_9 i_5} = 0.5, \\ W_{s_7 i_9} = W_{s_8 s_9} = W_{o_3 o_6} = W_{t_6 o_6} = W_{o_1 o_4} = W_{t_2 o_4} = 0.5, \\ W_{i_8 s_1} = W_{i_9 s_1} = W_{s_3 s_1} = 0.3333, \end{aligned} \tag{25}$$

and for all other links $W_{ij} = 1.0$. The algorithm computes the following:

$$\xi^{\text{in}} := \begin{pmatrix} \xi_{i_1} \\ \xi_{i_2} \\ \xi_{i_3} \\ \xi_{i_4} \\ \xi_{i_5} \\ \xi_{i_6} \\ \xi_{i_7} \\ \xi_{i_8} \\ \xi_{i_9} \end{pmatrix} = \begin{pmatrix} 2.239459375 \\ 2.239459375 \\ 8.978918750 \\ 8.562487500 \\ 3.478918750 \\ 7.978918750 \\ 6.562487500 \\ 2.478918750 \\ 2.478918750 \end{pmatrix}, \quad \xi^{\text{scc}} := \begin{pmatrix} \xi_{s_1} \\ \xi_{s_2} \\ \xi_{s_3} \\ \xi_{s_4} \\ \xi_{s_5} \\ \xi_{s_6} \\ \xi_{s_7} \\ \xi_{s_8} \\ \xi_{s_9} \end{pmatrix} = \begin{pmatrix} 6.437500000 \\ 12.124975000 \\ 2.353931250 \\ 6.999987500 \\ 8.583175000 \\ 5.791637500 \\ 6.041650000 \\ 5.041637500 \\ 7.333275000 \end{pmatrix}, \tag{26}$$

$$\xi^{\text{out}} := \begin{pmatrix} \xi_{o_1} \\ \xi_{o_2} \\ \xi_{o_3} \\ \xi_{o_4} \\ \xi_{o_5} \\ \xi_{o_6} \\ \xi_{o_7} \\ \xi_{o_8} \\ \xi_{o_9} \end{pmatrix} = \begin{pmatrix} 1.000000000 \\ 3.000000000 \\ 0.500000000 \\ 1.000000000 \\ 2.000000000 \\ 0.000000000 \\ 0.000000000 \\ 0.000000000 \\ 0.000000000 \end{pmatrix}, \quad \xi^{\text{tt}} := \begin{pmatrix} \xi_{t_1} \\ \xi_{t_2} \\ \xi_{t_3} \\ \xi_{t_4} \\ \xi_{t_5} \\ \xi_{t_6} \end{pmatrix} = \begin{pmatrix} 0.000000000 \\ 1.000000000 \\ 3.500000000 \\ 2.500000000 \\ 1.500000000 \\ 0.500000000 \end{pmatrix}. \tag{27}$$

This result is shown in Figure S6B.

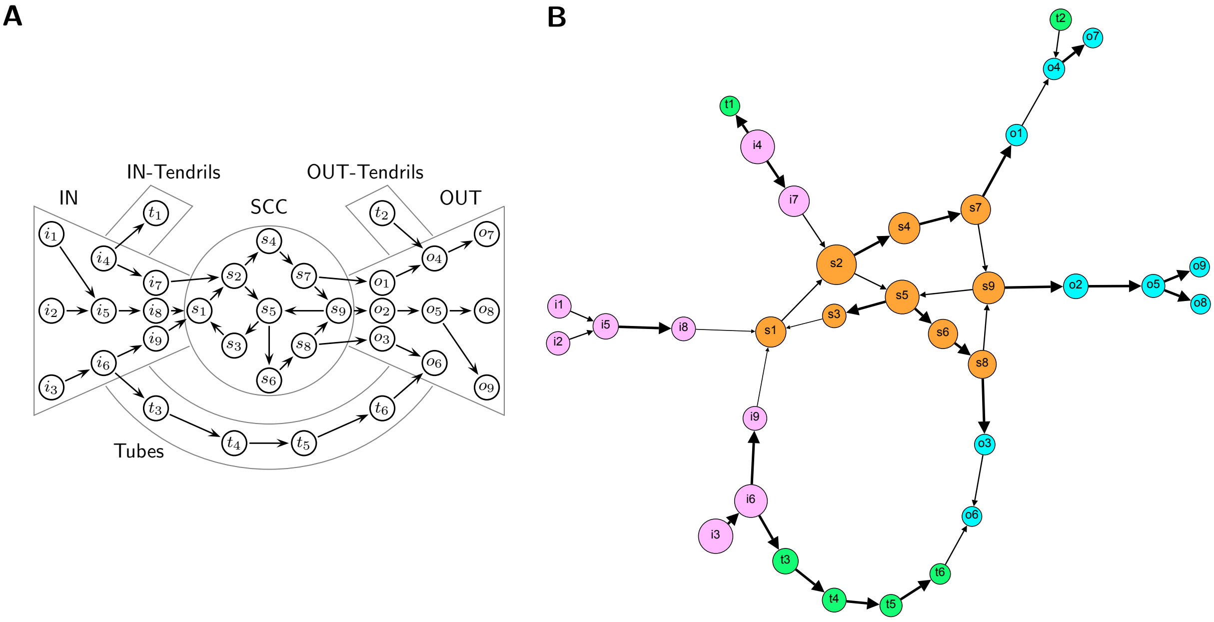

Figure S6. Bow-tie network topology. (**A**) An example consisting of an in-section (IN), an out-section (OUT), a strongly connected component (SCC) or core, and tubes and tendrils (TT). Note that these sections make up what is known as a connected component. (**B**) A different layout of the bow-tie seen in (A), where the node sizes are scales with their respective ξ_i values, the colors reflect the bow-tie components, and the links are scaled by the ownership weights. See details in the text.

1.6.6 Summary and Discussion

For directed and weighted networks without cycles, we do the following. By extending the notion of the direct portfolio value, defined in Equation (5), the indirect portfolio value is constructed in Equation (6), incorporating network effects. Combining these two measures yields the Influence Index value ξ_i for shareholder i. In simple terms, this quantity captures the fraction of the value of all downstream nodes of i that can flow up through the weighted ownership paths or, alternatively, the value i can potentially influence via its downstream subnetwork. It was shown in Equations (14) and (15) that the Influence Index value ξ_i is also a variant of an eigenvector centrality $\hat{\chi}_i$, defined in Equation (11).

In the presence of cycles, our methodology prevents the flow of value from passing multiple times through the loops in the network. This is achieved by focusing on the trails in the evaluation of the indirect portfolio. These are unique paths in the network, where each node is only visited once. In effect, ξ_i is algorithmically computed and gives a lower bound for the analytical eigenvector centrality.

Note that cutting the cycles in the network for the computation of the Influence Index results in the flow of value dissipating in the cycles. This induces the following effects. Firstly, not all the value for the algorithmic computation of ξ_i will flow to the root nodes, as would otherwise happen for the analytical calculation of $\hat{\chi}_i$. To illustrate, let $\mathcal{R}$ be a single root node in a tree network. In the analytical formulation, $\mathcal{R}$ will always accumulate the total of the value present in the nodes of its downstream network, irrespective of the specific topology

$$\hat{\chi}_{\mathcal{R}} = \sum_{i \in \mathcal{I}} v_i, \tag{28}$$

where $\mathcal{I}$ denotes the indices of all downstream nodes. In contrast, in the presence of cycles in the downstream network, the Influence Index value gets diminished due a fraction of the value not propagating through the cycle

$$\xi_{\mathcal{R}} < \hat{\chi}_{\mathcal{R}}. \tag{29}$$

Secondly, in the algorithmic formulation, the nodes in a cycle will themselves see less inflow of value and hence have a lower Influence Index value than in the analytical case. Now, the value only flows once through the cycle and does not get amplified. For a node $\mathcal{C}_i$ in a cycle

$$\xi_{\mathcal{C}_i} < \hat{\chi}_{\mathcal{C}_i}. \tag{30}$$

These are desirable features for networks with a bow-tie topology, as it prevents nodes in the SCC and IN from dominating the ranking. In the bow-tie example seen in Figure S6A one finds, for instance

$$\xi_{s_2} = 12.124975 < 17.99958 = \hat{\chi}_{s_2}, \tag{31a}$$

$$\xi_{i_1} = \xi_{i_2} = 2.239459375 < 2.7497900042 = \hat{\chi}_{i_1} = \hat{\chi}_{i_2}. \tag{31b}$$

In the context of an economic interpretation, the issue related to the overestimation of the relevance due to inter-firm cross-shareholdings has been previously addressed in the literature (Baldone et al., 1998; Rohwer and Pötter, 2005). The authors presented a solution adjusting the right-hand side of Equation (12), modifying $\hat{\chi}$. However, this analytical adaption, while taming the cycles, leads to undesired situations, where a single root node in a tree will have the highest modified centrality score, regardless of the level of interconnectivity in the network (Glattfelder, 2013). By adjusting the ranking of the nodes in cycles, this solution results in the potential overestimation of root nodes. In effect, our methodology solves the problem of the overestimation of nodes in cycles in a natural way, without incurring additional problems of overestimation elsewhere in the network. More details are discussed in the following section.

See Section 2.1 for a discussion on the relevance of the network in the computation of the Influence Index value for the global ownership network, relating to indirect ownership, leverage, and portfolio depth. Then, Section 2.2 discusses the related notion of shareholder power. Finally, Section 2.4 presents the empirical findings.

1.6.7 Comparison with Existing Measures

Originally, (Brioschi et al., 1989) introduced the notion of integrated ownership as a simple algebraic model of ownership structures that reflects the direct and indirect ownership relations. The authors analyze a specific setting where a single external shareholder owns shares in a cluster of firms, which are themselves connected by cross-shareholdings.

In (Vitali et al., 2011; Glattfelder, 2013) these concepts where generalized to generic ownership networks. As a result, the constrained perspective given in (Brioschi et al., 1989) is found in the general formalism of the eigenvector centrality presented in Section 1.6.2, namely Equation (11). In the context of shareholder control, this measure is referred to as integrated control $\hat{\chi}$.

It was realized, that this analytical approach was problematic when the analyzed ownership network contained cycles. In detail, the numerical results grow as a function of the number of inter-firm cross-shareholdings. Consequentially, the economic interpretation becomes problematic as the computation is seen to overestimate the values in the presence of cycles. Based on the original methodology, a solution was proposed, addressing the issue of cross-shareholdings (Baldone et al., 1998; Rohwer and Pötter, 2005). In effect, a correction operator is introduced, modifying Equation (13). This yields the loop-corrected integrated control $\hat{\chi}^*$. For details, see (Vitali et al., 2011; Glattfelder, 2013).

While $\hat{\chi}^*$ addresses the problem of overestimation, it introduces a new problem: root nodes become dominant. As discussed in the last section, namely Equation (28), a single root node $\mathcal{R}$ will always accumulate all the value in the downstream sub-network. As a result, $\mathcal{R}$ will

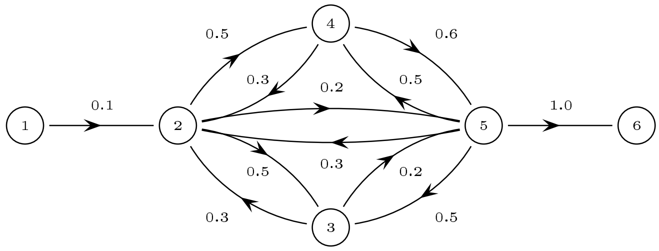

Figure S7. Simple bow-tie network example with a high degree of interconnectedness of the firms in the SCC. All nodes have unit value $v_i = 1$. Reproduced from (Vitali et al., 2011; Glattfelder, 2013).

invariably be the highest ranking node, as measured by $\hat{\chi}^*$. This is clearly an undesirable effect, if one wants to rank the nodes in a bow-tie. Again, see (Vitali et al., 2011; Glattfelder, 2013) for details.

As a consequence, in (Vitali et al., 2011) another solution ν^{int} was offered, remedying the problems related to cycles and root nodes. The methodology builds on the calculation of $\hat{\chi}^*$ for the nodes in the SCC, but modifies the values of the IN-nodes. While this procedure yields the desired results, it is cumbersome to compute, as the bow-tie structure of the network being analyzed needs to be know in advance and nodes get treated differently, according to their network position. See Section 2.7 for a comparison of the current work to (Vitali et al., 2011).

The methodology presented here is an improvement on (Vitali et al., 2011). It remedies both addressed problems while providing a simple algorithmic recipe for computing the Influence Index ξ for all nodes. It gives a lower limit to all previous methods and is hence a more stringent measure of economic influence. Moreover, it is also computable for pathological cases, where the analytical computations ($\hat{\chi}, \hat{\chi}^*, \nu^{\text{int}}$) all break down. For instance, a sub-network of k firms which are all entirely owned by the k firms themselves. Now the matrix $(\mathbb{1} - W)$ in Equation (12) becomes singular and cannot be inverted. More details are found in (Glattfelder, 2013).

Figure S7 presents the bow-tie example introduced in (Vitali et al., 2011; Glattfelder, 2013). One finds:

$$\hat{\chi} = \begin{pmatrix} 5 \\ 49 \\ 26 \\ 48 \\ 54 \\ 0 \end{pmatrix}, \ \hat{\chi}^* = \begin{pmatrix} 5.000 \\ 4.900 \\ 4.216 \\ 4.571 \\ 4.629 \\ 0.000 \end{pmatrix}, \ \nu^{\text{int}} = \begin{pmatrix} 0.500 \\ 4.000 \\ 3.378 \\ 3.667 \\ 3.714 \\ 0.000 \end{pmatrix}, \ \xi = \begin{pmatrix} 0.360 \\ 2.600 \\ 1.400 \\ 2.520 \\ 3.050 \\ 0.000 \end{pmatrix}. \tag{32}$$

In summary, the Influence Index value ξ preserves the original ranking order of centrality[2] found in $\hat{\chi}$, while giving a lower bound to the values of the nodes in the SCC and the IN. In other words, ξ is the most conservative measure of influence in terms of economic value.

1.6.8 The Algorithm: Pseudocode and Java Implementation

In Algorithm 1 and 2 the pseudocode for computing the Influence Index is shown. Algorithm 1 is the wrapper for the recursive method seen in Algorithm 2, crawling the network paths downstream. Given is a directed graph $G = (V, E)$, a set of vertices V and a set of edges E. Every weighted and directed link $r \in E$ is associated with two nodes $n, m \in V$ and a weight W_{nm}. Symbolically, $r = \{n, m, W_{nm}\}$, where n is the start node of the link and m the end node.

[2]Note that ν^{int} inherits the ranking order from $\hat{\chi}^*$.

Algorithm 1 $\mathcal{W}(G)$

initialize: deactivate all nodes; nodes n have a value v_n assigned
for all nodes n in graph G **do**
  $\xi \leftarrow 0$
  for all relationships r in set of all outgoing relationships of n **do**
    activate n
    $\xi \leftarrow \mathcal{CD}(r, 1.0, \xi)$
    deactivate n
  end for
  assign ξ to node n as ξ_n
end for

Algorithm 2 $\mathcal{CD}(r, \hat{w}, \xi)$

$s \leftarrow$ end node of r
if s active **then**
  return ξ
end if
$v_s \leftarrow$ value of s
$w_r \leftarrow$ weight of r
$\bar{w} \leftarrow w_r \cdot \hat{w}$
$\bar{\xi} \leftarrow \bar{w} \cdot v_s$
$\hat{\xi} \leftarrow \bar{\xi} + \xi$
activate s
if s has no outgoing relationships **then**
  deactivate s
  return $\hat{\xi}$
end if
for all relationships $\hat{r}$ in set of all outgoing relationships of s **do**
  $\hat{\xi} \leftarrow \mathcal{CD}(\hat{r}, \bar{w}, \hat{\xi})$
end for
deactivate s
return $\hat{\xi}$

In the following, a Java implementation is presented using Neo4j[3], an open-source graph database management system. All the network-related computations for this publication where implemented using Neo4j. There exists a repository on GitHub which embeds the following Java code in a workable project. Go to `https://github.com/jbglattfelder/influenceindex`.

```java
private static enum NodeSwitch {ON, OFF};
private org.neo4j.graphdb.GraphDatabaseService gdbs =
  new org.neo4j.graphdb.GraphDatabaseFactory().
  newEmbeddedDatabaseBuilder("/home/myNeo4jData/graph.db").
  newGraphDatabase();
private org.neo4j.graphdb.Direction out = org.neo4j.graphdb.Direction.OUTGOING;
private String weight = "myWeight";
private String nodeSwitch = "myNodeSwitch";
private String nodeValue = "myNodeValue";
private String nodeInfluenceIndex = "myNodeInfluenceIndex";

```

[3] `http://neo4j.com`

```java
private void Wrapper() {
  // Loop through whole graph
  for (Node n : GlobalGraphOperations.at(graphDatabaseService).getAllNodes()) {
    // Initialize
    double influenceIndex = 0.0;
    // Get all outgoing relationships of node and iterate
    Iterable<Relationship> iterableRel = n.getRelationships(out);
    for (Relationship relationship : iterableRel) {
      // Mark node as active
      n.setProperty(nodeSwitch, NodeSwitch.ON.toString());
      // Recursive algorithm
      influenceIndex = crawlDownstream(relationship, 1.0, influenceIndex);
      // Deactivate if active
      if (n.getProperty(nodeSwitch).equals(NodeSwitch.ON.toString())) {
        n.setProperty(nodeSwitch, NodeSwitch.OFF.toString());
      }
    }
    // Assign Influence Index
    n.setProperty(nodeInfluenceIndex, influenceIndex);
  }
}
private double crawlDownstream(Relationship relationship, double indirectWeight, double influenceIndex) {
  // Initialize
  Node successor = relationship.getEndNode();
  // Been here, go back up
  if (successor.getProperty(nodeSwitch).equals(NodeSwitch.ON.toString())) {
    return influenceIndex;
  }
  // Get node value that flows up through trail to predecessor as Infl. Index
  double initValue = (double) (successor.getProperty(nodeValue));
  // Compute indirect weight
  double w = (double) relationship.getProperty(weight);
  double newWeight = w * indirectWeight;
  // Compute Influence Index
  double currentInfluenceIndex = newWeight * initValue;
  // Update Influence Index and activate successor
  double newInfluenceIndex = currentInfluenceIndex + influenceIndex;
  successor.setProperty(nodeSwitch, NodeSwitch.ON.toString());
  // Continue recursively along trails (DFS): Get successors at next level
  Iterable<Relationship> iterableRel = successor.getRelationships(out);
  // Reached leaf node, go back up
  if (!iterableRel.iterator().hasNext()) {
    // Deactivate if active
    if (successor.getProperty(nodeSwitch).equals(NodeSwitch.ON.toString())) {
      successor.setProperty(nodeSwitch, NodeSwitch.OFF.toString());
    }
    return newInfluenceIndex;
  }
  // Iterate through relationships
  for (Relationship newRelationship : iterableRel) {
    // Retrieve Influence Index from recursive call
    newInfluenceIndex = crawlDownstream(newRelationship, newWeight, newInfluenceIndex);
  }
  // Deactivate if active
  if (successor.getProperty(nodeSwitch).equals(NodeSwitch.ON.toString())) {
    successor.setProperty(nodeSwitch, NodeSwitch.OFF.toString());
  }
  // No more relationships, go back up
  return newInfluenceIndex;
}
```

1.6.9 The Algorithm: Performance

The algorithm described above crawls each subnetwork reachable from every shareholder moving downstream. This is efficient only if a majority of the nodes in the network is associated with a value. Otherwise many trails will be traversed in vain which contain no value.

In Table S2 the fraction of nodes in the global ownership network with a value for their operating revenue was reported. Less than one-sixth of nodes have a value. To speed up the computation, the algorithm can be adapted in the following way: for each node with operating revenue, this value will be distributed up-stream to all the direct and indirect shareholders. The pseudocode is seen in Algorithms 3 and 4. In detail, Algorithm 4 for crawling is simply the reverse of Algorithm 2, and its adjusted wrapper is Algorithm 3.

Finally, another computational optimization can be implemented. We are analyzing chains of indirect ownership, where the percentages of direct ownership are multiplied. For instance $\mathcal{W}_{il} := W_{ij}W_{jk}W_{kl}$ denotes the indirect percentage of shareholder i in company l via the chain $i \to j \to k \to l$. If any of the direct ownership percentages are small, then $\mathcal{W}_{il}$ will be negligible. As a result, not only the computation will be prolonged unnecessarily, but also the indirect ownership becomes meaningless.

A simple remedy is to implement a cutoff for the indirect ownership. In other words, if $\mathcal{W}_{il} < x$, for some predefined percentage x, the corresponding trail will not be explored any further. In effect, the value has dissipated. The code for this optimization is given in Lines 7–9 of Algorithm 4 for the indirect ownership $\tilde{w}$ and the cutoff $w_{\min}$. Similarly, such an optimization can also be implemented for $\bar{w}$ in Algorithm 2. See also Section 1.8 for numerical details.

Algorithm 3 $\widehat{\mathcal{W}}(G)$

initialize: deactivate all nodes; some nodes n have a value v_n assigned
for all nodes n in graph G **do**
    $v_n \leftarrow$ value of n
    for all relationships r in set of all incoming relationships of n **do**
        activate n
        $\mathcal{CU}(r, v_n, 1.0, 0)$
        deactivate n
    end for
end for

Algorithm 4 $\mathcal{CU}(r, v_n, \hat{w}, l)$

$p \leftarrow$ start node of r
if p active **then**
  return
end if
$w_r \leftarrow$ weight of r
$\bar{w} \leftarrow w_r \cdot \hat{w}$
if $\bar{w} < w_{\min}$ and $l > 0$ **then**
  return
end if
$\bar{\xi} \leftarrow \bar{w} \cdot v_n$
$\xi_p \leftarrow$ influence index of p
$\hat{\xi} \leftarrow \bar{\xi} + \xi_p$
assign $\hat{\xi}$ to node p
activate p
if p has no incoming relationships **then**
  deactivate p
  return
end if
$l \leftarrow l + 1$
for all relationships $\hat{r}$ in set of all incoming relationships of p **do**
  $\mathcal{CU}(\hat{r}, v_n, \bar{w}, l)$
end for
deactivate p
return

1.7 The Cumulative Influence Index $\xi_{\mathcal{A}}$

Observe that the total value in the network example seen in Figure S6 is $\sum_{i=1}^{27} v_i = 27.0$. However, summing up all the individual Influence Index values yields $\sum_{i=1}^{27} \xi_i = 122.20625625$. This is the result of double-counting. While the ξ_i values allow a ranking of nodes, they cannot

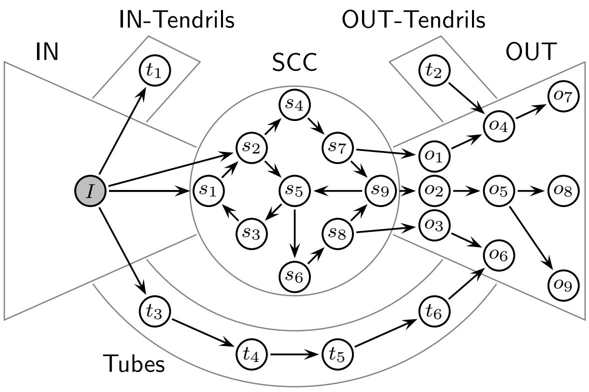

Figure S8. Cumulative Influence Index. The same bow-tie example seen in Figure S6, where all the IN-nodes are now aggregated into a single node I. This network is the basis for the computation of the cumulative Influence Index value ξ^{in}.

be naïvely summed up. This can be easily explained in the current example by focussing on the path $t_3 \to t_4 \to t_5 \to t_6$, i.e., the tube:

$$\begin{pmatrix} \xi_{t_3} \\ \xi_{t_4} \\ \xi_{t_5} \\ \xi_{t_6} \end{pmatrix} = \begin{pmatrix} 3.5 \\ 2.5 \\ 1.5 \\ 0.5 \end{pmatrix} \tag{33a}$$

$$= \begin{pmatrix} W_{t_3t_4}W_{t_4t_5}W_{t_5t_6}W_{t_6o_6}v_{o_6} + W_{t_3t_4}W_{t_4t_5}W_{t_5t_6}v_{t_6} + W_{t_3t_4}W_{t_4t_5}v_{t_5} + W_{t_3t_4}v_{t_4} \\ W_{t_4t_5}W_{t_5t_6}W_{t_6o_6}v_{o_6} + W_{t_4t_5}W_{t_5t_6}v_{t_6} + W_{t_4t_5}v_{t_5} \\ W_{t_5t_6}W_{t_6o_6}v_{o_6} + W_{t_5t_6}v_{t_6} \\ W_{t_6o_6}v_{o_6} \end{pmatrix}. \tag{33b}$$

In this subnetwork there is a total value of $v_{t_3} + v_{t_4} + v_{t_5} + v_{t_6} + W_{t_6o_6}v_{o_6} = 4.5$ flowing upstream. However, due to double-counting the total sum of Influence Index values in the tube is $\xi_{t_3} + \xi_{t_4} + \xi_{t_5} + \xi_{t_6} = 8.0$. To illustrate, the value of 0.5 coming from v_{o_6} is counted for the Influence Index value of each node in the tube. If we sum the individual index values, the contribution of the 0.5 flowing through the tube is $2 = 4 \cdot 0.5$.

This problem is remedied by introducing the concept of the cumulative Influence Index defined for a set of nodes. In detail, a group of nodes is treated as one single node ignoring any existing links among themselves. An example of such a node aggregation can be seen in Figure S8. The results of this computation for the bow-tie example are:

$$\begin{aligned} \xi^{\text{in}} &= 17.020325, \\ \xi^{\text{scc}} &= 7.500000, \\ \xi^{\text{tt}} &= 1.500000, \\ \xi^{\text{in}\cup\text{scc}} &= 13.000000, \\ \xi^{\text{in}\cup\text{tt}} &= 13.020325, \\ \xi^{\text{in}\cup\text{scc}\cup\text{tt}} &= 9.000000. \end{aligned} \tag{34}$$

Note that for the calculation of each bow-tie section's cumulative Influence Index value, the corresponding nodes were compacted. For instance, the nodes in the tubes and tendrils are transformed into a set of three nodes $t_1, t_2, \tilde{t}_3 = \{t_3, t_4, t_5, t_6\}$. As a result

$$\begin{aligned} \xi^{\text{tt}} &= \xi_{t_1} + \xi_{t_2} + \xi_{\tilde{t}_3} \\ &= 0.0 + 1.0 + 0.5 = 1.5. \end{aligned} \tag{35}$$

To further illustrate with an economic example, consider the combination of ownership during mergers and acquisitions of companies. In such an event, two shareholders A and B, not holding shares in each other, become aggregated into a single node

$$C := A \cup B. \tag{36}$$

By construction, this results in the additivity of the cumulative Influence Index

$$\xi^C = \xi^A + \xi^B. \tag{37}$$

In the following, the adaptions to Algorithms 1–4 are shown, implementing the cumulative version of the Influence Index. For instance, Algorithm 5 describes the changes to the Wrappers 1 and 3. Then, in Algorithms 6 and 7 the simple alterations to the Crawlers 2 and 4, respectively, are seen.

Algorithm 5 $\mathcal{W}_c(G)$

initialize: tag nodes in set $\mathcal{S}$ for which $\xi_{\mathcal{S}}$ will be computed
... ▷ *Insert the following after Line 2 in Algorithms 1 or 3:*
if n is tagged **then**
    continue in for loop
end if
... ▷ *Finalize by summing individual ξ_n contributions:*
$\xi_{\mathcal{S}} \leftarrow \sum_{n \in \mathcal{S}} \xi_n$

Algorithm 6 $\mathcal{CD}_c(r, \hat{w}, \xi)$

... ▷ *Insert the following after Line 1 in Algorithm 2:*
if s is tagged **then**
    return ξ
end if
...

Algorithm 7 $\mathcal{CU}_c(r, v_n, \hat{w}, l)$

... ▷ *Insert the following after Line 1 in Algorithm 4:*
if p is tagged **then**
    return
end if
...

1.8 In a Nutshell: The Utilized Algorithms

For the computation of the Influence Index value over the operating revenue in the yearly snapshots of the global ownership network, we utilized the following algorithms:

- Individual Influence Index value: Algorithms 3 and 4, with a cutoff of 0.1% (i.e., 0.001).
- Cumulative Influence Index value: Algorithms 5 and 7, with a cutoff of 0.1% (i.e., 0.001).

The empirical results for the global ownership network are given in Section 2.4.1 for the individual Influence Index values and Section 2.5.1 for the cumulative version Also, see the corresponding GitHub repository for the code: `https://github.com/jbglattfelder/influenceindex`.

2 Supplementary Text

2.1 The Importance of the Network

Does the network really matter for the computation of the Influence Index value? In other words, is the indirect portfolio value relevant? To answer this question, recall Equation (18) defining the Influence Index value for a shareholder i as $\xi_i = p_i + \tilde{p}_i$. The equation utilizes the direct portfolio value p_i and the indirect portfolio value $\tilde{p}_i$, which is computed by only traversing the trails in the subnetwork downstream of i and hence excludes cycles. To gauge the importance of the network on these measures, in the following, the notions of leverage and portfolio depth will be introduced, next to the presentation of a closer analysis of the indirect portfolio values.

2.1.1 Leverage

An ideal measure that reflect the importance of the indirect portfolio value is leverage. The leverage of a shareholder i is defined as

$$l_i := \frac{\xi_i}{p_i}. \tag{38}$$

Only for shareholders with an indirect portfolio will the leverage exceed unity. The leverage helps answer the following question: With a direct investment of x U.S. dollars (approximated by $p_i = x$), what multiple of that value can the shareholder indirectly influence, via chains of indirect ownership?

In Figure S9 a real-world example of an ownership tree found in Orbis is shown. The root node is shareholder X, a natural person. X only has a single company in its direct portfolio, named 1, and hence $p_X = W_{X1}v_1$. The rest of the subnetwork is comprised of the indirect portfolio at different levels of depth. At the maximal depth of 5, X has indirect ownership in companies 5_a–5_d. In this subnetwork example there is also a total of 368,027,000 USD to be found by summing over the operating revenue of the companies. However, the data is

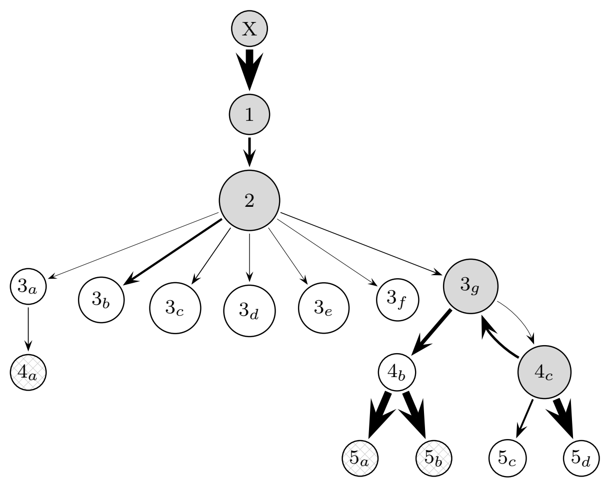

Figure S9. Ownership subnetwork. Shareholder X is a natural person with a 5-level portfolio comprised of the 16 companies $1, 2, 3_a, \ldots, 5_d$. The node sizes of companies are scaled by operating revenue, except for the three nodes filled with a crosshatch pattern for which this data is unavailable. In this subnetwork, only the following Influence Index values for the shaded nodes are non-zero: $\xi_X, \xi_1, \xi_2, \xi_{3_g}$, and ξ_{4_c}. The arrows are scaled by ownership weight. The cycle is, as always, not traversed, as the algorithm only utilizes trails in the network.

	X	**1**	**2**	$\mathbf{3}_g$	$\mathbf{4}_c$
Portfolio depth	5	4	3	2	3
Leverage l_i	1.77	5.99	1.07	1.01	1.04

Table S5. The network matters. Shareholders can have high leverage, i.e., gain influence over larger value via the many levels of depth in their portfolios.

incomplete in this real-world example, as there are no operating revenue values reported for the three nodes $4_a, 5_a$, and 5_b. The average ownership relation is 36.33% and the median is 23.91%. Computing the Influence Index value reveals that company 2 receives the highest score with $\xi_2 = 6.90\%$ of the total operating revenue in this system. The remaining values are $\xi_X = 6.13\%, \xi_1 = 2.66\%, \xi_{3_g} = 0.84\%$, and $\xi_{4_c} = 5.00\%$. For these five shareholders, the corresponding leverage is seen in Table S5. Company 1 can hence influence nearly six times more value than it invested directly via ownership in company 2. Also shareholder X can indirectly influence 77% more value than directly invested.

Another real-world example, demonstrating the relevance of leverage, is related to Mr. Marco Tronchetti Provera. Via a pyramidal group of indirect ownership, Mr. Tronchetti Provera gained control over Telecom Italia, the sixth largest telecommunication company in the world by turnover, around 2004. The resulting leverage was estimated to be approximately 26. In other words, "for each Euro invested by the controlling family, the market value moved was more than 26 Euro" (Meoli et al., 2006).

There is, however, one caveat to the analysis of leverage. Due to the sparsity in the distribution of operating revenue (recall Section 1.5), some shareholders have a tiny direct portfolio value. If such a shareholder holds one firm with a big Influence Index value in its portfolio, the computed leverage will be very large. To avoid such artifacts, we impose a minimal portfolio

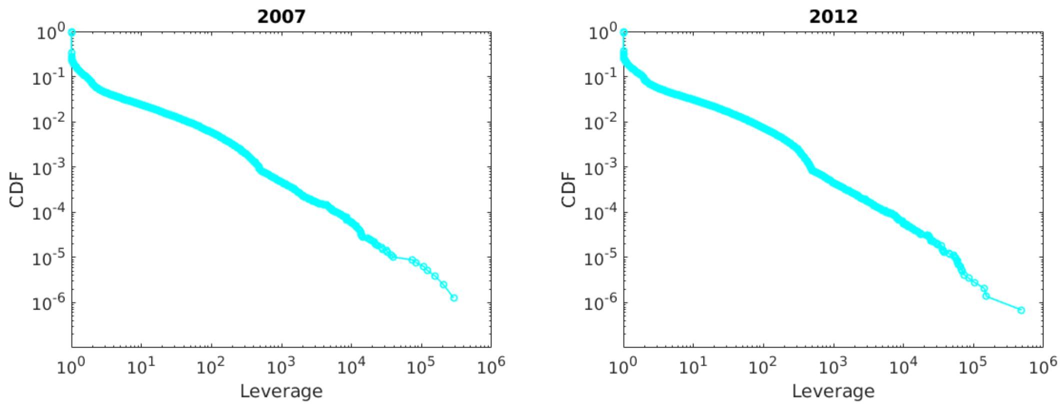

Figure S10. Leverage in the global ownership network. While most economic actors only have small leverage, there exist shareholders who can gain very large leverage from the network and hence indirectly influence much more market value than what they could via their direct investments. The analysis here is restricted to the largest connected component (see Section 2.3) of the global ownership network for two yearly snapshots. In order to adjust for very small direct portfolio values skewing the results, a leverage threshold of 500 was imposed, above which a shareholder is required to have a direct portfolio value of at least USD 50,000, in order to be considered for the distribution function. Without these restrictions, the range of leverage increases by a few orders of magnitude, whilst flattening the distribution curve overall.

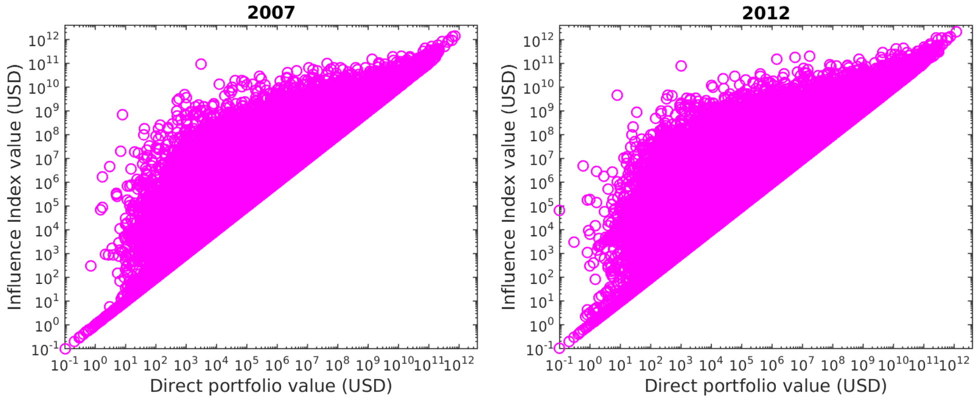

Figure S11. Direct vs indirect portfolio scatter-plot. The x-axis shows the value of the direct portfolio p_i of the shareholders in the largest connected component (see Section 2.3) of the global ownership network. The y-axis reflects the Influence Index value of the shareholders, computed as $\xi_i = p_i + \tilde{p}_i$, as seen in Equation (18). Two yearly snapshots are evaluated.

value for a leverage factor above a certain threshold. In Figure S10 the resulting distribution of the leverage values in the global ownership network is shown for two snapshots. The network is seen to significantly amplify the indirect portfolio value $\tilde{p}_i$ resulting in large leverage for a select group of shareholders. To summarize, a strategic chain of indirect investments can give shareholders a large leverage. This is reflected in the market value that can be indirectly influenced (and which is captured by ξ_i). Finally, the result for 2007, seen in Figure S10, is similar to what was reported in the smaller study (Vitali et al., 2011). See Section 2.7 for a comparison of this work to the 2011 study.

Recall that, by construction (as seen in Equation (11) defining the related centrality measure), the Influence Index value ξ_i of a shareholder depends on the values v_j of the firms in its direct portfolio and also on their individual scores for the Influence Index values ξ_j. As a result, it is often natural persons, like founders, who can gain a lot of leverage by holding shares in a firm with a large Influence Index value. In 2007, Barclays had a leverage factor of 1.96, with a direct portfolio comprised of 8,193 firms. For BlackRock (see Section 2.4.3), in 2012, the leverage was 1.89, with a 8,762-firm direct portfolio. More on the relevance of Barclays and BlackRock can be found in Section 2.4.1.

2.1.2 Direct and Indirect Portfolios

In a next step, we disentangle the contributions to the Influence Index value coming from the direct and indirect portfolio values. In other words, how do shareholders in detail obtain an Influence Index value from their direct and indirect portfolios?

In Figure S11 the direct portfolio values p_i of the shareholders in the global ownership network are plotted against their Influence Index values ξ_i. The diagonal is comprised of shareholders with $\xi_i = p_i$. These are thus shareholders who do not benefit from an indirect portfolio, meaning that they also have leverage $l_i = 1$. For small direct portfolio values, the value of the Influence Index is similar in magnitude. Then the network is seen to significantly amplify the indirect portfolio values: shareholders with moderate direct portfolio value can gain very large ξ_i. The economic actors with the largest direct portfolio values can only utilize the network marginally to increase their already large ξ_i score. In summary, there are very many economic actors who can significantly increase their Influence Index value via the network of indirect ownership relations.

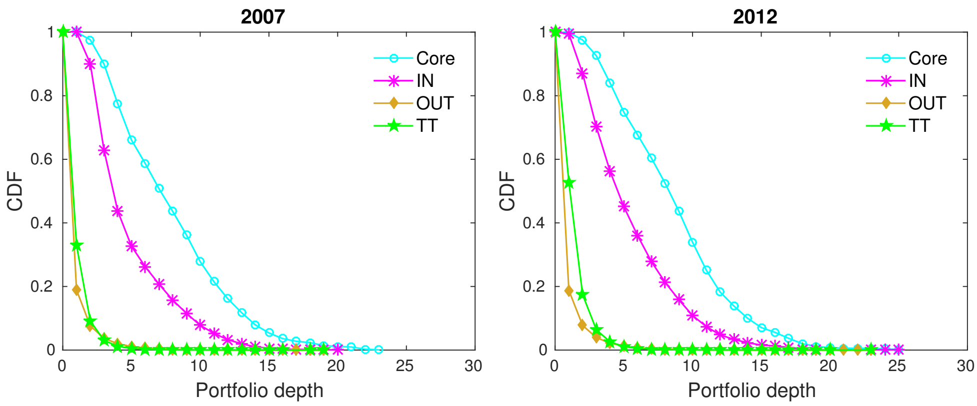

Figure S12. Portfolio depth. The distribution of the levels of the indirect portfolios of the shareholders in the largest connected component (see Section 2.3) of the global ownership network is shown for two yearly snapshots. The nodes are sorted by their location in the bow-tie components. The indirect ownership cutoff is $W_{\text{cutoff}} = 0.001$ or 0.1%.

2.1.3 Portfolio Depth

It can be objected that the results presented in the last two sections, and the notion of the Influence Index value in general, are spurious due to the following observation. As an indirect ownership path increase in length its corresponding indirect ownership percentage becomes minuscule. However, even such a tiny indirect ownership value can lead to a large ξ_i contribution, if the operating revenue of the indirectly owned company is very large. Thus, even if numerically significant, this contribution should be irrelevant in practice.

We address this issue by imposing a cutoff for the minimum of indirect ownership, as described in Lines 7–9 of Algorithm 4 in Section 1.6.9. As a result, the notion of portfolio depth becomes relevant, indicating the levels of indirect ownership that can be reached which are still associated with meaningful indirect ownership percentages and therefore realistic Influence Index values. In detail, whenever the indirect ownership in a trail falls below W_{cutoff}, the recursive computation is ended. Consider a trail $i \to j_1 \to \cdots \to j_m \to k$ where $\mathcal{W}_{ij_m}$ represents the indirect ownership from shareholder i to company j_m, and the direct ownership from j_m to k is given by W_{j_mk}. If $\mathcal{W}_{ik} = \mathcal{W}_{ij_m} W_{j_mk} < W_{\text{cutoff}}$ the algorithm will not consider company k. Although such a cutoff guarantees that the indirect ownership does not disperses and still holds a meaning, a similar cutoff could also be implemented directly for the indirect portfolio value $\mathcal{W}_{ik} v_k$. However, we choose to focus on bounding indirect ownership only, as this is a more conservative approach that can be further justified, as discussed in Section 2.2. An additional benefit of such a cutoff is related to the optimization of the algorithm.

As a result of introducing the cutoff for the indirect ownership paths, the notion of the portfolio depth emerges. If there is no cutoff, every trail originating from a shareholder will be traversed until a leaf node (i.e., a node with no children) is reached in the OUT-section of the bow-tie (see Section 2.3). For nodes in the IN-section or the core of the bow-tie, this can result in exceedingly deep portfolios. Indeed, the network diameter, defined as the longest of all the existing shortest paths in a network, is found in the portfolio depth of root nodes in the IN-section, with indirect ownership paths leading down to the leaf nodes. In essence, the introduction of the cutoff reduces, localizes and focusses the region of influence of any shareholder.

In Figure S12 the portfolio depth for the global ownership network for two snapshots is shown, corresponding to an indirect ownership cutoff of 0.1%, i.e., $W_{\text{cutoff}} = 0.001$. As expected, the nodes in the various bow-tie components show different characteristics. While the shareholders in the core have a median portfolio depth of 7 in 2007 (8 in 2012), the owners in the IN-section have a median depth of 3 in 2007 (4 in 2012), and the remaining OUT and TT-sections are shallow. Again, there exist economic agents with exceptionally deep portfolios in specific bow-tie sections, once more highlighting the relevance of the network.

2.1.4 Summary

The network matters. Simply by focussing on direct ownership, i.e., on a portfolio depth of one, the potential for the network to come into effect is missed. Via trails of indirect ownership, select shareholders can gain disproportionate influence, which only becomes visible if the indirect portfolio values $\tilde{p}_i$ are considered. In other words, shareholders can utilize the network in a way that opens up channels which can amplify the propagation of influence, resulting in large Influence Index values ξ_i. Only by considering the structure of all the weighted ownership links, and the distribution of the operating revenue in the network, can the full picture of influence be uncovered. But what does this mean in terms of shareholder power?

2.2 Reflecting on Power

The Influence Index value ξ_i has two possible interpretations:

1. The monetary value of the direct and indirect portfolio, measured in USD, of a shareholder. This represents the economic value an actor can potentially influence via paths of direct and indirect ownership in the network. See Sections 1.6 and 2.1.

2. A modified eigenvector centrality suitable for directed and weighted networks with a bow-tie topology, where the nodes have an intrinsic non-topological value assigned to them. See Section 1.6.2.

In essence, the Influence Index reveals which nodes are relevant in the network and assigns a score to them, reflecting the economic value within their potential sphere of influence. This means that ξ_i can also be interpreted as a measure of shareholder power.

It is noteworthy that the assessment of shareholder power has been somewhat overlooked in the scholarly literature (Hill and Thomas, 2015, p. 1):

> Much of the history of corporate law has concerned itself, not with shareholder power, but rather with its absence. Yet [...] there have been major shifts in capital market structure that require a reassessment of the role and power of shareholders.

We hope to contribute to this ongoing discussion with the empirical analysis and novel methodology presented here.

2.2.1 Shareholder Power

In order to properly assess shareholder power, the associated concepts need to be clarified. In the most generic interpretation, a "shareholder" is understood as being an economic actor holding claims to a firm's assets and certain rights to elect the firm's directors and vote on specific business related issues. In this sense, ownership is associated with control, which is discussed in the next section.

The notion of "power" is more ethereal. A weak definition in the context of ownership sees power as "the ability of shareholders to influence or sway those controlling the corporation" (Hill and Thomas, 2015, p. 13). In other words, power becomes manifest by the exertion of influence. A stronger and broader definition of power is given by Max Weber. He understands the notion primarily as the potential for coercion (Weber, 1978, p. 53):

> Power is the probability that one actor within a social relationship will be in a position to carry out his wishes despite resistance, regardless of the basis on which this probability rests.

Moreover, Weber stresses that there can be a wide variety of power bases (Weber, 1978, p. 53):

> All conceivable qualities of a person and all conceivable combinations of circumstances my put him in a position to impose his will in a given situation.

In summary, the more channels of influence an actor can access, the greater the probability that power will be exerted.

Further complicating matters is the fact that power can be covert, meaning that "genuine power may be invisible" (Hill and Thomas, 2015, p. 3), also discussed in (Fichtner et al., 2017). This implies that the absence of an overt and visible execution of power does not mean that influence has not been wielded out of public view. Finally, even an economic actor holding a lot of power can strategically choose not to exert it for a certain period of time. Again, an absence of clear power execution does not imply that this cannot suddenly surface at some other occasion.

2.2.2 Ownership and Control

In the scholarly literature, ownership is associated with corporate control. This notion is related to the amount of voting rights of a shareholder, which can be exercised at shareholder meetings. The more voting rights a shareholder holds in a company, the greater the level of influence and hence control. Bureau van Dijk's Orbis database, introduced in Section 1.1, describes their data as follows (Bureau van Dijk, 2014):

> This dataset is intended to track control relationships rather than patrimonial relationships. Whenever available, the percentage of ownership refers to shares associated with voting rights.

However, this very specific interpretation of ownership as shareholder power can be plagued by technical issues and potential pitfalls: dual classes of shares (golden shares), proxy votes, voting right ceilings, non-voting shares, etc. As a consequence, while ownership is an objective quantity, readily available from data providers, control needs to be estimated. Different models aimed at deriving control based on the distribution of ownership have been proposed:

- One-share-one-vote rule: A linear model where the ownership percentages yield identical percentages of voting rights (La Porta et al., 1999; Goergen et al., 2005).
- Threshold model: A fixed threshold of ownership is introduced, above which full control is assumed, rendering all other shareholders powerless (La Porta et al., 1999; Chapelle and Szafarz, 2005).
- Relative majority model: Based on what is known as power indices in a game theoretic approach to voting and employing a concentration measure similar to the Herfindhal index, the relative fraction of ownership shares that each shareholder has with respect to the overall distribution is evaluated (Glattfelder and Battiston, 2009).

See (Vitali et al., 2011; Glattfelder, 2013) for more information.

In detail, the ownership adjacency matrix W_{ij} is replaced by the control matrix $\mathcal{C}_{ij}$, calculated according to one of the chosen models. Now the indirect control can be, for instance, computed as

$$\widetilde{\mathcal{C}} := (\mathbb{1} - \mathcal{C})^{-1}\mathcal{C}, \tag{39}$$

also called integrated control (Brioschi et al., 1989; Glattfelder, 2013). Compare the formula for $\widetilde{\mathcal{C}}$ with Equation 12.

For this study, the following results are significant. In the analysis of the ownership network restricted to transnational corporations (Vitali et al., 2011), all three models for estimating control from ownership were compared. In effect, three different networks were analyzed, with varying local link structures. It was shown that the three fundamentally different models, resulting in varying micro-structures, revealed very similar aggregated network statistics. The ranking of influential shareholders, the distribution of shareholder power, overall and in the bow-tie components, displayed a remarkable level of robustness. As a result, we are encouraged to only employ the ownership network W_{ij}, i.e., a linear model, in all computations of shareholder power, without fearing an introduction of a bias in the analysis of the Influence Index.

2.2.3 The Influence Index

The notion of shareholder power in the guise of corporate control not only has conceptual issues but can also depend on specific national settings. Moreover, control invokes the intuition of a digital measure and not a spectrum of values. In order to address these challenges we choose to reframe the notion of shareholder power. In general, the measure we offer is a proxy that

- focusses on influence, i.e., the ability to sway those in control or resist the opposition of others;
- corresponds to a spectrum of probabilities;
- identifies channels benefitting the propagation of influence.

In detail, the Influence Index value, expressed in USD, reflects a shareholder's propensity to potentially influence that amount of economic value. It considers the context of the network the shareholder is embedded in and the overall distribution of value in the system. The computation of the Influence Index value is straightforward, efficient, and addresses all previously encountered problems related to the existence of cycles in the network (described in Section 1.6.3). Importantly, in its cumulative version, it is easily and meaningfully applied to a group of shareholders, denoting shared ownership and influence (seen in Section 1.7).

Finally, the Influence Index value represents a lower bound to the true value. This is due to the construction of the algorithm ignoring cycles (see Section 1.6.3), the implemented cutoff for indirect ownership (see Section 2.1.3), and in general, the lack of operating revenue for companies reported in the data (see Section 1.5), and missing links (see Section 1.3).

It is beyond the scope of our study to demonstrate that shareholders with large Influence Index values do indeed exert their power. However, the top influencers are in the position to execute considerable power, either formally or via informal negotiations. In summary, given the presence of channels with the potential to greatly extend the reach of influence of individual actors, we cannot exclude that these will be, in some way, utilized in their favor at some point in time.

The empirical results related to the computation of the Influence Index are given in Section 2.4.1, as yearly rankings of individual actors. In Section 2.4.2 alternative rankings are compared and discussed. Then, Section 2.5 analyzes the cumulative influence of cohesive shareholder groups. In other words, power structures can be identified and their relevance assessed, a feat that was previously not possible. This is especially relevant for gauging the level of concentration of ownership and shareholder power (see Section 2.6).

2.2.4 Institutional Investors

The issues related to the shareholder power institutional investors can gain via their equity holdings are complex, as both positions relating to shareholder activism and passivity have been argued. The empirical and theoretical debate is still ongoing. In the following, we will present a brief history of the rise of the institutional investor and outline why their shareholder power should not be ignored.

In 1932, a classic text identified the separation of ownership from control in the US (Berle and Means, 1932). A large body of equity holders, exercising hardly any control, was faced with a small group of controlling managers. Indeed, in such a "Berle-Means corporation" shareholders were seen as powerless. This was understood as an agency problem, due to the perceived unaccountability of managers. The analysis of Berle and Means would cast the paradigm of widely held firms for Anglo-Saxon countries for the next decades.

Then, around 1960, another shift occurred and a new pattern emerged. The widely dispersed ownership started to concentrate in large shareholders: the institutional investor emerged. This new distribution of ownership has been termed "agency capitalism" (Gilson and Gordon, 2015). Between 1980 and 2005, institutional ownership of equity grew from about 30% to almost 75% (Davis, 2008). Interestingly, a study of the national ownership networks in 48 countries in 2007 revealed an unintuitive picture. Even in markets with many widely held corporations, this local distribution of ownership actually goes hand in hand with a global concentration of ownership and control, only visible from the bird's-eye view given by the network perspective (Glattfelder and Battiston, 2009).

This new concentration of shareholding was also seen to imply power (Wells, 2015, p. 24):

> The market for corporate control [characterized by hostile takeovers] gave new power to shareholders, particularly institutional investors.

By the 1990s, "shareholder passivity had crumbled" (Wells, 2015, p. 24). The following narrative was offered, explaining the motivation for institutional shareholders to exert power (Wells, 2015, p. 25):

> Institutional investors were also more likely to realize an economic benefit from activism than would a small shareholder. When a small investor was unhappy with her corporation, simply selling her shares was the economically rational thing to do, as the costs of activism would quickly swamp whatever benefits the shareholder could gain trough agitation. For an institutional investor with a stake worth tens or hundreds of millions of dollars, however, the costs of activism might well be recouped if a company's stock rose sharply, and the possibility of reducing the costs of activism by acting in concert with other investors made such activism still more likely.

Moreover (Fichtner et al., 2017):

> [L]arge blockholders are expected to vote because otherwise managers would be too powerful. Legally, the fiduciary responsibility of institutional investors towards their clients includes that they are expected to fulfill their role as a shareholder, including voting at the annual general meeting.

Indeed, selling shares—the small shareholder's last resort—is not attractive for institutional investors. Simply by holding large parts of the market, selling becomes unattractive or even impossible (Hawley and Williams, 2000). Moreover, a shareholder owning a block of stock that might be 1% or more of a firm's shares would see the market move against them if they would sell (Gillan and Starks, 2000). Hence, alternative channels facilitating the influence over companies in an investor's portfolio present themselves as a more attractive option. In other words, exerting power becomes a rational choice for shareholders of a certain size.

This trend towards universal owners nearly owning the whole market raises novel issues. Firstly, the bigger a shareholder is, the more externalities he or she becomes exposed to, raising issues related to corporate governance. Secondly, what kind of market actually emerges when a handful of institutional investors own the most valuable companies in the world (see Section 2.6)? Finally, at a certain threshold of ownership the option of shareholder activism can appear more appealing than the usual "Wall Street Walk", with the negative consequences of divestments outlined above.

Such challenges can also affect purely passive indexed funds and ETFs as they grow in size. These new developments reframe the question of shareholder activism and power (Fichtner et al., 2017):

> Consequently, they [passive funds] can only use "voice" in order to influence their returns. The re-concentration of corporate ownership entails a re-concentration of corporate control as well, since asset managers have the ability to exercise the voting power of the shares owned by their funds.

Unsurprisingly, the following is predicted (Coates IV, 2015, p. 93):

> [P]urely passive funds are on a path to owning a majority of US public equity. One result of this trend is likely to be increasing pressure on index funds to find ways to engage in governance activities.

Regardless of the level of activism, empirical findings indicate that major passive investors do have the possibility to actively exert shareholder power (Fichtner et al., 2017):

> The analysis of the voting behavior underscores that the Big Three [BlackRock, Vanguard, and State Street] may be passive investors, but they are certainly not passive owners. They evidently have developed the ability to pursue a centralized voting strategy—a fundamental prerequisite to using their shareholder power effectively. In addition to this direct exercise of shareholder power, the extent of the concentration of ownership in the hands of the Big Three may also lead to a position of structural power.

In Section 2.4.3 the spectacular rise of BlackRock, becoming the largest asset manager in the world, is detailed. The company's proxy voting is led by an in-house team, considering not only economic interests, but also environmental issues, and corporate governance matters. BlackRock has been documented taking activist stances (Bloomberg News, 2017). A similar story can be told for the Norwegian Government Pension Fund Global, managed by Norges Bank, more commonly known as Norway's petroleum fund. It is the world's biggest sovereign wealth fund and is known for its willingness in taking an activist approach to companies that fail to meet its ethical standards. As an example, the fund divested from over 50 coal companies in 2014 (The Guardian, 2015). Seven years earlier, the fund had started excluding certain companies for various reasons: environmental damage, breaches of human rights, and activities relating to tobacco and weapons production (Norges Bank Investment Management, 2007).

The institutional shareholder's rise to power is also chronicled by the appearance of proxy advisors. These are private firms that analyze corporate elections and advise institutional investors on how to vote their shares. The emergence of shareholder activism and the recognition that neglecting corporate governance issues poses a risk, have increased the demand for these services. In turn, the leading advisory firms have themselves gained an influential position. Indeed, proxy advisors "are recent and potentially powerful new players in the corporate governance world" (Choi et al., 2010). Two prominent proxy advisory services together cover 59,000 corporate meetings per year[4]. However, the actual effectiveness of shareholder activism depends on many factors (Choi et al., 2010).

As "one major development saw a new institutional investor, the hedge fund, come to the force" (Wells, 2015, p. 27), we devote special attention to this type of shareholder in the following. Hedge funds deploy a wider array of strategies and take larger stakes in publicly-held firms than more traditional shareholders. As a result, they push more vigorously for changes in corporate strategies and management (Wells, 2015). Indeed, this is a novel development (Partnoy, 2015, p. 99):

> Hedge fund activism is a recent, but now prominent, topic in academic research. Since 2006, scholarship on hedge fund activism has grown from virtually non-existent to mainstream.

In contrast to the US, hedge fund activism in Europe is often conducted in private. However, the lack of such data in Europe does not imply an absence of shareholder activism. Indeed, the lack of shareholder proposals could be the result of real shareholder power that only needs to surface occasionally (Becht et al., 2015). Again, it should be noted that the answers that have been offered to the fundamental questions relating to hedge fund activism, like how relevant it really is, are mixed.

In summary (Wells, 2015, p. 27):

> Entering the twenty-first century we also enter ongoing debates [about shareholder power], with new developments [...] whose full implications are still working themselves out.
>
> [...] this latest iteration of shareholder activism appeared to have genuinely changed the dynamics of shareholder power.

As the empirical and theoretical debates continue, we can offer the following results. While most existing studies only focus on the direct portfolio level, our data and methodology considers the whole network of interaction, opening up new possibilities for understanding the dynamics behind shareholder activity. The ownership data considers voting rights whenever possible (see Section 2.2.2) meaning that the issue of non-beneficial ownership and custodians can be circumnavigated. Then, our methodology ranks not only the shareholder power of institutional investors but all participating economic actors in the network (see Section 2.4.1). In a nutshell, it unveils the channels for the propagation of influence, where influence is now indexed and reflects the value in USD a shareholder can potentially affect, directly and indirectly. A crucial and novel contribution is the assessment of the influence gained by cohesive groups of shareholders, enabling the identification of power structures (see Section 2.5).

Finally, it is important to interpret this notion of influence in terms of a probability (see Section 2.2.1). By recalling that "genuine power may be invisible" (Hill and Thomas, 2015, p. 3), it would be very imprudent to gloss over these findings, even if we cannot prove that this influence is really wielded. Indeed (Fichtner et al., 2017):

> Unlike the times of Morgan and Rockefeller, today's blockholders do not exert their power by directly taking seats on the boards of the firms they control. If they do influence corporate decision making, they do so through more "hidden" forms of power.

What we can claim, however, is that we cannot exclude that these channels for exerting influence are, in some way, utilized in favor of the shareholder, at some time. Especially observing the current trend that sees even passive institutional investors being forced into an activist role and hence tempted to utilize existing channels of influence.

[4]Retrieved from their websites on the 7th of September 2016: `http://www.glasslewis.com` and `http://www.issgovernance.com`.

	2007	2008	2009	2010	2011	2012
IN	15,980	17,957	10,727	12,263	8,645	13,375
Core	3,005	3,151	2,320	2,574	2,110	2,554
OUT	634,773	678,336	738,775	748,072	738,737	761,571
TT	5,464,982	5,577,945	6,754,951	6,432,513	6,484,955	5,156,336
LCC	6,118,740	6,277,389	7,506,773	7,195,422	7,234,447	5,933,836
OCC	10,517,611	12,530,419	15,806,200	17,161,047	23,328,652	29,905,254
Total	16,636,351	18,807,808	23,312,973	24,356,469	30,563,099	35,839,090

Table S6. Bow-tie structure. Number of nodes in the various components of the network. The acronyms are explained in the text and Figure S6.

2.2.5 Who Rules the World?

Questions relating to corporate power have been a research topic for social scientist for a long time. See for instance (Domhoff, 1967, 1983, 1998). However, quantitative information on the growing and globalized economic interactions is slowly revealing an empirical description of "Who Rules the World?" We close this section with a quote (Peetz and Murray, 2012, p. 50):

> The people who ran, and run, transnational corporations can be thought of as a transnational *elite* in that they share increasingly strong social, political and cultural networks. But now we can also speak of a true transnational *class*: a group that, sometimes directly, sometimes indirectly, sometimes consciously and sometime unconsciously, controls the exercise of economic power across and within national boundaries. Their power is exercised in part through individual agency but even more so through the collective structures of ownership of very large corporations.

2.3 The Bow-Tie

The global ownership network is comprised of one major largest connected component (LCC) and many other connected components (OCC). These OCCs are small isolated subnetworks. The LCC itself displays a bow-tie topology, sketched in Figure S6. It is characterized by a tiny core, or strongly connected component (SCC), a small IN-section, and a large OUT-section, as shown in Table S6.

2.3.1 Wealth

Most of the economic value, in terms of operating revenue v, is located in the LCC, as seen in Table S7. This justifies the analysis focusing solely on the LCC and ignoring the OCC.

Looking at the distribution of economic value in the bow-tie, most of it is locates in the OUT. This means that all other bow-tie components are competing for influence over this wealth. From this perspective, the TT are in competition with the core, while the IN has the possibility to reap the benefits from all other bow-tie components.

2.3.2 Disruption and Stability

While, overall, the network is growing in time, the number of nodes in the bow-tie components remains stable. This inertia in the face of constant influx indicates structural stability. In other words, as the network size approximately doubles between 2007 and 2012, most new nodes are refused affiliation with the LCC, resulting in the size of the OCC tripling. See Table S6.

	2007	2008	2009	2010	2011	2012
IN	1.70	1.52	1.77	1.73	1.28	1.66
Core	10.71	9.42	8.85	8.33	8.58	9.56
OUT	57.91	59.52	56.97	58.84	57.81	57.55
TT	18.61	18.01	19.60	18.25	18.66	18.24
LCC	88.93	88.47	87.19	87.15	86.33	86.01

Table S7. Bow-tie topology. Distribution of operating revenue v in the LCC, expressed as a percentage of the total reported in Table S3.

If we envision the LCC as a popular club in a city, we observe constant membership numbers over the years, despite the overall city population increasing. Continuing with this metaphor, the core (and to some extent the IN) represents the exclusive VIP area, with even more restricted access. Indeed, there is a very specific path to follow, for becoming a member of the "in-crowd". The greatest influx to the IN comes from the TT, and the core recruits the most new members from the OUT. Vice-versa, in times when the number of members is decreased, most of the excluded nodes from the IN migrate back to the TT and, similarly, core nodes move back to the OUT.

While a resistance to change can be observed in the relevant topological network features, this structural robustness is offset by a groundswell of individual node turnover—especially in times of global turmoil. In Table S8 the yearly percentages of outflux of nodes exiting the bow-tie components are shown. Conversely, Table S9 shows the yearly percentages of influx of nodes entering the bow-tie components. As an example, from the bow-tie node numbers shown in Table S6 it can be seen that the IN increased from 15,980 to 17,957 nodes from 2007 to 2008. This increase by 12.37% is due to an outflux of 21.70% (Table S8) and an influx of 34.07% (Table S9). As a result, 78.30% (=100.00% - 21.70%) of the IN-nodes present in 2007 remained in the IN in 2008. There are two reasons why bow-tie components gain or lose nodes. Either nodes reallocate to/from other parts of the network structure or new nodes are added to the network, respectively existing nodes are removed from it. In the current example, we see that 57.35% of the outflux, i.e., 12.44% of IN-nodes (meaning 1,989 nodes), reallocated to other bow-tie components (mostly to the TT). Hence 42.65% of the outflux (9.26% of IN-nodes) is due to shareholders not being present in the 2008 Orbis database anymore. Conversely, 53.55% of the influx (18.25% of IN-nodes) is due node reallocation (mostly from the TT), while 46.45% (15.83% of IN-nodes) is a result of new shareholders appearing in the database in 2008.

While it is impossible to deduce this complex behavior from the micro-behavior of agents, there are certain events which coordinate the node flux in the network. Two examples that can be observed in the data are the 2007/2008 financial crisis and the 2010/2011 sovereign debt crisis. These were disruptive world-spanning events that had the power to reshape the ownership network. For instance, the global financial crisis becomes detectable in 2009, when the IN and core suffered considerable losses in their number of members. In detail (see Tables S8 and S9), the IN lost 69.70% of nodes (72.61% of this due to reallocation), while the core lost 50.97% (97.76% thereof due to reallocation). By accounting for the influx, the IN shrunk overall by 40.26% and the core by 26.37%, respectively, in the wake of the crisis. At the same time, the TT gained 21.10% (=36.99%-15.89%), mostly (97.97%) due to the appearance of new nodes in 2009. The sovereign debt crisis, observable in 2011, had a similar but less pronounced effect. The IN and core shrunk overall by 29.50% (=53.99%-24.49%) and 18.02% (=37.45%-19.43%), respectively. Again, most of the outflux was due to the reallocation of nodes (69.42% in the IN and 92.84% in the core). In contrast to the global financial crisis, there is no other bow-tie

	IN	Core	OUT	TT
	Outflux (realloc.)	Outflux (realloc.)	Outflux (realloc.)	Outflux (realloc.)
2007/2008	21.70 (57.35)	24.36 (95.63)	18.22 (29.12)	18.53 (3.57)
2008/2009	69.70 (72.61)	50.97 (97.76)	16.82 (29.28)	15.89 (4.35)
2009/2010	35.63 (68.18)	25.04 (93.80)	18.35 (20.44)	14.96 (3.76)
2010/2011	53.99 (69.42)	37.45 (92.84)	21.53 (25.15)	36.71 (1.34)
2011/1012	30.54 (56.74)	29.76 (94.43)	21.40 (24.43)	39.69 (1.36)

Table S8. Bow-tie node turnover: Outflux. Yearly percentages reflecting number of nodes exiting the various bow-tie components. In parenthesis the fraction of the change is shown that is attributed to nodes migrating to other components, i.e., reallocation. As a result, the remaining part is due to nodes being removed from the network. See text for discussion.

	IN	Core	OUT	TT
	Influx (realloc.)	Influx (realloc.)	Influx (realloc.)	Influx (realloc.)
2007/2008	34.07 (53.55)	29.22 (94.76)	25.08 (21.27)	20.60 (3.10)
2008/2009	29.44 (48.15)	24.60 (93.42)	25.73 (21.54)	36.99 (2.03)
2009/2010	49.95 (64.05)	35.99 (95.45)	19.61 (24.23)	10.18 (4.30)
2010/2011	24.49 (40.06)	19.43 (95.40)	20.28 (20.62)	37.52 (1.85)
2011/1012	85.25 (73.35)	50.81 (97.11)	24.49 (16.78)	19.20 (3.13)

Table S9. Bow-tie node turnover: Influx. Yearly percentages reflecting number of nodes entering the various bow-tie components. In parenthesis the fraction of the change is shown that is attributed to nodes migrating from other components, i.e., reallocation. As a result, the remaining part is due to new nodes being added to the network. See text for discussion.

component substantially gaining nodes. Moreover, the IN and core appear to recover in 2012, as they regained members. In detail, the IN grew overall by 54.71% (=85.25%-30.54%) and the core by 21.04% (=50.80%-29.76%). This significant rebound one year after the disruptive effects of the sovereign debt crisis indicates structural resilience. However, the changes in the number of nodes present in the bow-tie components are only a superficial gauge of how the network reacts and adapts to shocks. The relevant measure to track disruptions, robustness, and resilience in the network is the evolution of the cumulative Influence Index (Section 1.7). In other words, the focus shifts from the structure of the bow-tie components to their function as power aggregators. This will be discussed in Section 2.5, especially Subsection 2.5.3.

To summarize, structural stability of the LCC and its bow-tie components is observed in the face of considerable network growth. Moreover, this part of the network accounts for a very large and stable percentage of economic value in the system. The exclusive bow-tie components, namely the IN and core, recruit new members mostly through very specific conduits in the network, further highlighting the importance of the network position of nodes. Finally, the disruptive effects of two global upheavals can be seen in the IN and core, decimating their member numbers. While the global financial crisis permanently reshaped the components, the IN and core recovered from the sovereign debt crisis in 2012.

In Figures S13 and S14 a selection of influential nodes in the bow-tie is shown, with the nodes colored according to specific attributes.

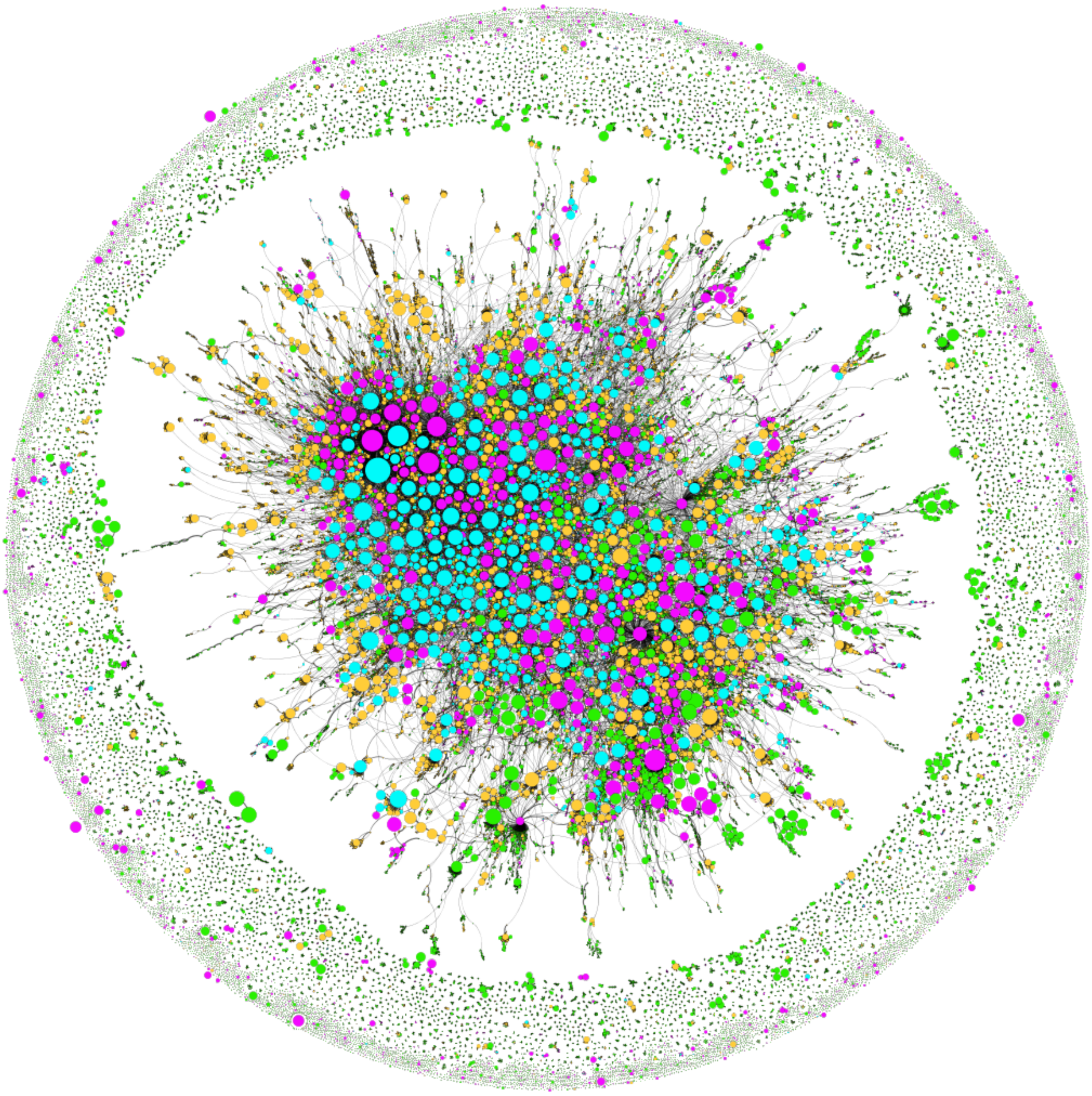

Figure S13. Zooming into the LCC. The layout of the top 1.2% of influential actors (with $\xi_i > 100$ million USD, i.e., 70,952 nodes) in the LCC in 2012, with only their ownership relations above 5% shown (i.e., 66'990 links), resulting in the halo of apparently isolated nodes. Nodes are scaled by Influence Index values and colored by bow-tie affiliation (pink: IN; cyan: core; green: TT; orange: OUT).

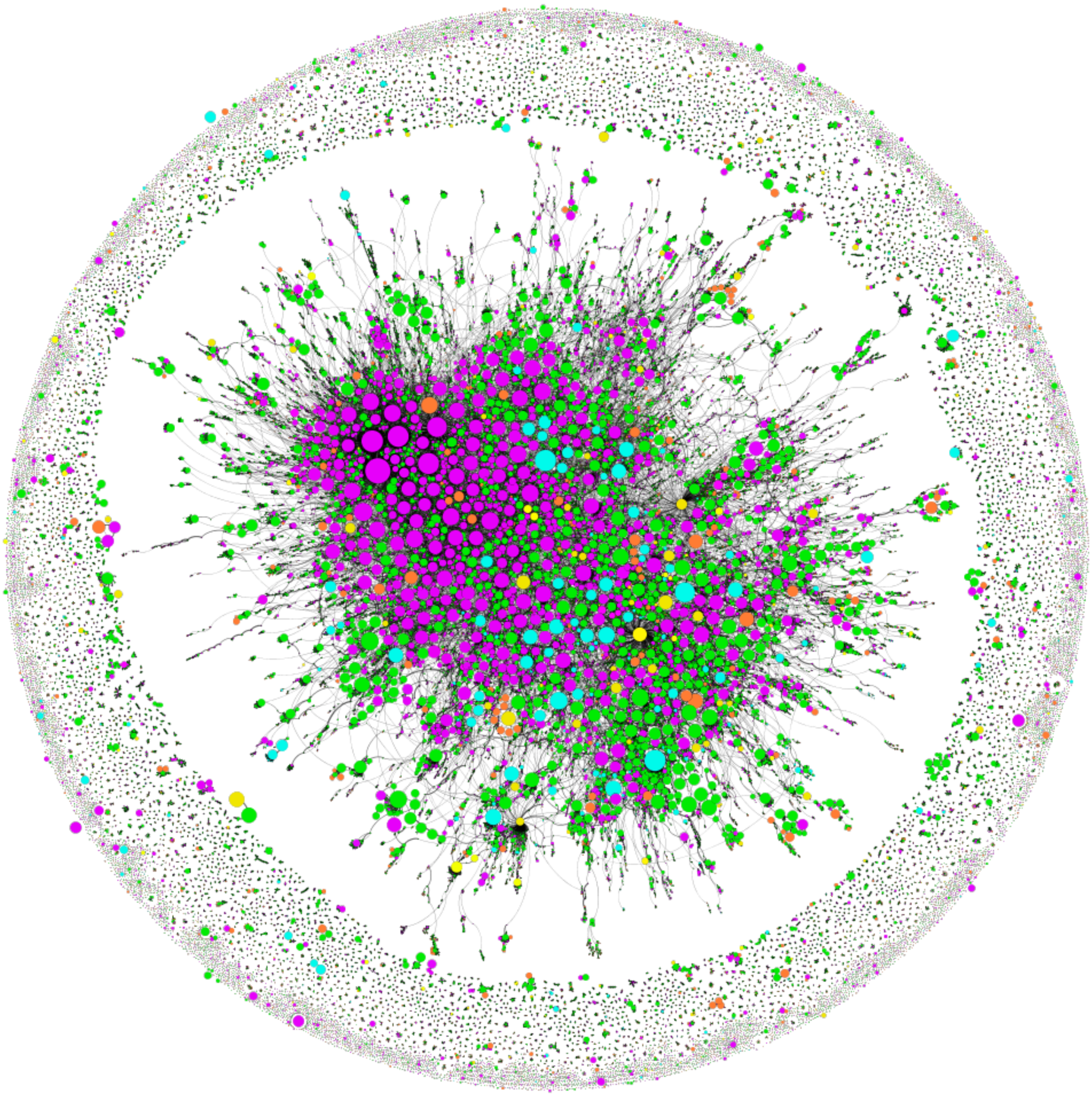

Figure S14. Zooming into the LCC. Same layout as in Figure S13. Nodes are scaled by Influence Index values and colored by type (pink: financial service companies; cyan: public authorities, states, and governments; green: industrial companies; orange: individuals or families).

2.4 Influence: Indexing the Global Ownership Network

2.4.1 The Yearly Rankings

In the following, the yearly Influence Index values ξ_i of the individual shareholders in the largest connected component (LCC, see Section 2.3) is shown in Tables S10 to S15. There, the top 14 influencers are ranked by their individual Influence Index scores, in trillion USD and, alternatively, as a percentage of the total sum of all individual ξ_i values ξ^{tot}.

Note that we are analyzing the individual ξ_i for each shareholder i. As a result

$$\xi^{\text{tot}} = \sum_i \xi_i > \sum_i v_i = v^{\text{tot}}. \tag{40}$$

In effect, by summing the individual ξ_i more value is reported than what is present in the network. However, as we are focusing on the individual importance of each shareholder and, most importantly, their rankings, we postpone the analysis of the cumulative influence. This issue is addressed by introducing the cumulative Influence Index value, described in Section 1.7, with the empirical results reported in Section 2.5.

Name	**Country**	**Bow-tie**	**Influence Index**	
			t USD	% of ξ^{tot}
BARCLAYS PLC	GB	SCC	1.448	1.218
CAPITAL GROUP COMPANIES	US	SCC	1.316	1.107
AXA	FR	SCC	0.950	0.799
FMR LLC	US	SCC	0.949	0.799
JPMORGAN CHASE & CO	US	SCC	0.823	0.693
STATE STREET CORPORATION	US	SCC	0.779	0.655
GOVERNMENT OF FRANCE	FR	IN	0.567	0.477
VANGUARD GROUP INC	US	IN	0.524	0.441
LEGAL & GENERAL GROUP PLC	GB	SCC	0.522	0.439
CENTRAL PEOPLE'S GOVERNMENT OF CN	CN	IN	0.437	0.368
ROYAL DUTCH SHELL PLC	GB	SCC	0.417	0.351
ALLIANZ SE	DE	SCC	0.402	0.338
UBS AG	CH	SCC	0.396	0.333
FRANKLIN RESOURCES INC	US	SCC	0.387	0.325

Table S10. Influence Index ranking. 2007.

Name	Country	Bow-tie	Influence Index	
			t USD	% of ξ^{tot}
BARCLAYS PLC	GB	SCC	1.377	1.095
CAPITAL GROUP COMPANIES	US	IN	1.271	1.011
AXA	FR	SCC	0.910	0.724
FMR LLC	US	IN	0.887	0.706
STATE STREET CORPORATION	US	SCC	0.842	0.669
JPMORGAN CHASE & CO	US	SCC	0.824	0.655
VANGUARD GROUP INC	US	IN	0.633	0.504
GOVERNMENT OF FRANCE	FR	IN	0.560	0.446
CENTRAL PEOPLE'S GOVERNMENT OF CN	CN	IN	0.549	0.437
LEGAL & GENERAL GROUP PLC	GB	SCC	0.475	0.378
ROYAL DUTCH SHELL PLC	GB	SCC	0.469	0.373
BANK OF AMERICA CORPORATION	US	SCC	0.453	0.360
BANK OF NEW YORK MELLON CORP	US	SCC	0.440	0.350
GOVERNMENT OF NORWAY	NO	IN	0.415	0.330

Table S11. Influence Index ranking. 2008.

Name	Country	Bow-tie	Influence Index	
			t USD	% of ξ^{tot}
BLACKROCK INC	US	SCC	1.811	1.336
CAPITAL GROUP COMPANIES	US	IN	1.194	0.882
BARCLAYS PLC	GB	SCC	0.960	0.708
FMR LLC	US	IN	0.876	0.647
JPMORGAN CHASE & CO	US	SCC	0.829	0.612
AXA	FR	SCC	0.809	0.597
STATE STREET CORPORATION	US	SCC	0.807	0.596
VANGUARD GROUP INC	US	IN	0.688	0.508
GOVERNMENT OF FRANCE	FR	IN	0.512	0.378
GOVERNMENT OF NORWAY	NO	IN	0.459	0.339
CENTRAL PEOPLE'S GOVERNMENT OF CN	CN	IN	0.450	0.332
LEGAL & GENERAL GROUP PLC	GB	SCC	0.433	0.319
ALLIANZ SE	DE	SCC	0.385	0.284
ROYAL DUTCH SHELL PLC	GB	SCC	0.370	0.273

Table S12. Influence Index ranking. 2009.

Name	Country	Bow-tie	Influence Index	
			t USD	% of ξ^{tot}
BLACKROCK INC	US	SCC	2.147	1.346
CAPITAL GROUP COMPANIES	US	IN	1.296	0.812
FMR LLC	US	IN	0.969	0.608
GOVERNMENT OF FRANCE	FR	IN	0.909	0.570
CENTRAL PEOPLE'S GOVERNMENT OF CN	CN	IN	0.875	0.549
VANGUARD GROUP INC	US	IN	0.870	0.546
STATE STREET CORPORATION	US	SCC	0.866	0.543
AXA	FR	SCC	0.838	0.525
SASAC	CN	IN	0.816	0.512
BARCLAYS PLC	GB	SCC	0.642	0.402
JPMORGAN CHASE & CO	US	SCC	0.557	0.349
GOVERNMENT OF NORWAY	NO	IN	0.555	0.348
ROYAL DUTCH SHELL PLC	GB	SCC	0.522	0.327
THE MINISTER OF FINANCE	JP	TT	0.483	0.303

Table S13. Influence Index ranking. 2010.

Name	Country	Bow-tie	Influence Index	
			t USD	% of ξ^{tot}
BLACKROCK INC	US	SCC	2.234	1.308
CAPITAL GROUP COMPANIES	US	IN	1.243	0.728
VANGUARD GROUP INC	US	IN	1.105	0.647
CENTRAL PEOPLE'S GOVERNMENT OF CN	CN	IN	1.002	0.587
STATE STREET CORP	US	SCC	0.991	0.580
GOVERNMENT OF FRANCE	FR	IN	0.977	0.572
FMR LLC	US	IN	0.961	0.563
SASAC	CN	IN	0.953	0.558
GOVERNMENT OF NORWAY	NO	IN	0.883	0.517
ROYAL DUTCH SHELL PLC	GB	SCC	0.608	0.356
AXA	FR	SCC	0.591	0.346
JPMORGAN CHASE & CO	US	SCC	0.566	0.331
PRAVITELSTVO ROSSIISKOI FEDERATSII	RU	TT	0.512	0.300
E.ON SE	DE	SCC	0.511	0.299

Table S14. Influence Index ranking. 2011.

Name	Country	Bow-tie	Influence Index	
			t USD	% of ξ^{tot}
BLACKROCK INC	US	SCC	2.177	1.236
VANGUARD GROUP INC	US	IN	1.314	0.746
GOVERNMENT OF NORWAY	NO	IN	1.220	0.692
SASAC	CN	IN	1.210	0.687
CAPITAL GROUP COMPANIES	US	IN	1.201	0.682
STATE STREET CORP	US	SCC	1.190	0.675
GOVERNMENT OF FRANCE	FR	IN	0.982	0.557
FMR LLC	US	IN	0.955	0.542
BARCLAYS PLC	GB	SCC	0.675	0.383
ROYAL DUTCH SHELL PLC	GB	SCC	0.619	0.351
JPMORGAN CHASE & CO	US	SCC	0.572	0.325
CENTRAL PEOPLE'S GOVERNMENT OF CN	CN	IN	0.565	0.301
AXA	FR	SCC	0.529	0.300
BANK OF NEW YORK MELLON CORP	US	SCC	0.516	0.293

Table S15. Influence Index ranking. 2012.

While it is true that the list of top influencers is not surprising (Murray and Peetz, 2010), the ranking per se is not the whole story. It has to be emphasized, that all the top influencers in the core are all highly interconnected with each other, giving rise to emergent power structures (see Section 2.5). Moreover, the Influence Index value reveals a clear ranking of the economic actors and the distance between them, measured in USD. Furthermore, the evolution of the top rankings shows a shift in power, hinted at in the literature (Haberly and Wójcik, 2017; The Economist, 2015). Namely, it chronicles how mostly European universal banks have lost their prevailing position of power in the wake of the financial crisis. This power has shifted towards US asset managers, epitomized by BlackRock (see Section 2.4.3).

The prevailing influence of the top ranked governments is attributed to their targeted investments. For instance, the Government of France holds many shares in influential companies from the energy, finance, telecommunication, automobile, and transportation sectors. The Central People's Government of China gains influence via large holdings in utility and financial corporations. The Government of Norway is heavily invested in companies with a high Influence Index value, like Statoil ASA and many of the top influencers from the financial sector. Indeed, in 2012 it held 7.1% of shares in BlackRock. It also completely owns Norges Bank, which in turn manages the Norwegian Government Pension Fund Global. Then, Royal Dutch Shell gains a large Influence Index value via a pyramidal holding structure. See also Section 2.6.1.

Finally, it should be noted that some major investment management companies could be misattributed to the IN-section of the bow-tie. This can happen for private and independent companies who do not disclose their ownership structure. For instance, Capital Group Companies, FMR, and Wellington Management. Others can have special tailored ownership, like Vanguard[5]:

> At Vanguard, there are no outside owners, and therefore, no conflicting loyalties. The company is owned by its funds, which in turn are owned by their shareholders.

Recall that the role and influence of institutional holders in general was discussed in detail in Section 2.2.4.

[5] From `https://about.vanguard.com/what-sets-vanguard-apart/why-ownership-matters/`, retrieved on the 5th of September 2016.

	2007	2008	2009	2010	2011	2012
$\mathcal{J}_{100}(\{\xi_i\},\{v_i\})$	0.1364	0.1173	0.1494	0.1173	0.1050	0.0870
$\mathcal{J}_{10000}(\{\xi_i\},\{v_i\})$	0.1635	0.1710	0.1813	0.1938	0.1889	0.1848
$\mathcal{J}_{100}(\{\xi_i\},\{k_i^{\text{out}}\})$	0.2903	0.3423	0.3245	0.3072	0.2821	0.2903
$\mathcal{J}_{10000}(\{\xi_i\},\{k_i^{\text{out}}\})$	0.1667	0.1700	0.1727	0.1810	0.1745	0.1710

Table S16. Comparing rankings. The ranked set of top shareholders by Influence Index value ξ_i is compared to the ranking by operating revenue v_i and the ranking by out-degree k_i^{out}, by virtue of the Jaccard Index $\mathcal{J}_n$, for two sets of varying length (100 and 10,000 elements).

2.4.2 Alternative Rankings

In order to assess the relevance of the proposed Influence Index, ultimately justifying its application, other proxies for relevance need to be considered. In the following, we compare a measure of value that ignores the network, a simple network measure, and the Influence Index values based not on operating revenue but on market capitalization and total assets. To address this question of comparison, we utilize the Jaccard Index, a statistic used for assessing the similarity of sets (Jaccard, 1912). It is defined as

$$\mathcal{J}(A,B) := \frac{|A \cap B|}{|A \cup B|}, \tag{41}$$

where a value of one indicates a total overlap of the sets.

Can the relevance of economic actors in the global ownership network be deduced from their wealth alone? For instance, how does the ranking of actors according to operating revenue (see Section 1.5) compare to the ranking by Influence Index value? In detail, what are the values of $\mathcal{J}_n(\{\xi_i\},\{v_i\})$, where n indicates the length of the lists to be compared. We find that the ranking in operating revenue is a bad predictor for influence, in particular for the lists of the top 100 actors, as seen in Table S16. The similarity measure only detects an overlap between 8.70% and 14.94%.

In a next step, we consider a proxy of relevance utilizing the network. A simple measure is

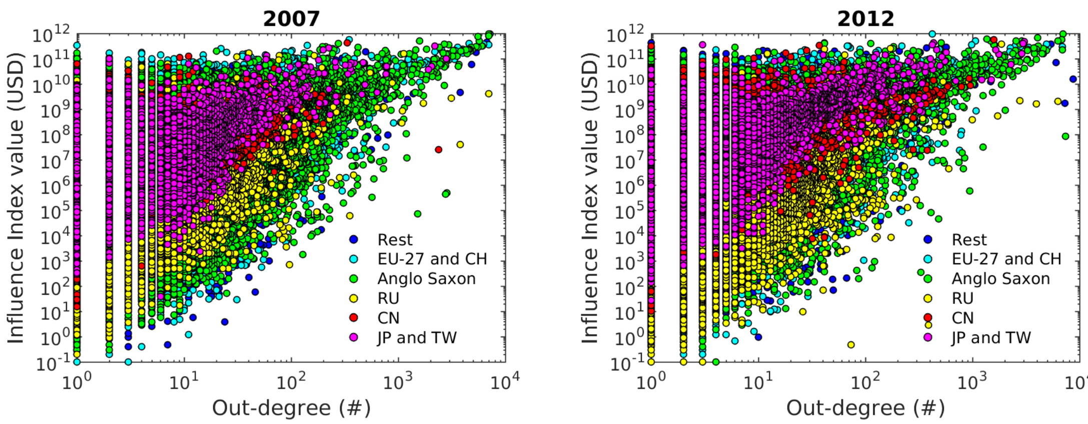

Figure S15. Out-degree vs. Influence Index value scatter-plot. The x-axis shows the number of outgoing links k_i^{out} for each shareholder in the largest connected component (LCC) of the global ownership network. The y-axis reflects the Influence Index value for the shareholders. Two yearly snapshots are evaluated. See discussion in text.

	2007	2008	2009	2010	2011	2012
$\mathcal{J}_{100}(\{\xi_i\}, \{\xi_i^{\text{mc}}\})$	0.4815	0.4706	0.4925	0.4815	0.4815	0.5152
$\mathcal{J}_{10000}(\{\xi_i\}, \{\xi_i^{\text{mc}}\})$	0.3050	0.3032	0.3025	0.3119	0.3141	0.3152
$\mathcal{J}_{100}(\{\xi_i\}, \{\xi_i^{\text{ta}}\})$	0.1598	0.1462	0.1598	0.1264	0.1136	0.1062
$\mathcal{J}_{10000}(\{\xi_i\}, \{\xi_i^{\text{ta}}\})$	0.1892	0.1959	0.2043	0.2143	0.2100	0.2069
$\mathcal{J}_{100}(\{\xi_i^{\text{mc}}\}, \{\xi_i^{\text{ta}}\})$	0.1512	0.1314	0.1445	0.1314	0.1250	0.1379
$\mathcal{J}_{10000}(\{\xi_i^{\text{mc}}\}, \{\xi_i^{\text{ta}}\})$	0.0995	0.1022	0.1062	0.1091	0.1109	0.1077

Table S17. Comparing rankings. The set of top shareholders by Influence Index value based on operating revenue ξ_i is compared to the Influence Index value ranking based on market capitalization ξ_i^{mc} and total assets ξ_i^{ta} for two rankings of varying length. Finally, the two alternative rankings are compared to each other.

the degree measuring the number of links of the nodes in the network. We focus on the out-degree of a shareholder i, denoted as k_i^{out} (see Section 1.4), which corresponds to the number of firms the shareholder holds shares in. Hence it can be seen as a rough measure of the portfolio diversification. Again, the similarity is computed as $\mathcal{J}_n(\{\xi_i\}, \{k_i^{\text{out}}\})$. Table S16 indicates that there is a correlation $\xi_i \sim k_i^{\text{out}}$ for top influencers. Indeed, this relationship is visualized in Figure S15. However, it should be noted that there exist many economic actors with high Influence Index values for the whole range of k_i^{out}. In other words, a small out-degree does not necessarily imply a small Influence Index value.

Recall from Section 1.6.1 that the Influence Index values computed for the yearly network snapshots can be based on three proxies for value: operating revenue, market capitalization, and total assets (see Section 1.5). While market capitalization is only available for a small set of listed companies (approximately between 21,000 and 33,500 firms), total assets introduce a bias in favor of financial institutions. Our default choice is hence operating revenue. However, we also ran the algorithm for the other two proxies of firm value. Let ξ_i^{mc} and ξ_i^{ta} denote the Influence Index value based on the distribution of market capitalization and total assets, respectively. Unsurprisingly, ξ_i^{ta} returns large global universal banks as top influencers, due to their balance sheet positions. The ranking of ξ_i^{mc} is more insightful, as it represents the reduced ownership network related to listed companies. In Table S17 it is shown that for the top hundred ranked actors there is a significant overlap between the rankings based on operating revenue and market capitalization. Comparing the ranking of ξ_i^{ta} shows little overlap with any of the other rankings. In effect, total assets should not be utilized as the value proxy of companies, unless one is focussing solely on financial institutions. The similarity between ξ_i and ξ_i^{mc} does in fact suggest a certain robustness of the Influence Index. While market capitalization is only available for a fraction of the companies, the Influence Index based operating revenue yields the most comprehensive picture.

To summarize, just by looking at the value and the first level of connectivity of shareholders one cannot gain enough information to assess their influence in the global ownership network. The broadest ranking is given by the Influence Index based on operating revenue. While the names of the top influencers are not unexpected, the following should be considered. Firstly, the top influencers are highly interconnected, a fact that will be analyzed in Section 2.5. Secondly, the Influence Index value gives a vast spectrum, measured in USD, categorizing shareholders. Finally, the evolution of the top ranking actors is inline with what other scholars have independently observed. Namely a shift of power from US and EU universal banks, financial services providers, and insurance companies to US asset managers (Haberly and Wójcik, 2017; The Economist, 2015).

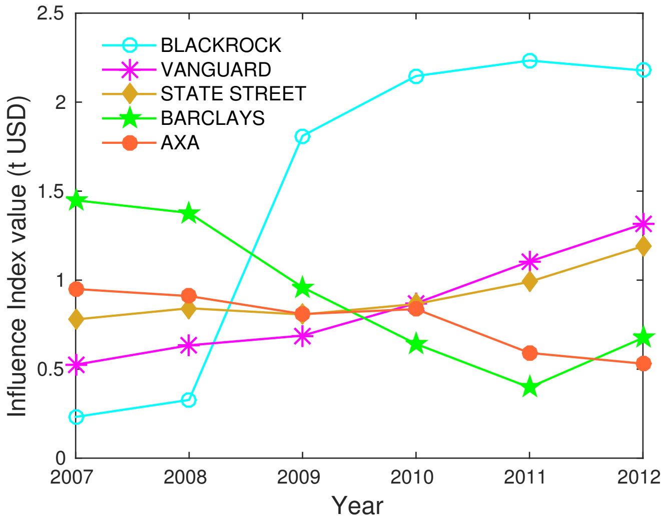

Figure S16. Evolution of a selection of top influencers. BlackRock is seen rising while the former number one, Barclays, is in decline.

2.4.3 BlackRock Rising

Two main reasons can be discerned which help explain the stellar rise of BlackRock, documented in Figure S16. One is related to the company's role in the post-crisis turmoil in the US[6] (The Economist, 2013a):

> As crashing banks revealed how spectacularly poorly the financial world had understood the complex and shady instruments it had put its money into, BlackRock, far from needing a bail-out, was something of an antidote. When the American government found itself owning or guaranteeing toxic assets, it turned to BlackRock, which was seen as having more limited conflicts of interest than everyone else concerned, to analyse, value and sell them. The company got similar business from Greece and Britain.

As a result (Peetz et al., 2013):

> The most important shareholder in the US is one that has risen to that position through the global financial crisis, Blackrock Inc., a New York-based finance company and funds manager [...].

Then, in 2009, BlackRock purchased Barclays' fund-management arm, called Barclays Global Investors, creating the largest fund-management group in the world with about 2.7 trillion USD in assets (The Economist, 2009), in effect, dethroning the reigning champion. In 2013, the following was observed (The Economist, 2013b):

> [BlackRock] is easily the biggest investor in the world, with $4.1 trillion of directly controlled assets (almost as much as all private-equity and hedge funds put together) and another $11 trillion it oversees through its trading platform, Aladdin.

Unsurprisingly, the financial press and other news media describe the company and its CEO and co-founder Larry Fink in the grandest of terms:

- "BlackRock today is one of, if not the, most influential financial institutions in the world" (Bloomberg News, 2010).

[6] Related to US Treasury contracts under the Troubled Asset Relief Program (TARP).

- "[T]here is nothing but admiration for the vast power of BlackRock" (Vanity Fair, 2010).
- "[BlackRock] is the biggest shareholder in half of the world's 30 largest companies" (The Economist, 2013a).
- "[BlackRock] has control over investments it holds on behalf of others—which gives it great influence" (The Economist, 2013b).
- "Though few Americans know his name, Larry Fink may be the most powerful man in the post-bailout economy" (Vanity Fair, 2010).

Or put in a broader context (Davis, 2013):

> [...] the US has never before seen corporate ownership this concentrated in the hands of a small number of financial institutions. In relative terms, BlackRock is far more massive than J.P. Morgan ever was.

As BlackRock holds the shares of companies on behalf of its clients it can also vote on behalf of them, a process known as proxy voting (see also Section 2.2.4). The issue related to the influence BlackRock gains from the multitude of such votes is complex. The company issues clear guidelines for proxy voting[7]. Their voting process is led by a Corporate Governance and Responsible Investment team. Next to long-term economic interests, the company claims to consider social, ethical, and environmental issues next to general corporate governance matters. Indeed, BlackRock is known to have taken an activist stance with respect to shareholder voting. Analyzing 50 board fights from 2009 through 2013, it was found that BlackRock had voted for 34% of the dissident directors nominated. Moreover, in 2012 the company considered nearly 130,000 management and shareholder proposals and voted against management in 10% of them. See (Fortune, 2014).

Undoubtedly, BlackRock wields great influence. The sheer size of its assets under management eclipses its rivals. This position of power has also raised political discussions in the US, whether BlackRock is a "systemically important financial institution" and hence should receive stricter regulation. The company has successfully argued that, as long as it does not invest in its own funds, it offers little if any systemic risk (The Economist, 2013a). In the words of Fink: "We're just an asset manager, not a systemic threat in any way" (Fortune, 2014). See Section 2.6.3 for more details on systemic risk issues.

Other scholars have also detected the rise of BlackRock, Vanguard, and State Street, seen in Figure S16. To quote from (Fichtner et al., 2017):

> Since 2008, an unprecedented shift has occurred from active towards passive investment strategies. We showed that this passive index fund industry is dominated by BlackRock, Vanguard, and State Street. In fact, seen together, these three giant passive asset managers already constitute the largest shareholder in at least 40 percent of all U.S. listed companies and 88 percent of the S&P 500 firms. Hence, we see indications of a reunification of corporate ownership and control through rapidly rising equity holdings managed by a small group of very large passive index fund managers, which we call the Big Three.

Moreover, the ability of such major passive investors to actively exert shareholder power was discussed in Section 2.2.4. To restate (Fichtner et al., 2017):

> [T]he extent of the concentration of ownership in the hands of the Big Three may also lead to a position of structural power.

[7]Consult their FAQ found here: `https://www.blackrock.com/corporate/en-in/literature/fact-sheet/blk-responsible-investment-faq-global.pdf`.

	2007	2008	2009	2010	2011	2012
$\hat{\xi}_{0.01}$ (USD)	$7.17 \cdot 10^7$	$7.66 \cdot 10^7$	$6.43 \cdot 10^7$	$8.19 \cdot 10^7$	$9.11 \cdot 10^7$	$1.35 \cdot 10^8$
$\hat{\xi}_{0.001}$ (USD)	$2.16 \cdot 10^9$	$2.21 \cdot 10^9$	$1.92 \cdot 10^9$	$2.435 \cdot 10^9$	$2.59 \cdot 10^9$	$3.47 \cdot 10^9$

Table S18. Monetary thresholds for the top 1% and 0.1% in the LCC. Values of the 99%, and 99.9% quantile, respectively, in the distribution of the individual Influence Index.

Finally, recall that the role and influence of institutional holders in general was also discussed in detail in Section 2.2.4.

2.5 Power Structures

Focusing on individual shareholders in the global ownership network represents the first level of analysis. While these rankings of influence are themselves of interest (see Section 2.4), an immediate follow-up question concerns the interrelatedness of the actors. Namely: To what degree are the top influencers interconnected with each other? In order to address this question, a cumulative version of the Influence Index is presented in Section 1.7. This methodology is applicable to cohesive groups of shareholders and avoids previously encountered issues of double-counting.

Naturally defined groups of shareholders can be identified by the delimitations given by the network topology, as described in Section 2.3. Such topological groups are the differenet sections of the bow-tie. Furthermore, by utilizing the knowledge of the individual Influence Index values, nested power structures can be uncovered deeper in the network. In the following, we analyzing at the distribution of the individual Influence Index values of the top influencers located in the different bow-tie components. This allows the identification of power structures.

Let $\hat{\xi}_{0.01}$ denote the 0.99-quantile of the individual ξ-distribution in the LCC. In detail, this means

$$\hat{\xi}_{0.01} = \inf \{\xi|_{\text{LCC}} : \mathcal{P}[\xi_i \leq \xi] \geq 0.99\} . \tag{42}$$

Correspondingly, for the 0.999-quantile

$$\hat{\xi}_{0.001} = \inf \{\xi|_{\text{LCC}} : \mathcal{P}[\xi_i \leq \xi] \geq 0.999\} . \tag{43}$$

In Table S18 the values (in USD) of the thresholds are shown above which the top influencers are defined. Now the overall Influence Index value distribution in the LCC can be dissected for the top influencers according to their location in the bow-tie components. This is seen in Figure S17. While all bow-tie components are populated with top influencers, the IN and core contain the most influential economic actors of each quantile. There is a gap of roughly one order of magnitude (approximately 1.6 trillion USD in 2012) separating the highest influencers in the IN and core from the ones in the OUT and TT. As a result, we can identify the IN and core as power structures. Indeed, the core is more dominant and the IN gained structural influence between 2007 and 2012. This categorization will be confirmed, when the cumulative Influence Index values for the bow-tie components are computed, presented in Section 2.5.1.

However, to what extent such groups of shareholders will have aligned common interests, and hence will act together on them, is beyond the scope of this work. What can be suggested in the context of shareholder activism (see Section 2.2.4) is the following (Wells, 2015, p. 25):

> [T]he possibility of reducing the costs of activism by acting in concert with other investors made such activism still more likely.

The broader ramifications related to concentrated ownership and power are discussed in Section 2.6.

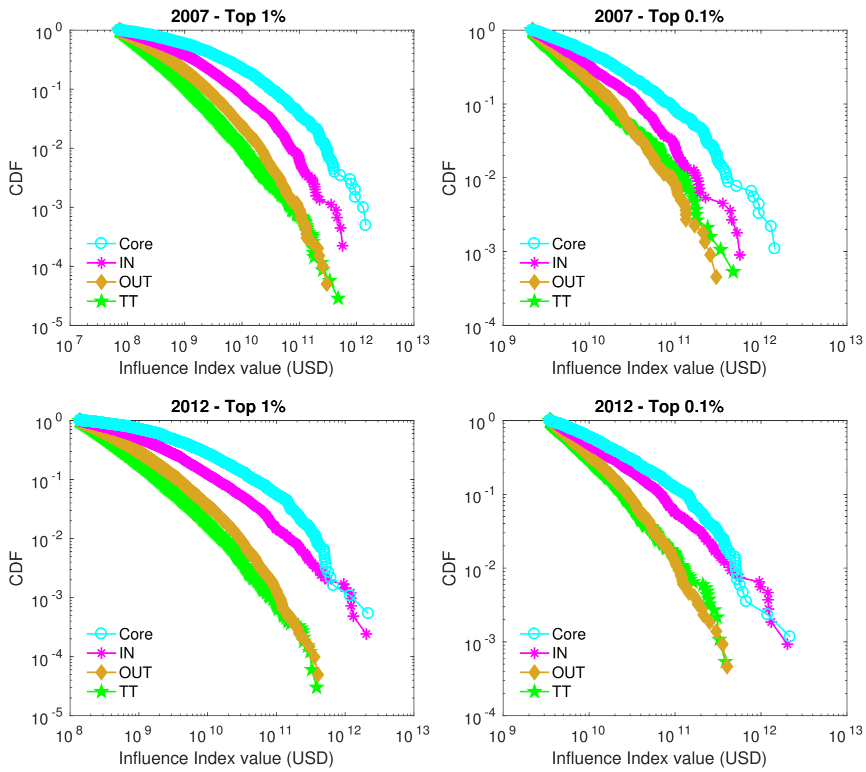

Figure S17. Identifying power structures. Distributions of the Influence Index values for the top influencers (i.e., $\xi_i > \hat{\xi}_{0.01}$ and $\xi_i > \hat{\xi}_{0.001}$, respectively) in the different bow-tie components, shown for two years.

2.5.1 The Bow-Tie Components

Recall that the the largest connected component, comprised approximately of 6.72m ± 0.79m nodes, decomposes into a small IN-section and a tiny core. In approximate number of nodes, 13.3k ± 4.6k and 2.6k ± 0.5k, respectively. See Section 2.3 for more details.

In Table S19 the results of the computation of the cumulative Influence Index value for the bow-tie components are presented. Note that the different bow-tie sections command different spheres of influence. While the IN-section can in theory influence the core, the OUT-section, and the tubes and tendrils, the core can itself only affect the value in the OUT-section. Moreover, the Influence Index values of the sections are not additive. As ξ-contributions flow upstream, by construction they dissipate in the cycles of downstream segments. To illustrate, this effect

		2007	**2008**	**2009**	**2010**	**2011**	**2012**
ξ^{IN}	(%)	21.60	24.77	23.99	24.43	22.37	24.63
	(t USD)	19.09	23.71	24.24	28.92	28.56	31.32
ξ^{Core}	(%)	20.27	17.80	18.03	17.90	17.97	18.07
	(t USD)	17.91	17.04	18.22	21.18	22.94	22.98

Table S19. Topological power structures Cumulative Influence Index value of selected bow-tie components. The values are expressed in absolute numbers (trillion USD) and as percentages of the yearly total operating revenue in the system.

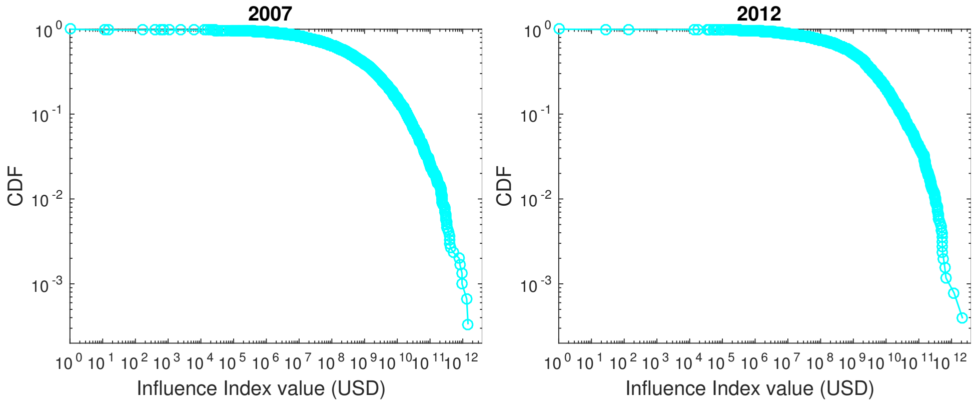

Figure S18. Influence Index in the core. Distribution of the individual Influence Index values of the nodes in the core, shown for two yearly snapshots.

explains why the IN-section does not gain a much larger Influence Index value than the core, despite its bigger sphere of influence. The many cycles in the core act as sinks for the ξ-contributions, preventing a significant fraction from the OUT-section and the core itself to flow upstream to the IN-section.

For the tubes and tendrils we find: $\xi^{\mathrm{TT}} = 11.17\% \pm 0.56\%$. Finally, $\xi^{\mathrm{OUT}} = 0$, by definition, as there are no additional nodes to which the OUT-section can link to. In effect, the IN and core are topological power structures. Recall the discussion at the beginning of Section 2.5.

2.5.2 The Emerging Super-Entity

Throughout this section, the special role of the core has been revealed. It is a tiny but highly interconnected group of individually influential shareholders, commanding vast cumulative influence. As a distinct network structure, the core is described in Table S20. In a next step, we investigate if the core itself has additional substructures.

Figure S18 shows the distribution of the individual Influence Index values in the core. The observed skewness implies that many nodes in the core are actually not overly influential but only add to the structural connectivity. In contrast, a handful of nodes are disproportionally influential. In other words, there exists an emergent power structure nested within the core of the global ownership network. Such a structure was hinted at in (Vitali et al., 2011). In the following, we introduce a more rigorous definition and analyze the evolution of this emerging super-entity over time.

In a first step, we define the super-entity as those actors located in the core who are also in the top 5% quantile of the individual ξ-distribution within the core. Let $\hat{\xi}$ denote the 0.95-quantile in the distribution of the Influence Index value in the core. This means that

$$\hat{\xi} = \inf \{\xi|_{\mathrm{Core}} : \mathcal{P}[\xi_i \leq \xi] \geq 0.95\} . \tag{44}$$

	2007	**2008**	**2009**	**2010**	**2011**	**2012**
$\lvert V^{\mathrm{Core}}\rvert$ (#)	3,005	3,151	2,320	2,574	2,110	2,554
$\lvert E^{\mathrm{Core}}\rvert$ (#)	25,586	24,849	20,370	21,734	18,593	22,570

Table S20. The core. Number of nodes (in the set core nodes V^{Core}) and number of links (in the set of inter-core links E^{Core}).

		2007	2008	2009	2010	2011	2012
$\hat{\xi}$	(b USD)	47.45	43.22	61.82	65.72	99.28	76.36
$\lvert V^{\mathrm{SE}} \rvert$	(#)	146	150	111	123	101	123

Table S21. The super-entity. Values of the 95% quantile $\hat{\xi}$ in the distribution of the individual Influence Index in the core. Number of nodes in the resulting super-entity V^{SE} comprised of the top 5% influencers in the core.

If V^{Core} denotes the set of nodes in the core, then

$$V^{\mathrm{SE}} := \left\{ v \in V^{\mathrm{Core}} : \xi_v > \hat{\xi} \right\}, \tag{45}$$

represents the set of all nodes in the super-entity, i.e., the core nodes in the top 5% quantile of the individual Influence Index distribution. The results are presented in Table S21.

In a second step, the cumulative Influence Index value for the super-entity is computed. The outcome is shown in Table S22. Indeed, as a cohesive group, the super-entity commands at least 97.5% of the cumulative Influence Index value that was assigned to the core (see Table S19). This high degree of concentration justifies the delimitation of the super-entity as an emergent power structure in the network. On average, a node in the super-entity contributes 119.38 billion USD to the group's cumulative Influence Index value in 2007. In 2012, this number is 165.40 billion USD. As a consequence, the few nodes in the super-entity are by far the most influential in the whole network.

Looking at the composition of the super-entity over time, we find that there is an inner group of 70 nodes that are present in all yearly snapshots from 2007 through to 2012. This means that $58.0\% \pm 11.3\%$ of the nodes in the super-entity are persistent and make up the temporally stable core of the super-entity in the analyzed time horizon. A selection of these actors is shown in Table S23.

2.5.3 The Architecture of Power

To summarize, we identify two topological power structures, the IN and the core. They are both comprised of the highest ranked influencers in the top quantiles of the individual Influence Index distribution. Both structures are also distinguished by high cumulative Influence Index values. Then, an emergent power structure was uncovered in the core, the super-entity.

In essence, the global ownership network displays a fractal nature. By zooming into its fabric one finds a hierarchy of nested structures. Starting with the largest connected component ($6.7\mathrm{m} \pm 0.8\mathrm{m}$ nodes, see Section 2.5.1) containing most of the economic value ($87.6\% \pm 1.3\%$, see Section 2.3), the core of this structure is tiny ($2.6\mathrm{k} \pm 0.5\mathrm{k}$ nodes, see Section 2.5.1) but highly

		2007	2008	2009	2010	2011	2012
ξ^{SE}	(%)	19.72	16.90	16.26	16.10	15.44	16.00
	(t USD)	17.43	16.18	16.43	19.06	19.71	20.34

Table S22. The influence of the super-entity. Cumulative Influence Index value of the nodes in the super-entity. The values are expressed in absolute numbers (trillion USD) and as percentages of the yearly total operating revenue in the system.

Name	Country
BLACKROCK INC	US
STATE STREET CORPORATION	US
BARCLAYS PLC	GB
ROYAL DUTCH SHELL PLC	GB
JPMORGAN CHASE & CO	US
AXA	FR
BANK OF NEW YORK MELLON CORP	US
BP PLC	GB
FRANKLIN RESOURCES INC	US
T. ROWE PRICE GROUP INC	US
MITSUBISHI UFJ FINANCIAL GROUP INC	JP
JAPAN TRUSTEE SERVICES BANK LTD	JP

Table S23. Temporally stable core in the super-entity. Selection of top influencers in the group of 70 nodes that are present in the super-entity for all years, ranked by their individual Influence Index value of 2012.

influential ($\xi^{\text{Core}} = 19.0\% \pm 1.2\%$, see Section 2.5.1). Finally, within the core the super-entity is uncovered, identifying a minuscule group (126 ± 25 nodes) that wields a disproportionally high degree of influence ($\xi^{\text{Core}} = 17.6\% \pm 2.1\%$). In conclusion, the super-entity is the smallest and most influential power structure in the global ownership network. It has its own stable core of 70 influential shareholders, which are all present in the super-entity of each yearly network snapshot.

Figure S19 summarizes the evolution of the cumulative Influence Index value for the power structures in the network. The impact of the 2007/2008 global financial crisis and the 2010/2011 sovereign debt crisis can be observed. In detail, in 2007, the IN, core, and super-entity commanded comparable influence. The crisis had the largest impact on the core, and the super-entity

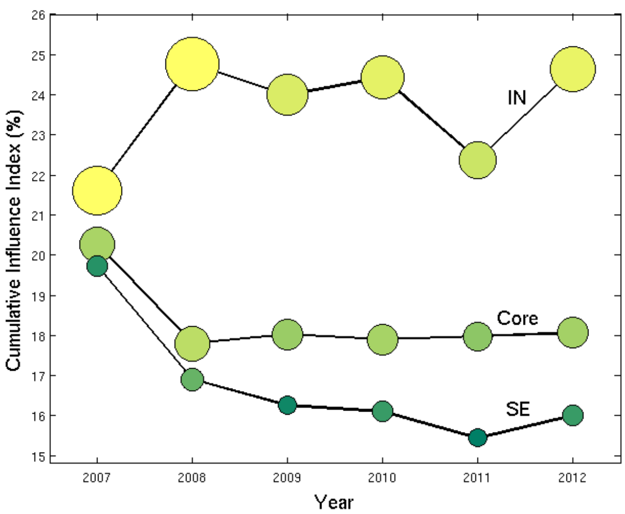

Figure S19. The architectures of power. The evolution of the cumulative Influence Index values of the power structures $\mathcal{S}$ (where $\mathcal{S}$ represents the IN-section, the core, and the super-entity, respectively). The size of the circles is indicative of the number of nodes in the corresponding structure ($n^{\mathcal{S}} = |V^{\mathcal{S}}|$). The color represents the average individual Influence Index value per node ($\xi^{\mathcal{S}}/n^{\mathcal{S}}$), the darker, the higher the value. See also text for discussion.

nested within, draining cumulative Influence Index value. Interestingly, this power is captured by the next larger power structure, the IN. The core consolidates after the global financial crisis and hence its yearly cumulative Influence Index values stay stable. This is in contrast to the IN, and to a lesser extent the super-entity, feeling the disruptive effects of the sovereign debt crisis in 2011, again draining power from the structures. Interestingly, both affected power structures recover the year after, showing resilient behavior. In a nutshell, there is disruption, stability, and resilience to be observed in the power structures of the global ownership network in the face of shocks.

But how did the network structures underlying these transformations evolve? In Section 2.3.2 the differences in the number of nodes in the IN and core were analyzed. One can observe varying behavior for all three power structures. In the IN, the changes in size correlate with the changes in ξ^{IN}: more nodes result in a higher cumulative Influence Index value. For the core, there is mostly an anti-correlation to be seen, while the super-entity shows both correlation and anti-correlation between the changes in node numbers and the changes in ξ^{SE}. This varied behavior shows that the cumulative Influence Index value of a network structure is an emergent feature, not explained by the sum of properties of its parts. Moreover, while the tubes and tendrils (TT) also experience large fluctuations in their member nodes over the years, their cumulative Influence Index values stay nearly constant ($\xi^{\mathrm{TT}} = 11.17\% \pm 0.56\%$). To summarize, all this diverse behavior highlights the complex interplay between the structure and function of the network components. Furthermore, it also emphasizes the important role of the structures themselves over their actual node composition. For instance, while the micro-picture can vary substantially, the emergent macro-behavior can remain stable. In conclusion, once a power structure emerges, it is persistent in time and represents a meta-level of organization, detached from the actual identities of the individual nodes present at a certain time. Such architectures of power show robust and resilient behavior in the face of global crisis.

2.6 The Problems of Concentration

There has been a noted re-concentration of ownership occurring since the global financial crisis nearly a decade ago (Davis, 2008; Murray and Peetz, 2010; Davis, 2013; Peetz et al., 2013; Haberly and Wójcik, 2017; Fichtner et al., 2017). Ia a nutshell (Peetz et al., 2013):

> The concentration of ownership by the top two [BlackRock and Capital Group] is heaviest in the US, the country thought of as being the epitome of dispersed ownership. If the crisis dispelled the credibility of finance capital's logic, it did nothing to dispel its control, and in particular the influence of a small fraction of finance capital.

In the wake of this shift in corporate ownership structures, it has been argued that a small group of influential economic actors, previously assumed to have behaved in a passive manner in relation to shareholder activism, is being forced to embrace their potential shareholder power (Wells, 2015; Partnoy, 2015; Coates IV, 2015; Fichtner et al., 2017).

In this study of the global ownership network, we also detect a high concentration of shareholder power (see Section 2.2), quantified as Influence Index values (see Section 1.6), in the hands of few economic actors. In detail, we can show that there exist distinct power structures in the network, comprised of small groups of highly interconnected and influential actors (see Sections 1.7, 2.4.1, and 2.4.3). These architectures of powers show a high degree of resilience (see Section 2.5). There exist potential threats associated with this newly emerging concentration of ownership and power that should be addressed.

2.6.1 Anti-Competitiveness

Previous studies have shown how small cross-shareholding structures, at a national level, can negatively affect market competition in sectors such as airline, automobile and steel, as well as the financial one (O'Brien and Salop, 1999; Gilo et al., 2006). More recently, some works have documented the anti-competititive effect of concnetrated ownership (Azar and Schmalz, 2017). For instance, common ownership in the US airline industry has resulted in inflated ticket prices (Azar et al., 2015). Furhtermore, relating to banking competition, common ownership by asset managers and cross-ownership structures are significantly correlated with higher client fees and higher deposit rate spreads (Azar et al., 2016). In essence, "common ownership by large asset managers leads to decreased macroeconomic efficiency through reduced product market competition and thus has significant hidden social costs" (Fichtner et al., 2017).

2.6.2 Tax Avoidance

In our analysis, not only actors from the financial sector gain disproportionally high influence. Multinational oil and gas companies, electric utility service providers, and automotive manufacturers have created webs of ownership channeling and concentrating vast influence (see Section 2.4.1).

Independently, it has recently been faulted that the "rise of corporate colossus threatens [...] the legitimacy of business" (The Economist, 2016a). This critique relates to the entrenchment of a group of "superstar" companies at the core of the global economy. As a result of a string of mergers and acquisitions, there has been a high concentration of corporate power. One negative result of this development is the following (The Economist, 2016a):

> Paying taxes seems to be unavoidable for individuals but optional for firms.

There appears to be the need for a reinvention of antitrust for the digital age. For instance, the OECD countries have started to draft common rules to prevent companies from utilizing tax havens. More details in (The Economist, 2016a).

Indeed, the global ownership network can in general be utilized to identify offshore financial centers (OFCs). In other words, the micro network structure reveals highly complex international corporate financial structures at the macro level. What is very telling, and contrary to expectations, is that most identified OFCs are actually in highly developed countries. In other words, countries that have actually signed tax treaty agreements. This also highlights the general relevance of empirical network analysis for policy makers and regulators. See (Garcia-Bernardo et al., 2017) for details.

2.6.3 Systemic Risk

During the financial crisis the colloquialism "too big to fail" was popularized. It captures the notion, that by identifying and assisting the major economic actors in the system, financial distress can be averted. This approach, however, is not sufficient for networks where feedback effects exist. In systems where the actors are interconnected and hence codependent, the notion of systemic risk becomes relevant. In other words, only by uncovering the architecture of the network, the level of propagation of financial distress throughout the system can be assessed. For an overview, see (Glattfelder, 2016).

Unfortunately, network effects can be counterintuitive. For instance, by increasing the interconnectivity of financial systems, the outcome is expected to be more stability, as actors diversify their individual risks by increasing the shared links with others. However, in systems with feedback loops there exists a threshold of interconnectivity, above which the continued diversification attempts will in fact result in an increase of systemic risk (Battiston et al., 2012a).

A paradox emerges: While individual economic actors become more resilient, the overall failure probability in the system increases. Against this backdrop, the highly interconnected core of the global ownership network—and the super-entity nested within—looms ominously (see Section 2.5). This tight-knit group of important actors appears like an ideal precondition for financial distress to propagate through the network by spreading like an epidemic, infecting major financial institutions node by node. This potential issue was already raised in (Vitali et al., 2011). Indeed, no one knows what would have happened, if the bailout of the US financial system would not have been implemented. In effect, the Emergency Economic Stabilization Act of 2008, resulting in the purchase of distressed assets worth about 700 billion USD (Muolo, 2008), fundamentally changed the evolution of the network.

Moreover, as the Influence Index is also a centrality variant (see Section 1.6.2), it allows for the identification of the most important actors in the whole network, taking the architecture of interconnectivity, plus the distributions of ownership weights and firm values into account. In essence, our methodology allows for the detection of "too central to fail" entities in the global ownership network. This is in the spirit of (Battiston et al., 2012b, 2015). Uncovering such hubs of systemic relevance can be of great value to policy makers and regulators.

In detail, the enormous concentration of ownership in the hands of a few asset managers (see Section 2.4) could be indicative of a new type of systemic risk. Traditional reasoning sees asset managers as not being systemically relevant (see Section 2.4.3). In contrast to banks, these managers are not leveraged and do not provide credit. In other words, the risk of insolvency is low. However, not everyone agrees (Fichtner et al., 2017):

> A major concern that has been voiced in recent years is that a further increasing market share of passive index funds could impair efficient price finding on equity markets, as the proportion of actively traded shares would continue to shrink. One of the most outspoken regulators in this regard is Andrew Haldane from the Bank of England. In a speech in 2014, he argued that we have potentially entered the "age of asset management" due to enormous growth of assets under management in the last decades and the relative retreat of banks after the global financial crisis. He sees indications that ETFs and index mutual funds could increase investor herding and thus lead to more correlated movements of markets. In this way, passive index funds could intensify the pro-cyclicality of financial markets.

To summarize (Fichtner et al., 2017):

> [T]he rise of passive index funds could increase investor herding and impair efficient price finding, thus potentially creating new systemic risk. These developments already lead to growing unease among regulators. Securities and Exchange commissioner Luis Aqualar recently confronted fellow regulators with the rhetorical question whether they should consider curtailing the growth of passive investors?

2.6.4 Too Influential to Fail?

The emergence of the super-entity (see Section 2.5.2), a tiny, highly interconnected, and disproportionally influential group of economic actors, raises the following question. If an actor is aware of the fact that it is part of an elite group that is expected to benefit in times of distress (protection, bailouts, . . .), would this knowledge not affect the incentives? In other words, wouldn't the rational behavior be to take on more risk in the operation of one's business?

It is notoriously hard to avoid the temptation to exploit positions of privilege. Do the power structures identified in this study create new moral hazards, like regulatory capture? In essence, the question relating to the function, structure and future role of antitrust agencies and regulators is raised yet again.

2.6.5 The End of Capitalism?

Some commentators see the emergence of all-powerful passive investment funds threatening the very fabric of capitalism itself. A few have been very candid with their opinion (The Economist, 2016b):

> In August [2016] analysts at Sanford C. Bernstein, a research firm, thundered: "A supposedly capitalist economy where the only investment is passive is worse than either a centrally planned economy or an economy with active market-led capital management."

In its extreme conclusion, a financial system comprised mostly of passive funds could indeed spell the end of capitalism (The Wall Street Journal, 2016):

> Even John C. Bogle, the founder of Vanguard Group who launched the first index mutual fund 40 years ago this month, agrees that passive investing can get too big for anybody's good. "What happens when everybody indexes?" he asks. "Chaos, chaos without limit. You can't buy or sell, there is no liquidity, there is no market."

See also Sections 2.4.1, 2.4.3, and 2.2.4.

2.7 The Network of Global Corporate Control

This study can be understood as a continuation of the work started in (Vitali et al., 2011). In the following, we would like to explain the differences of the two works.

In a first step, (Vitali et al., 2011) analyzed the the topology of the global ownership network built around 43,060 transnational corporations (TNCs) in 2007. This network comprised 600,508 nodes, of which only the TNCs had an economic value (operating revenue) assigned to them, and 1,006,987 ownership relations. Most of the value was concentrated in the largest connected component (LCC) of the network, made up of 463,006 nodes and 889,601 relations. Further analyzing the LCC uncovered a bow-tie structure, with a small IN-section and a tiny core.

Unsurprisingly, comparing the topology of the TNC network to the whole global ownership network analyzed here yields a similar picture, as seen in Section 2.3. In effect, the TNC network is a miniature subnetwork of the entire global ownership network. However, not only is the scope of the current analysis nearly two orders of magnitude larger, crucially, we are now investigating the temporal dynamics of the network, a feat that has never been performed before.

Then, (Vitali et al., 2011) offered a novel methodology extending the known methods for computing control from ownership. In detail, control was proxied by the potential control over the TNCs operating revenue, referred to as network control in the paper. For the estimation of control, three different models were used. It was shown that the aggregated network statistics (the ranking of influential shareholders, the distribution of shareholder power, overall and in the bow-tie components) displayed a remarkable level of robustness.

Here, we have heavily improved on this methodology by introducing the Influence Index value, a shift in emphasis away from control towards a more generic definition of influence. Our measure now has a clear interpretation (see Section 2.2):

> The monetary value of the direct and indirect portfolio, measured in USD, of a shareholder. This represents the economic value an actor can potentially influence via paths of direct and indirect ownership in the network. See Sections 1.6 and 2.1. This value can also be understood as representing a spectrum of probabilities.

Moreover, the Influence Index value directly relates to shareholder power, as influence is seen as the ability to sway those in control or resist the opposition of others. The methodology also identifies the channels of indirect ownership benefitting the propagation of influence. The discussions relating to the interpretation of the Influence Index value in terms of shareholder power are given in Sections 2.2 and 2.4.

Furthermore, our novel methodology is a simple recursive algorithm that can be implemented efficiently for very large networks. Crucially, it overcomes all previously reported problems related to the appearance of cycles in the network. While (Vitali et al., 2011) offered a cumbersome solution which requires the preexisting knowledge of the bow-tie topology, the new methodology elegantly solves the issue of cycles by focussing on the trails in the network. These are unique paths where each node is only visited once, thus terminating any further propagation of influence through cycles. In effect, the Influence Index value can be interpreted in a generic network context:

> A modified eigenvector centrality suitable for directed and weighted networks with a bow-tie topology, where the nodes have an intrinsic non-topological value assigned to them (see Section 1.6.2).

For more details, consult Section 1.6 in general and the beginning of Section 2.2. A comparison of methods is given in Section 1.6.7.

A further important contribution of the current study is the notion of the cumulative Influence Index value. This refers to the influence that can be assigned to a cohesive group of shareholders, avoiding the pitfall of double-counting. This is presented Sections 1.7 and 2.5. With this new concept of group influence, power structures can be identified in the network and their evolution in time tracked. For instance, (Vitali et al., 2011) introduced the notion of the economic “super-entity” for 2007. This was defined as the intersection of top-ranked shareholders and the core, identifying a group of 147 TNCs. Here we formalize this notion of the super-entity and observe its dynamics, see Section 2.5.

To summarize, (Vitali et al., 2011) gave a glimpse of the structure of the TNC network. Here, we unveil the whole global ownership network it is embedded in. In addition, the methods evaluating shareholder power have become simpler and more meaningful and can be extended to groups of shareholders. However, the biggest contribution comes from the fact that not only a single yearly network snapshot is analyzed, but the evolution of the system from 2007 through to 2012 is described. All these efforts uncover the power architectures in, and the dynamics of, the global ownership network.

Recent work (Brancaccio et al., 2018) has replicated the analysis carried out in (Vitali et al., 2011), utilizing a different database (Thomson Reuters) comprising a smaller dataset of listed companies worldwide (approximately 32,000 nodes and 73,000 links in 2007) and confirmed the finding on the level of concentration of control reported in (Vitali et al., 2011). The authors also analyze the evolution of the concentration of control from 2001 until 2016 (Brancaccio et al., 2018).

References

J. Azar and M. C. Schmalz. Common ownership of competitors raises antitrust concerns. *Journal of European Competition Law & Practice*, 8(5):329–332, 2017.

J. Azar, M. C. Schmalz, and I. Tecu. Anti-competitive effects of common ownership. *Ross School of Business working paper no. 1235*, 2015.

J. Azar, S. Raina, and M. C. Schmalz. Ultimate ownership and bank competition. *Working paper*, 2016. URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2710252`.

S. Baldone, F. Brioschi, and S. Paleari. Ownership measures among firms connected by cross-shareholdings and a further analogy with input-output theory. *4th JAFEE International Conference on Investment and Derivatives*, 1998.

S. Battiston, D. Gatti, M. Gallegati, B. Greenwald, and J. Stiglitz. Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control*, 36(8):1121–1141, 2012a.

S. Battiston, M. Puliga, R. Kaushik, P. Tasca, and G. Caldarelli. DebtRank: Too central to fail? Financial networks, the FED and systemic risk. *Scientific Reports*, 2, 2012b.

S. Battiston, G. Caldarelli, M. D'Errico, and S. Gurciullo. Leveraging the network: A stress-test framework based on DebtRank. 2015.

M. Becht, J. Franks, and J. Grant. Hedge fund activism in Europe. In J. G. Hill and R. S. Thomas, editors, *Research Handbook on Shareholder Power*. Edward Elgar Publishing Limited, Cheltenham, 2015.

A. Berle and G. Means. *The Modern Corporation and Private Property.* Mac Millan, N.Y., 1932.

Bloomberg News. The Colossus of Wall Street, 2010. URL `http://www.bloomberg.com/news/articles/2010-12-09/the-colossus-of-wall-street`. December 9.

Bloomberg News. Occidental Holders Override Board in Approving Climate Proposal, 2017. URL `https://www.bloomberg.com/news/articles/2017-05-12/blackrock-to-back-climate-shareholder-proposal-at-occidental`. May 12.

P. Bonacich. Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology*, 2(1):113–120, 1972.

P. Bonacich. Power and centrality: A family of measures. *The American Journal of Sociology*, 92(5):1170–1182, 1987.

E. Brancaccio, R. Giammetti, M. Lopreite, and M. Puliga. Centralization of capital and financial crisis: a global network analysis of corporate control. *Structural Change and Economic Dynamics*, 45:94–104, 2018.

F. Brioschi, L. Buzzacchi, and M. Colombo. Risk capital financing and the separation of ownership and control in business groups. *Journal of Banking and Finance*, 13:747–772, 1989.

Bureau van Dijk. BvD historical ownership databases — User Guide, 2014.

A. Chapelle and A. Szafarz. Controlling firms through the majority voting rule. *Physica A*, 355: 509 – 529, 2005.

S. J. Choi, J. E. Fisch, and M. Kahan. The power of proxy advisors: Myth or reality? *Emory Law Journal*, 59:869, 2010.

J. Coates IV. Thirty years of evolution in the roles of institutional investors in corporate governance. In J. G. Hill and R. S. Thomas, editors, *Research Handbook on Shareholder Power*. Edward Elgar Publishing Limited, Cheltenham, 2015.

G. Davis. A New finance Capitalism? Mutual Funds and Ownership Re-Concentration in the United States. *European Management Review*, 5(1):11–21, 2008.

G. F. Davis. After the corporation. *Politics & Society*, 41(2):283–308, 2013.

G. W. Domhoff. *Who Rules America?* Englewood Cliffs, New Jersey, 1967.

G. W. Domhoff. *Who Rules America Now?* Simon & Schuster, New York, 1983.

G. W. Domhoff. *Who Rules America? Power and Politics in the Year 2000*. Mayfield Publishing, Mountain View, 1998.

J. Fichtner, E. M. Heemskerk, and J. Garcia-Bernardo. Hidden power of the Big Three? Passive index funds, re-concentration of corporate ownership, and new financial risk. *Business and Politics*, 19(2), 2017. URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2798653`.

Fortune. BlackRock: The $4.3 trillion force, 2014. URL `http://fortune.com/2014/07/07/blackrock-larry-fink`. July 7.

J. Garcia-Bernardo, J. Fichtner, E. M. Heemskerk, and F. W. Takes. Uncovering offshore financial centers: Conduits and sinks in the global corporate ownership network. *Scientific Reports*, 0, 2017. URL `https://arxiv.org/abs/1703.03016`.

S. L. Gillan and L. T. Starks. Corporate governance proposals and shareholder activism: The role of institutional investors. *Journal of financial Economics*, 57(2):275–305, 2000.

D. Gilo, Y. Moshe, and Y. Spiegel. Partial cross ownership and tacit collusion. *RAND Journal of Economics*, 37(1):81–99, 2006.

R. Gilson and J. Gordon. Agency capitalism: Further implications of equity intermediation. In J. G. Hill and R. S. Thomas, editors, *Research Handbook on Shareholder Power*. Edward Elgar Publishing Limited, Cheltenham, 2015.

J. B. Glattfelder. *Decoding Complexity: Uncovering Patterns in Economic Networks*. Springer, Heidelberg, 2013.

J. B. Glattfelder. Decoding Financial Networks: Hidden Dangers and Effective Policies. In Bertelsmann Stiftung, editor, *To the Man with a Hammer: Augmenting the Policymakers Toolbox*. Verlag Bertelsmann Stiftung, Gütersloh, 2016.

J. B. Glattfelder and S. Battiston. Backbone of complex networks of corporations: The flow of control. *Physical Review E*, 80(3):036104, 2009.

M. Goergen, M. Martynova, and L. Renneboog. Corporate governance convergence: Evidence from takeover regulation reforms in Europe. *Oxford Review of Economic Policy*, 21(2):243–268, 2005.

D. Haberly and D. Wójcik. Earth incorporated: Centralization and variegation in the global company network. *Economic Geography*, 93, 2017. URL `http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2699326`.

J. P. Hawley and A. T. Williams. *The Rise of Fiduciary Capitalism: How Institutional Investors Can Make Corporate America More Democratic*. University of Pennsylvania Press, Philadelphia, 2000.

J. G. Hill and R. S. Thomas. *Research Handbook on Shareholder Power*. Edward Elgar Publishing Limited, Cheltenham, 2015.

C. Hubbell. An input-output approach to clique identification. *Sociometry*, 28(4):377–399, 1965.

P. Jaccard. The distribution of the flora in the alpine zone. *New Phytologist*, 11(2):37–50, 1912.

L. Katz. A new status index derived from sociometric analysis. *Psychometrika*, 18(1):39–43, 1953.

R. La Porta, F. L. de Silanes, and A. Shleifer. Corporate ownership around the world. *Journal of Finance*, 54(2):471–517, 1999.

M. Meoli, S. Paleari, and G. Urga. When controlling shareholders 'live like kings'. The case of Telecom Italia. *Working paper*, 2006. URL http://papers.ssrn.com/papers.cfm?abstract_id=883655.

P. Muolo. *$700 Billion Bailout.* John Wiley & Sons, Hoboken, 2008.

G. Murray and D. Peetz. Who owns the world: Some empirical findings. *XVII World Congress of Sociology, Göteborg, International Sociological Association*, 2010.

Norges Bank Investment Management. Annual Report, 2007. URL https://www.nbim.no/en/transparency/reports/2011-and-older/2007/nbim-annual-report-2007/.

D. O'Brien and S. Salop. Competitive effects of partial ownership: Financial interest and corporate control. *Antitrust Law Journal*, 67:559, 1999.

L. Page, S. Brin, R. Motwani, and T. Winograd. The pagerank citation ranking: Bringing order to the web. Technical report, Stanford InfoLab, 1999.

F. Partnoy. US hedge fund activism. In J. G. Hill and R. S. Thomas, editors, *Research Handbook on Shareholder Power*. Edward Elgar Publishing Limited, Cheltenham, 2015.

D. Peetz and G. Murray. The financialization of global corporate ownership. In G. Murray and J. Scott, editors, *Financial Elites and Transnational Business*. Edward Elgar Publishing Limited, Cheltenham, 2012.

D. Peetz, G. Murray, and W. Nienhüser. The new structuring of corporate ownership. *Globalizations*, 10(5):711–730, 2013.

G. Rohwer and U. Pötter. *Transition Data Analysis User's Manual.* Ruhr-University Bochum, 2005.

The Economist. BlackRock and a hard place, 2009. URL http://www.economist.com/node/13848711. June 12.

The Economist. The monolith and the marketsk, 2013a. URL http://www.economist.com/node/21591164. December 7.

The Economist. The rise of BlackRock, 2013b. URL http://www.economist.com/node/21591174. December 7.

The Economist. A world of pain, 2015. URL http://www.economist.com/node/21645807. March 7.

The Economist. A giant problem, 2016a. URL http://www.economist.com/node/21707210. September 17.

The Economist. Stealth socialism, 2016b. URL http://www.economist.com/node/21707191. September 17.

The Guardian. Norway's sovereign wealth fund drops over 50 coal companies, 2015. URL http://fortune.com/2014/07/07/blackrock-larry-fink/. March 16.

The Wall Street Journal. Are Index Funds Eating the World?, 2016. URL http://blogs.wsj.com/moneybeat/2016/08/26/are-index-funds-eating-the-world. August 26.

Vanity Fair. Larry Fink's $12 Trillion Shadow, 2010. URL http://www.vanityfair.com/news/2010/04/fink-201004. March 2.

S. Vitali, J. B. Glattfelder, and S. Battiston. The network of global corporate control. *PLoS one*, 6(10):e25995, 2011.

M. Weber. *Economy and Society: An Outline of Interpretive Sociology*. University of California Press, Berkeley, 1978.

H. Wells. Shareholder power in America, 1800–2000: A short history. In J. G. Hill and R. S. Thomas, editors, *Research Handbook on Shareholder Power*. Edward Elgar Publishing Limited, Cheltenham, 2015.

D. West. *Introduction to Graph Theory*. Prentice Hall, 2001.