Article:

Han, Lu orcid.org/0000-0001-7198-3380, Koenig-Archibugi, Mathias and Opsahl, Tore (2018) The social network of international health aid. Social science and medicine. pp. 67-74. ISSN 1873-5347

https://doi.org/10.1016/j.socscimed.2018.04.003

The social network of international health aid

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Social Science & Medicine, 2018

Abstract. International development assistance for health generates an emergent social network in which policy makers in recipient countries are connected to numerous bilateral and multilateral aid agencies and to other aid recipients. Ties in this global network are channels for the transmission of knowledge, norms and influence in addition to material resources, and policy makers in centrally situated governments receive information faster and are exposed to a more diverse range of sources and perspectives. Since diversity of perspectives improves problem-solving capacity, the structural position of aid-receiving governments in the health aid network can affect the health outcomes that those governments are able to attain. We apply a recently developed Social Network Analysis measure to health aid data for 1990-2010 to investigate the relationship between country centrality in the health aid network and improvements in child health. A generalized method of moments (GMM) analysis indicates that, controlling for the volume of health aid and other factors, higher centrality in the health aid network is associated with better child survival rates in a sample of 110 low and middle income countries.

Keywords: Development assistance for health; health policy; developing countries; Social Network Analysis

1. Introduction

Development aid plays an important role in the health systems of many low and middle income countries. However, there is significant controversy over whether, when and how aid is effective in improving health outcomes (Martínez Álvarez & Acharya, 2012). In this article, we consider a neglected aspect of the debate: the fact that development aid constitutes an emergent social network connecting policy-makers of numerous governments, multilateral agencies and other large organizations (Han et al., 2012; Koenig-Archibugi, 2013). This global network is an emergent, unplanned structure because it evolved as a result of myriad individual aid allocation decisions driven by a variety of humanitarian, strategic, commercial, and political motives. Crucially, the global aid network is a *social* network. While flows of financial resources are an important dimension, network connections are by no means exhausted by them. Network links operate as a channel for a wide range of social processes, notably knowledge transmission, norm diffusion, social influence, and power. As such, they are likely to exercise significant influence on domestic health policy processes (Jones et al., 2017).

Thinking of development aid as an emergent social network connecting health policy-makers beyond national borders highlights a puzzle. Organizational research using the tools of Social Network Analysis (SNA) usually stresses the benefits of having many links to other actors: this condition is typically called "centrality", which has positive or at least neutral connotations – as "being in the thick of things" (Freeman, 1978, 219). This literature acknowledges the costs of maintaining network ties, but suggests that they are generally outweighed by the benefits. A recent survey of a large body of empirical research on knowledge transmission in social networks concludes that "[m]any studies across all levels have found that a central network position, defined either in terms of the number of direct contacts or both direct and indirect contacts, has a positive influence on knowledge creation, transfer, and adoption" (Phelps et al., 2012, 1138). An emerging literature on networks of health policy practitioners in *domestic* contexts also tends to stress the benefits that network connections can bring to performance (Blanchet & James, 2013; Blanchet et al., 2014; Browne et al., 2017; Gold et al., 2008; Jippes et al., 2010; Khosla et al., 2016; Merrill et al., 2010; Pagliccia et al., 2010; Weishaar et al., 2015).

The favourable assessment of high connectivity that pervades SNA-inspired research stands in stark contrast with the perceptions of most analysts and practitioners in the field of development aid, who tend to stress the *disadvantages* of the proliferation of ties between aid providers and aid recipients (Acharya et al., 2006). Even the word typically used to convey the fact that each aid recipient is linked to a variety of aid agencies – "fragmentation" of aid – has negative connotations. The most prominent indices and rankings of the quality of aid donors penalize them in direct proportion to their contribution to the proliferation of donor-recipient ties (Birdsall et al., 2010; Easterly & Williamson, 2011; Stephen Knack et al., 2011). Governments have repeatedly pledged to take steps to address the perceived problem. In the landmark Paris Declaration on Aid Effectiveness of 2005, major players in official development assistance (ODA) stated that "[e]xcessive fragmentation of aid at global, country or sector level impairs aid effectiveness" and promised to reduce it.

The contrast between the perceptions of most development practitioners and analysts on the one hand and the insights of organizational research on the other hand is striking. It may partly reflect the fact that flows of development aid have not yet been examined from a social network perspective, leading to the neglect of important causal mechanisms (Blanchet & James, 2012; Schoen et al., 2014). This article fills this research gap by applying the substantive insights of the social network literature and recent additions to the SNA toolbox to the study of the global aid network. To our knowledge, it is the first article that does this. More specifically, the article develops and tests the hypothesis that the centrality of recipient countries in the international health aid network is associated with better population health outcomes, specifically child survival rates.

The article is organized as follows. The next section draws on sociological institutionalism and discusses the reasons why transnational connectivity can be expected to affect health policies and outcomes. The third section examines causal mechanisms involving specifically the health aid network, and develops the hypothesis that higher centrality of recipients in the international health aid network improves population health. The fourth section presents our methodology for measuring country centrality in the international health network, in which government officials in recipient countries are linked to multilateral and bilateral aid agencies directly and to other recipients indirectly through their aid providers. The second part of the fourth section presents the design of a statistical analysis of the effect of network centrality on child survival rates, based on 110 low and middle income countries from 1990 to 2010. Crucially, the analysis has to take into account the possibility of selection, whereby countries are more central due to unobserved conditions that are systematically related to child mortality. We fit a generalized method of moments (GMM) model to address the self-dependence in child mortality over time, the potential endogeneity of some independent variables, and country-specific fixed effects. The fifth section presents our findings and the sixth section discusses them.

2. Transnational connectivity and health outcomes

An influential analytical tradition emphasizes the impact that transnational connections have on the principles, norms and knowledge that guide public policies and on the welfare outcomes that such policies are able to attain. A prominent tradition within sociological institutionalism, World Polity Theory, interprets state action as embedded in an overarching polity composed of governmental and non-governmental organizations that both constrain and enable action in a variety of domains (Boli & Thomas, 1997; Meyer et al., 1997). While early proponents of World Polity Theory saw the world as "a unitary social system, increasingly integrated by networks" (Boli and Thomas 1997, 172), more recent work in this tradition has highlighted patterns of stratification and fragmentation in the world polity. Jason Beckfield, for instance, found that, since 1945, the network of intergovernmental organizations has become more fragmented, more heterogeneous, less cohesive, and less "small-worldly" in its structure (Beckfield, 2010).

World Polity Theory thus encourages researchers to examine how transnational connections shape the norms and knowledge that guide policy making, and at the same time to be sensitive to *variation* in how and how much national actors are connected transnationally. This analytical tradition has generated a fruitful empirical research agenda, which has shown how stronger links to the world polity have beneficial effects on wellbeing measures in a variety of domains. John Shandra and his co-authors have shown that, in democratic countries, a stronger presence of health-focused international non-governmental organizations (INGOs) are associated with lower infant mortality and HIV prevalence (Shandra et al., 2010; Shircliff & Shandra, 2011). Other authors have found that a stronger presence of child-rights INGOs are associated with higher state funding for education, reductions in child labor and increases in immunizations (Boyle & Kim, 2009; Kim & Boyle, 2012). Environmental INGOs are associated with lower deforestation and lower industrial organic water pollution in less developed countries (Jorgenson, 2009; Shandra et al., 2008).

Participation in transnational networks creates channels of communication. But why would the extent of network *centrality* matter for policy content and outcomes? Specifically, why should it be related to an improvement of health outcomes, such as child survival rates? All else being equal, central actors are more likely to receive information that is transmitted through the network. Centrality in transnational networks of health policy makers can be expected to result into faster access to more, richer and more diverse information relevant to health policy making. This expectation is in line with findings on the knowledge effects of network position in a range of interpersonal and interorganizational networks. As noted in the introduction, a recent survey of a large body of empirical research on knowledge transmission in social networks concludes that a central network position has a positive influence on knowledge creation, transfer, and adoption (Phelps et al., 2012).

To be sure, more and faster information does not necessarily mean *better* information. Social network analysis cannot tell us by itself whether centrality leads to better decisions and better policy outcomes. But we have good reasons to expect that centrality may not only increase the *quantity* of information that is received, but also improve the *quality* of information that shapes the domestic policy process. Higher centrality typically entails connections to a *more diverse* range of actors, and diversity of information and perspectives is beneficial for the quality of decisions. A growing body of research shows that the problem-solving ability of groups is affected by their cognitive diversity, which can be conceptualized in terms of their individual members' "perspectives", i.e. representations of solutions in the agent's internal language, and "heuristics", i.e. rules for mapping and searching for solutions. Collective problem-solving capacity tends to increase with cognitive diversity (Hong & Page, 2004; Page, 2007; Stahl et al., 2009). This body of research provides valuable microfoundations for the macro-level associations highlighted by World Polity Theory.

3. The health aid network and its consequences

In the remainder of this article, we focus on connectivity through one particular kind of transnational linkages that, to our knowledge, have not been conceptualized in social network terms yet: the network of officials connected through the provision of development assistance for health. First, we argue that the international aid network affects health policies by transmitting knowledge and norms in addition to material resources. Second, we argue that the structural position of countries in the network – notably their network centrality – affects health policy and health outcomes because it determines how fast and how deeply officials engage with new knowledge and new norms. Third, we argue that higher centrality in the international health aid network helps policy makers to attain better population health outcomes, because it exposes them to a more diverse range of information and perspectives.

If international health aid constitutes a social network, *what* exactly do the network links convey and *how* does that affect outcomes? At one level, it is obvious what is conveyed: financial and other material resources, such as vaccines and medical equipment. Typically, links between donors and recipients of health aid are quantified in terms of monetary values, so we can say that, for instance, the development assistance for health (DAH) provided by the government of Denmark to the government of Togo amounted to $845,000 in 2010. We do not intend to discount the importance of the financial dimension of health aid. However, in this article we want to emphasize the social and cognitive dimensions of aid relationships. Crucially, in the empirical analysis presented below we identify the effect of aid links beyond the strictly financial dimension by *including the volume of health aid per capita as a critical control variable* in our statistical models.

We expect that the effect of the non-material aspects of health aid links results mainly from the transmission of knowledge and norms, which we will also refer to as communication. There is a body of evidence indicating that aid-related communication among officials across borders is a major source of inputs in domestic health policy making and, especially in the case of states with little endogenous research capacity, it is often the *main* source of inputs (Okuonzi & Macrae, 1995; Parkhurst et al., 2010; Sumner & Harpham, 2008; Trostle et al., 1999). The selfperception of officials in agencies such as the World Bank is often as providers of knowledge (Barnes et al., 2016).

What is being diffused through network communication varies considerably. In some cases, government officials have clearly defined policy goals but imperfect information about cause-effect relationships. Communication in networks then provides officials with opportunities for "Bayesian" learning, by which the addition of new data leads them to revise their probability estimates of the truth of various hypotheses on the effectiveness of alternative policies (Simmons et al., 2008, 28). An example of learning promoted by health aid relationships concerns the adoption of the drug misoprostol for the prevention of postpartum haemorrhage (PPH) in in low-income countries. The Gates Foundation funded a PPH program run by Gynuity Health Projects (GHP) and, through the latter, the Misoprostol for PPH in Low Resource Settings Initiative of the International Federation of Gynaecology and Obstetrics, which promoted the use of misoprostol for PPH among policy makers and health care providers (Millard et al., 2015). In Uganda, international donors such as the aid agencies of USA, UK, Germany and the Netherlands funded NGOs that promoted the use of misoprostol and achieved its inclusion in treatment guidelines and national essential medicines list (Atukunda et al., 2015). The example of misoprostol also illustrates a key fact: learning is not a straightforward applications of scientific evidence to public policy, but also a social and political process (Carey & Crammond, 2015). Between 2003 and 2011, GHP or other organizations made five applications to add misoprostol for use in PPH to the WHO's Essential Medicines List (EML), and before 2011 they were all rejected because of insufficient scientific evidence (Millard et al., 2015). The inclusion of misoprostol in the EML in 2011 did not settle the matter, as the evidence for the efficacy of misoprostol in community settings continues to be controversial and critics advocate the removal of the drug from the WHO EML (Chu et al., 2012; Millard et al., 2015).

In some cases, the goals of government officials are not predetermined and exogenous to the interaction with external actors, but developed through processes of persuasion or emulation. An example of successful norm promotion concerns the norms that health systems should specifically target maternal health and neonatal mortality (Shiffman & Smith, 2007; Shiffman & Sultana, 2013). To be sure, pointing at processes of norm diffusion through aid channels does not imply that global norm adoption is automatic or independent of domestic political circumstances, since global norms can be significantly 'glocalised' by national actors (Brown, 2014).

Communication within health aid networks influences the health policies that are implemented in a country in various ways. Most directly, the knowledge and values of officials in aid agencies are reflected in the development projects that they fund. More indirectly, they may influence the views of government officials in recipient countries, and in turn this affects what the latter demand in negotiations on projects funded by other donors. Officials in recipient governments may implement the policy interventions supported by aid agencies also in projects and programmes that are financed exclusively with national means. For instance, in Thailand pilot projects on Hepatitis B immunization funded by Australia's aid agency were critical in persuading Ministry of Public Health officials to introduce nationwide immunization (Munira & Fritzen, 2007). Crucially, while recipient representatives interact directly with bilateral and multilateral aid agencies, the latter are also channels for the transmission of knowledge and norms between aid recipients. Our social network perspective makes no assumptions on where innovations and evidence originate.

In the previous section, we argued that what should matter for health outcomes is not simply the existence of connectivity, but a *broader range* of connections, i.e. higher centrality in transnational networks. This argument especially applies to the health aid network. This is for two complementary reasons. First, the relationship between aid agencies and aid recipients often displays hierarchical features, even when it is presented as a “partnership” (Aveling & Martin, 2013; Barnes et al., 2016). However, the simultaneous presence of many agencies may stimulate a competitive dynamic where aid agencies need to underpin their policy advice and prescriptions with more extensive and persuasive arguments and evidence, rather than expecting deference to authority.

Second, a higher number of aid providers are likely to be more *diverse* than a smaller number. Diverse perspectives are transmitted through the health aid network. Diversity can be found at various levels, from general paradigmatic differences in the way health policies are conceptualized down to specific issues such as assessments of the comparative effectiveness of certain drugs or health technologies. One example must suffice for reasons of space. In the 1990s, a so-called “like-minded” donor group, consisting initially for Nordic countries and later extending to the Netherlands, Switzerland and Canada negotiated with Mozambique’s ministry of health a sector-wide approach (SWAp), whereby health aid would be pooled and added to the government health budget rather than used for individual off-budget projects. The move towards pooled funding was resisted by the United States government, which was the largest single provider of health aid to Mozambique (and was labelled “single-minded donor” by some observers) (Pfeiffer et al., 2017). The tension between the horizontal approach promoted by some donors and the vertical approach favoured by others was exacerbated by the massive influx of funding for HIV/AIDS activities flowing from the U.S. President's Emergency Plan for AIDS Relief (PEPFAR) from 2004. Contrary to the national HIV/AIDS plan developed by Mozambique’s government in cooperation with the “like-minded donors”, which stressed common fund support and purchase of generic drugs, PEPFAR's plan for Mozambique included the use of expensive brand-name drugs and the channelling of funding to U.S. NGOs for implementation (Pfeiffer et al., 2017). A compromise was agreed after a series of confrontational meetings. The example shows how there can be fundamental disagreements between donors on the best way to organize and fund health services. The case of Mozambique is representative of a broader pattern. For instance, in 2010 the United States devoted most of its health aid to HIV/AIDS, most of Denmark's health aid was directed towards health sector support, and the United Kingdom distributed its health aid relatively evenly between those two areas (our calculation based on data by Ravishankar et al., 2009). Global health policy since World War II is to a large extent characterized by disagreements over the relative merits of vertical and horizontal approaches (Hafner & Shiffman, 2013; Shiffman, 2006). Health aid donors have different priorities even within the same health focus area. For instance, in the area of maternal health there are systematic differences among three types of large donors - bilateral donors, foundations, and companies - in the way they distribute their funding among specific diseases, family planning services, capacity building and research (Deleye & Lang, 2014). Among bilateral donors, some tend to outsource the delivery of aid to nonstate actors, while other prefer to support state management of aid, and the difference is rooted in different national orientations about the appropriate role of the state in public service delivery (Dietrich, 2016).

While systematic research on the effects of perspectival diversity in health policy is still lacking, anecdotal evidence suggest positive effects. During the 1990s, the Cambodian government embarked on two major programmes: a large-scale donor-funded tuberculosis programme and a major donor-supported general re-organization of its general health services. The two programmes reflected different perspectives on how to achieve substantial improvements in population health outcomes. When the perspectives of the two programmes where combined, notably by expanding the coverage of the WHO-sponsored "directly observed treatment, short-course" approach to tuberculosis (a key pillar of the first perspective) in the context of a shift from hospital-based delivery to health-centre delivery (a key pillar of the second perspective), Cambodia made significant progress in reducing tuberculosis incidence (Hill & Tan Eang, 2007).

While maintaining network ties with other actor can bring benefits, it also entails costs. For this reason, the arguments developed so far are compatible with the detrimental effects that are emphasised by most of the literature on “aid fragmentation”. Interacting with a larger number of aid agencies may involve more effort towards the negotiation of the agreements (*ex ante* transaction costs) and more cumbersome reporting obligations (*ex post* transaction costs). Meeting numerous separate donor missions is time-consuming and, since donor reporting requirements are seldom standardized, bureaucracies in recipient countries spend a considerable amount of time in learning how to comply with the various requirements as well as retrieving and presenting the requested information (World Bank, 2003). Dispersing aid across multiple recipients tends to raise the administrative cost of donors as well (Anderson, 2012). Moreover, scholars have argued that the more aid is fragmented, the larger the potential for harmful practices such as underfinancing government budgets, poaching managers, lax financial management, and aid tying (Acharya et al., 2006; Djankov et al., 2009; see also the discussion in Han & Koenig-Archibugi, 2015; S. Knack & Rahman, 2007; Stephen Knack & Smets, 2012).

Ultimately, it is an empirical question whether the benefits of centrality in the health aid network outweigh the costs, or vice versa. As a contribution to answering this question, the remainder of this article will provide a quantitative test of the following hypothesis: *Higher centrality of recipients in the international health aid network improves population health.*

4. Methods

4.1. Measuring centrality in the global health aid network

We test the hypothesis on 110 low and middle income countries, as classified by the World Bank, with populations of more than 1 million, since countries with smaller populations present significant missing data problems on the independent variables. Our dataset covers the period 1990-2010. Web-Appendix 1 presents the list of countries and years covered.

Ideally, we would measure connections through the health aid network by counting and perhaps weighing episodes of communicative interaction between officials in provider and recipient agencies. Gathering this information for a large number of countries over time would be prohibitively costly, and perhaps unfeasible for other reasons as well. We use as proxy the existence of monetary flows of aid. We address the limitations of this proxy in two ways. First, as detailed below we develop a procedure for making alternative assumptions about the relationship between the volume of aid and the quantity/quality of information transmission. As we will see, our findings are robust to these alternative assumptions. Second, we include the volume of health aid per capita as a critical control variable in our statistical models, which gives us confidence that our results capture the effect of aid links beyond the strictly financial dimension.

Our analysis of the health aid network is based on data on flows of development aid for health (DAH) for the period between 1990 and 2010 collected by the Institute of Health Metrics and Evaluation (IHME) (Ravishankar et al., 2009). The IHME dataset covers 22 bilateral aid agencies, 11 multilateral agencies and two large private organizations (the Bill & Melinda Gates Foundation and the Bloomberg Foundation). Two features make the IHME dataset particularly useful for our purposes. First, the IHME has been careful to avoid double-counting: if a donor provides aid through a multilateral agency, only the flow of resources from the agency to the recipient is recorded in the dataset. This meets our needs because the nature of the network effects hypothesized in the previous section means that we are interested above all in the interaction between recipients and the immediate provider of aid, rather than the ultimate source of the funds. Second, the IHME dataset records *disbursements* rather than *commitments* of DAH, which is preferable for our purposes because most network effects discussed above are conditional on projects and programmes being in place rather than merely proposed.

Among the various concepts proposed in SNA to capture centrality, "closeness centrality" has the best fit with our argument. It is defined as the inverted sum of distances to all other nodes in a network from the focal node. In other words, it indicates how quickly a node can reach, and be reached from, all the other nodes in a network (Freeman, 1978). We focus on closeness centrality because of the possibility that interactions occur in the following sequence: a norm or knowledge on the effectiveness of health policies is generated in a low or middle income country, then the norm or knowledge is incorporated in the development policies and practices of one or more of its aid providers, then these aid providers transmit that norm or knowledge to other aid recipients, and so forth. To the extent that ideas can diffuse through the health aid network through multiple paths, it is useful to take into account the total distance between an actor and all other actors in the health aid network, i.e. not only those that provide direct aid to the focal actor, but also other aid recipients, and the agencies providing aid to those recipients, and so on. Closeness centrality reveals patterns of connectivity that cannot be captured through the measures commonly used in the aid fragmentation literature, such as the Herfindal index, which only consider direct ties (Acharya et al., 2006; Djankov et al., 2009; Han & Koenig-Archibugi, 2015; S. Knack & Rahman, 2007; Stephen Knack & Smets, 2012).

The global health aid network is a *weighted* network, i.e. we have information not only on whether a link exists between two actors, but also on the "intensity" of that link. In the dataset we use, the intensity is expressed in terms of financial resources – the value in U.S. dollars of the aid provided by donor A to recipient B in year X. Since we want to be able to use information on the intensity of links, to calculate closeness centrality we use a measure recently developed by Opsahl, Agneessens and Skvoretz (Opsahl et al., 2010). Web-Appendix 2 discusses their approach in detail and provides illustrations relating to aid flows. In short, the measure allows us specify the relative importance of degree and node strength in determining centrality. The degree of a node is the number of adjacent nodes or ties that the focal node has, and captures the dispersion of involvement. The strength of a node is the sum of the tie weights from the focal node to other nodes, and captures the absolute level of involvement. The measure for closeness centrality developed by Opsahl et al. is defined as follows:

$$C_C^{W\alpha}(i) = \left[\sum_j^N d^{W\alpha}(i, j) \right]^{-1}$$

where d is the shortest distance between node i and j, w is the weighted adjacency matrix (in which w_{ij} is greater than 0 if the node i is connected to node j, and the value represents the weight of the tie), and α is a tuning parameter. There are two benchmark values for the tuning parameter: 0 and 1. If the parameter is set to 0, the outcome is solely based on the number of ties. In other words, tie weights are completely ignored. Conversely, if the value of the parameter is 1, the outcome is based on tie weights only. This implies that the number of ties is disregarded.

The tuning parameter needs to be set on the basis of theoretical and substantive considerations. In the following, we state the assumptions that correspond to different values/regions of the parameter in relation to the domain of health aid.

- Setting α = 0 reflects the assumption that centrality depends on the number of aid providers but not on the total value of health aid received. This assumption is plausible if interaction with an aid provider is sufficient to expose recipients to new knowledge about health policy effectiveness, irrespective of the financial value of that provider's aid.

- Setting $0 < \alpha < 1$ reflects the assumption that aid flows of larger economic value involve more opportunities for interaction between representatives of aid agencies and recipients at various stages and phases of the policy-making process, and therefore more opportunities for communication and commitment effects to develop.
- Setting $\alpha = 1$ reflects the assumption that centrality depends entirely on total aid flows, with the number of aid providers playing no role. This assumption is problematic in the light of the argument developed in the previous section. There are good reasons to expect that officials in recipient countries are exposed to more information and perspectives when they interact with a larger number of aid providers, even when keeping the sum of aid inflows constant. First, aid agencies are bureaucracies where the diversity of perspectives may be suppressed by a range of mechanisms, such as hierarchical direction, conformism, or career incentives. Second, recipients may not gain insight into the full range of diverse perspectives to be found in the aid agency, because the latter aims at presenting a single "official" position in its dealings with recipients. Hence, a plurality of aid providers should be seen as an essential component of a conception of centrality suitable to the health aid field, and ignoring tie numbers by setting the tuning parameter at 1 would be theoretically inappropriate.

For these reasons, below we test the effect of centrality when it is measured with reference to the number of ties only (α=0) and when incorporate both degree and node strength ($0<\alpha<1$, with α=0.5 to be used as a focal value in the statistical analysis), but not with the tuning parameter set at the value of 1.

Web-Appendix 3 uses this measure to show how the whole health aid network evolved between 1990 and 2010.

4.2. Estimating the impact of centrality on child health

We choose child survival as our indicator of health outcomes because it has been shown to be a good proxy for general population health (Reidpath & Allotey, 2003), because the coverage and quality of the data is higher than for other health indicators, and because of its substantive importance in national and global public policy. To measure child (under-5) mortality rates, we use the dataset compiled by the Institute for Health Metrics and Evaluation (IHME) (Rajaratnam et al., 2010).

In addition to the centrality measures explained above, our models include health aid per capita as crucial control variable, as our hypotheses posit an effect of centrality that goes beyond the effect of the volume of health aid received by a country in relation to its population size. We include in our estimation other control variables that according to the literature may have an effect on health outcomes in general and more specifically on child survival. We include GDP per capita, as the level of economic development is likely to influence the private and public resources that can be invested in health care, and moreover it is often considered a proxy for general state capacity (Mishra & Newhouse, 2009). A second control variable is trade as percentage of GDP, which we treat as an indicator of economic globalization. We include this measure because economic interactions across borders could generate spill-overs of knowledge relevant to health policies and practices (Owen & Wu, 2007). Including a measure of globalization also increases our confidence that our health aid network centrality measure does not simply capture a country's *general* level of connectivity with the rest of the world. A third control variable is urbanization, as it can be easier to provide health services to a population concentrated in urban areas than to a population more widely dispersed in rural areas. Our data captures urban population as percentage of total population. A fourth control variable is the type of political regime, since competitive democratic processes could result in public policies that are favourable to deprived sectors of the population, such as broader health care coverage (Ciccone et al., 2014; Krueger et al., 2015; Ross, 2006). We use the Polity2 variable from Polity IV dataset, which measures democratic and authoritarian features of regimes on the basis of measures that capture modes of executive recruitment, constraints on executive authority, and political competition. A fifth control variable captures political violence in a country, either internal or international, since violence could contribute to mortality either directly or indirectly by weakening public health systems (Kerridge et al., 2012). We do not include certain control variables, notably domestic health spending per capita, physicians per capita and years of schooling of women of reproductive age, because numerous missing values would reduce the number of observations drastically. Descriptive statistics and correlations are presented in Web-Appendix 4, which also presents the results of multicollinearity tests indicating that multicollinearity does not unduly affect our analysis. We use the logarithm of all dependent and independent variables in the estimations, except political violence and the Polity2 score, which are changed into dummy measures. Web-Appendix 5 explains these choices and discusses the implications. Data on GDP per capita, population and trade as a % of GDP are from http://databank.worldbank.org. Polity IV and major political violence data are from http://www.systemicpeace.org. Following the Polity IV codebook, we define partial democracy and full democracy as having a Polity2 score between +1 and +6 and between +7 and +10 respectively. The coefficients reported below refer to the effect of partial democracy and full democracy compared to the baseline category of autocracy (a negative or zero Polity2 score). To capture political violence, we use the variable “actotal” from the Major Episodes of Political Violence (MEPV2012) database, which measures the intensity of both interstate and intrastate violence. Countries with scores larger than zero are classified as suffering from political violence. We also incorporated year dummies to account for unobservable factors that might globally affect our health outcome of interest in a given year.

Our analysis has to address the problem of selection effects (Martínez Álvarez & Acharya, 2012). It is possible that donors are more likely to be present in, and/or channel more resources to, countries where child mortality is highest, for instance if they are responsive to need. Or donors may be more likely to be present in, and/or channel more resources to, countries where child mortality has declined faster in recent times, for instance if they wish to claim political credit for improvements of child survival rates. Therefore, we expect potential reverse causality between child mortality and a set of independent variables, such as centrality, aid per capita, and GDP per capita. We fit a two-step robust generalized method of moments (Difference GMM) model to examine our hypothesis. Our choice of estimation approach is explained and justified in Web-Appendix 6.

5. Findings

Table 1 presents the results of models that instrument with one lag (lag 2), which keep the number of instruments below the number of countries. In line with our hypothesis, closeness centrality has a negative and statistically significant effect on child mortality both when centrality depends only on tie number (α=0) and when tie number and tie weights are given equal consideration (α=0.5).

Table 1. Estimated effect of closeness centrality in the health aid network on under-5 mortality, 1990–2010. GMM models instrumenting with one lag (lag 2).

	(1)	(2)
Closeness centrality (α=0)	-0.006***	
	(0.002)	
Closeness centrality (α=0.5)		-0.004**
		(0.002)
GDP per capita	-0.145***	-0.114***
	(0.044)	(0.034)
Health aid per capita	-0.010	-0.007
	(0.008)	(0.007)
Trade (as % of GDP)	-0.021	-0.019
	(0.023)	(0.022)
Urbanisation	0.045	0.052
	(0.050)	(0.039)
Partial democracy	-0.001	-0.002
	(0.004)	(0.004)
Full democracy	-0.001	-0.001
	(0.003)	(0.003)
Political violence	0.005**	0.005*
	(0.003)	(0.003)
Lag 1 of under-5 mortality	0.611***	0.684***
	(0.174)	(0.159)
Lag 2 of under-5 mortality	0.188	0.173
	(0.156)	(0.151)
Country-specific fixed effects	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*
No. of observations	1,743	1,743
No. of groups	102	102
No. of instruments	95	95
AR(1)	-1.260	-1.340
AR(1) p value	0.208	0.180
AR(2)	0.342	0.506
AR(2) p value	0.733	0.613
Hansen stat	76.25	64.92
Hansen p value	0.205	0.549

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The Web-Appendices report several robustness checks and additional analyses. First, we find that our results hold when we replace the closeness centrality measure with a simpler measure of centrality (degree centrality) that considers only direct ties with aid providers and disregards indirect ties (Web-Appendix 7). Second, we find that re-estimating each model using two lags (lag 2 and 3) produces results that are consistent with those in Table 1 (Web-Appendix 8). The robustness of the findings across the two instrumentation choices increases our confidence in them. Third, we considered the possibility that the benefits of network connections may be moderated by the capacities of recipient governments (Beesley et al., 2011; Lang, 2014). We find that the effect of network centrality is not conditional on measures of state capacity (Web-Appendix 9). Finally, we find that the beneficial effect of network centrality persists if disbursements for health sector program support are subtracted from the total flows of health aid (Web-Appendix 10). This suggests that the effect of centrality does not depend on coordination among aid providers.

6. Discussion

Researchers have noted that, despite the costs entailed by aid "fragmentation", officials in developing countries are sometimes uninterested in, or even critical towards, efforts to reduce the number of aid providers, even if the volume of aid were not affected (Greenhill et al., 2013; Pallas et al., 2015). Our findings may contribute to explain this. We argued that ties in the health aid network are channels of the transmission of policy-relevant knowledge, ideas and norms in addition to material resources. More central governments receive health policy information faster and, more importantly, are exposed to a more diverse range of sources and perspectives originating from both donor and other recipient countries, something that can help them select the policies that are likely to be more effective and resist pressure to adopt uncorroborated policies.

We also found that, when health aid network centrality is taken into account, health aid per capita does not have a significant effect on child mortality. This suggests that the knowledge and norms transmitted through aid links are on the whole more beneficial than the mere transfer of financial and material resources, also considering health spending from domestic sources tends to decrease in response to inflows of health aid (Liang & Mirelman, 2014; Lu et al., 2010; Martínez Álvarez et al., 2016). Separating the ideational and the financial dimensions of health aid, as we tried to do here, may also help account for the mixed findings yielded by previous research on the impact of health aid. While some studies found that higher amounts of health aid lead to lower infant mortality rates (Chauvet et al., 2013; Mishra & Newhouse, 2009), others found no statistically significant effect (Mukherjee & Kizhakethalackal, 2013; Williamson, 2008; Wilson, 2011). Two studies (Dietrich, 2011; Feeny & Ouattara, 2013) find a positive link between health aid and two measures of child health promotion: immunization against measles and immunization against diphtheria–pertussis–tetanus. (It should be noted that, in contrast to our analysis, all these studies examine the effect of *committed* aid rather than disbursed aid.)

Two limitations of our analysis should be noted. First, we relied on monetary flows of aid as proxy for interaction between officials. While we developed two strategies for addressing the potential problems this could create – we checked robustness to alternative assumptions on the relationship between volume of aid and quantity/quality of information transmission, and we controlled for health aid per capita to account for the narrowly material effects of aid – the nature of the proxy should be kept in mind. Second, we could not include certain control variables because of severe missing data problems for the period we have network data for. We hope that this limitation can be overcome in future research thanks to improvements in data availability.

While this article's aims are primarily analytical, our findings yield some policy implications. Most directly, they suggest that the worry that there is too "aid fragmentation" and "duplication of effort" in the development aid system, which is widespread among policy-makers and motivated initiatives such as the 2005 Paris Declaration on Aid Effectiveness and 2008 Accra Agenda for Action, may be unwarranted, at least in the area of health aid. There is no doubt that having to maintain links with a multiplicity of donors involves costs, but they appear to be outweighed by the positive effects of network centrality. If our findings are confirmed by further research, then efforts to improve the effectiveness of development aid for health may be better directed towards other areas of reform.

Acknowledgments

Some of the arguments and evidence in this article were first presented at the workshop on Global Health, Political Economy and Beyond, City University London, December 2011, the International Studies Association Annual Convention, San Diego, CA, April 2012, and the American University in Paris, April 2012. For useful comments and suggestions, we are grateful to Leonardo Baccini, Richard Beardsworth, Dallas Blaney, Stefan Elbe, Tine Hanrieder, Sophie Harman, Anastasia Nesvetailova, Valbona Muzaka, Ronen Palan, Anne Roemer-Mahler, Richard Smith, the anonymous reviewers, and the health policy editor of *Social Science & Medicine*. We remain responsible for the limitations of the article. We gratefully acknowledge the financial support of the Agence Française de Développement.

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The social network of international health aid

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Social Science & Medicine, 2018

Supplementary Web-Appendices

Contents

Web-Appendix 1. Aid recipients included in the analysis

Table A1. Aid recipients included in the child mortality models and number of years for each country.

Country	Years	Country	Years
Afghanistan	21	Lebanon	21
Albania	21	Lesotho	21
Algeria	21	Liberia	21
Angola	21	Libya	21
Argentina	21	Macedonia	17
Armenia	19	Madagascar	21
Azerbaijan	19	Malawi	21
Bangladesh	21	Malaysia	21
Belarus	19	Mali	21
Benin	21	Mauritania	21
Bolivia	21	Mauritius	21
Bosnia and Herzegovina	18	Mexico	21
Botswana	21	Moldova	19
Brazil	21	Mongolia	21
Bulgaria	21	Morocco	21
Burkina Faso	21	Mozambique	21
Burundi	21	Myanmar	21
Cambodia	21	Namibia	21
Cameroon	21	Nepal	21
Central African Republic	21	Nicaragua	21
Chad	21	Niger	21
China	21	Nigeria	21
Colombia	21	Pakistan	21
Congo, Dem. Rep.	21	Panama	21
Congo, Rep.	21	Papua New Guinea	21
Costa Rica	21	Paraguay	21
Cote d'Ivoire	21	Peru	21
Cuba	21	Philippines	21
Dominican Republic	21	Romania	21
Ecuador	21	Rwanda	21
Egypt	21	Senegal	21
El Salvador	21	Serbia	17
Eritrea	17	Sierra Leone	21
Ethiopia	21	Somalia	21
Gabon	21	South Africa	21
Gambia	21	Sri Lanka	21
Georgia	19	Sudan	21
Ghana	21	Swaziland	21

Guatemala	21	Syria	21
Guinea	21	Tajikistan	19
Guinea-Bissau	21	Tanzania	21
Haiti	21	Thailand	21
Honduras	21	Timor-Leste	12
Hungary	21	Togo	21
India	21	Tunisia	21
Indonesia	21	Turkey	21
Iran	21	Turkmenistan	19
Iraq	21	Uganda	21
Jamaica	21	Ukraine	19
Jordan	21	Uzbekistan	19
Kazakhstan	19	Venezuela	21
Kenya	21	Vietnam	21
Korea, Dem. Rep.	21	Yemen	21
Kyrgyzstan	19	Zambia	21
Laos	21	Zimbabwe	21

Web-Appendix 2. Measuring centrality in the health aid network

As noted in the main text, the global health aid network is a *weighted* network, i.e. we have information not only on whether a link exists between two actors, but also on the "intensity" of that link. In the dataset we use, the intensity is expressed in terms of financial resources – the value in U.S. dollars of the aid provided by donor A to recipient B in year X.[1] There are various approaches to measuring centrality in weighted networks. One approach consists in disregarding weights and treating all ties as binary: either existing or non-existing. This approach has serious drawbacks whenever the intensity of ties conveys important information that should be taken into account. An alternative approach to measuring centrality consists in disregarding the number of ties and calculating centrality with reference to the sum of the

[1] In calculating the centrality measures explained below from the dyad-year dataset, we have assigned a centrality score of zero to country-years for which no health aid inflows were recorded (and to one country-year in which the net inflow has a negative sign).

weights attached to all ties. When the number of ties is an important dimension of a researcher's understanding of centrality, this approach also leads to a loss of crucial information.

The paper applies the framework proposed by Opsahl, Agneessens and Skvoretz, which incorporates those two approaches as special cases and allows researchers to specify the relative importance of degree and node strength in determining centrality.[2] The degree of a node is the number of adjacent nodes or ties that the focal node has, and captures the dispersion of involvement. The strength of a node is the sum of the tie weights from the focal node to other nodes, and captures the absolute level of involvement. Opsahl et al. develop measures for degree centrality, closeness centrality and betweenness centrality. While in the main text we apply the closeness centrality measure, here we consider degree centrality first as it is a simpler concept. The measure for degree centrality developed by Opsahl et al. is defined as follows:

$$C_D^{W\alpha}(i) = k_i \times \left(\frac{s_i}{k_i} \right)^{\alpha}$$

where k_i is the focal node's degree, s_i is the focal node's node strength, and α is the tuning parameter. There are two benchmark values for the tuning parameter: 0 and 1. If the parameter is set to 0, the outcome is solely based on the number of ties, and it is equal to the degree in a binary version of a network where all the ties with a weight greater than 0 are set to present. In other words, tie weights are completely ignored. Conversely, if the value of the parameter is 1, the outcome is based on tie weights only. This implies that the number of ties is disregarded.

The tuning parameter needs to be set on the basis of theoretical and substantive considerations. In the following, we state the assumptions that correspond to different values/regions of the parameter in relation to the domain of health aid. Setting $\alpha = 0$ reflects

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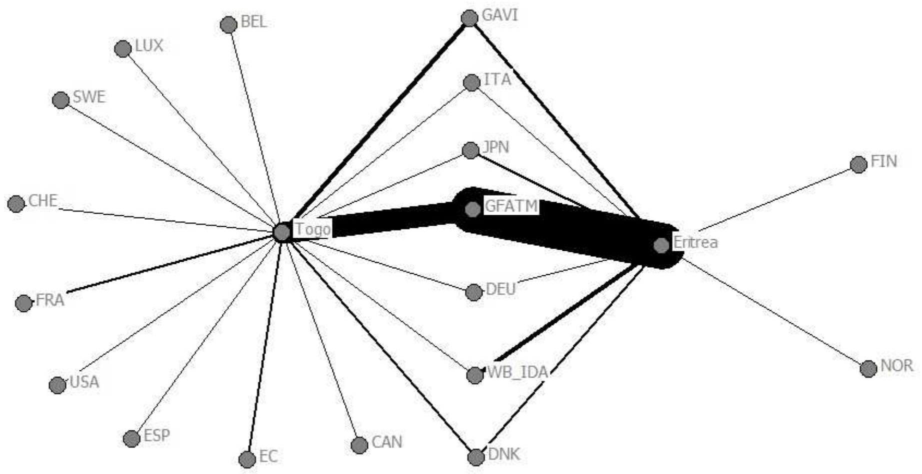
[2] Opsahl, Agneessens, and Skvoretz (2010).

the assumption that centrality depends on the number of donors but not on the total value of health aid received (assumption A). Setting $0 < \alpha < 1$ reflects the assumption that aid flows of larger economic value involve more opportunities for interaction between representatives of donors and recipients at various stages and phases of the policy-making process, and therefore more opportunities for communication and commitment effects to develop (assumption B). Setting $\alpha = 1$ reflects the assumption that centrality depends entirely on total aid flows, with the number of donors playing no role (assumption C).

We have explained in the main text why we regard assumptions A and B plausible, and assumption C implausible. In the following, we illustrate the implications of the different assumptions by comparing two economically and demographically similar countries, Eritrea and Togo in 2010. As Figure A1 shows, Togo had links with a larger number of health aid donors compared to Eritrea. However, Eritrea received a larger total volume of health aid from its donors, largely thanks to large flows from the Global Fund to Fight AIDS, Tuberculosis and Malaria.

Figure A1. Health aid ego networks of Eritrea and Togo, 2010.



Note: The width of a tie corresponds to the value (in U.S. dollars) of development assistance provided by donors to Eritrea or Togo.

Table A2 shows that Eritrea and Togo have similar levels of degree centrality (C_D^W) when both breadth and depth of ties are assumed to play a role (α = 0.5). By contrast, Togo has higher degree centrality than Eritrea if we assume that centrality depends only on the number of donors ($\alpha = 0$). Under the opposite assumption that only total health aid matters for centrality ($\alpha = 1$), Eritrea is more central than Togo.[3]

[3] The numerical values of centrality at $\alpha = 1$ are high because they coincide with the total quantity of U.S. dollars disbursed to each country.

Table A2 Comparison of Centrality Scores for Eritrea and Togo, 2010

			Eritrea	Togo
		0	9	16
Degree centrality	C_D^W when α =	0.5	20973	21100
		1	48875949	27827117
		0	95	102
Closeness centrality	C_C^W when α =	0.5	228	193
		1	244	161

Degree centrality is the simplest measure of centrality, as it considers only the connections between the focal node and other actors, but not the connections between those other actors. "Closeness centrality" is a more complex concept, which is related to the idea of reach. It is defined as the inverted sum of distances to all other nodes in a network from the focal node. In other words, it indicates how quickly a node can reach, and be reached from, all the other nodes in a network.[4] We explained in the main text why closeness centrality is particularly suited to capture the mechanisms we are interested in. To the extent that norms knowledge can diffuse through the health aid network through multiple paths, it can be useful to take into account the total distance between an actor and all other actors in the health aid network, i.e. not only those that provide direct aid to the focal actor, but also other aid recipients, and the donors to those recipients, and so on. When networks are weighted, traditional measures of closeness centrality suffer from the same problem of information loss that affects degree centrality. We address that problem by employing the procedure for weighted networks developed by Opsahl et al.[5] In their approach, tie strength can either be ignored ($\alpha = 0$) or taken into account on the assumption that stronger ties constitute shorter paths ($\alpha > 0$). As in the case of degree centrality,

[4] Freeman (1978).

[5] Opsahl et al. (2010).

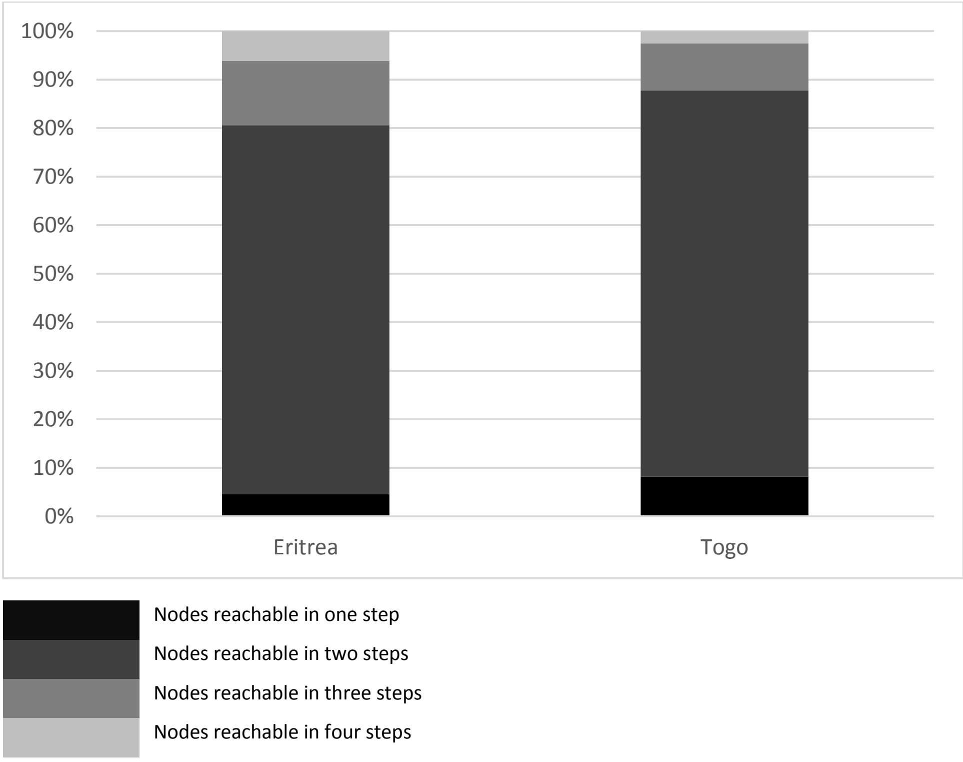
the choice of the value of the tuning parameter depends on whether a correlation between exposure to communication and monetary value of aid is assumed. The measure for closeness centrality developed by Opsahl et al. is defined as follows:

$$C_C^{W\alpha}(i) = \left[\sum_j^N d^{W\alpha}(i, j) \right]^{-1}$$

where d is the shortest distance between node i and j, w is the weighted adjacency matrix (in which w_{ij} is greater than 0 if the node i is connected to node j, and the value represents the weight of the tie), and α is the tuning parameter.

To illustrate, we can consider again the cases of Eritrea and Togo in 2010. Figure A2 shows graphically the percentage of nodes to which the countries have direct links and those to which they are connected indirectly through one or more intermediaries. Eritrea has direct links (one step) to about 5 per cent of the nodes in the health aid network, whereas Togo has direct links to nearly 10 per cent of the nodes. Both countries can reach over 80 per cent of all nodes in two steps or less, over 90 per cent of nodes in three steps or less, and 100 per cent of nodes in four steps or less. The lower section of table 1 shows how the closeness centrality scores (C_C^W) of the two countries compare under different assumptions about the relative importance of breadth and depth of ties. If tie depth is ignored ($\alpha = 0$), Togo has a slightly higher level of closeness centrality than Eritrea. If tie depth is thought to matter for centrality ($\alpha > 0$), Eritrea is substantially more central than Togo.

Figure A2. Eritrea's and Togo's distance from other nodes in the health aid network, 2010.



Web-Appendix 3. Evolution of the health aid network, 1990-2010

We can use the measures discussed in Web-Appendix 2 to trace the evolution of the health aid network as a whole over time. The average degree centrality and closeness centrality of the nodes provides a measure of the *density* of the network. Figures A3 and A4 show the average centrality of the sample of low and middle income countries analysed in the main text, using four measures of centrality: degree centrality with $\alpha = 0$ and $\alpha = 0.5$ and closeness centrality with $\alpha = 0$ and $\alpha = 0.5$. The figures indicate that between 1990 and 2010 the overall density of the network has increased substantially, regardless of whether it is measured only through direct links or also indirect links, and whether more intense connections are weighted differently from less intense connections or not.

Figure A3. Degree centrality by year, average of 110 low and middle income countries, 1990-2010.

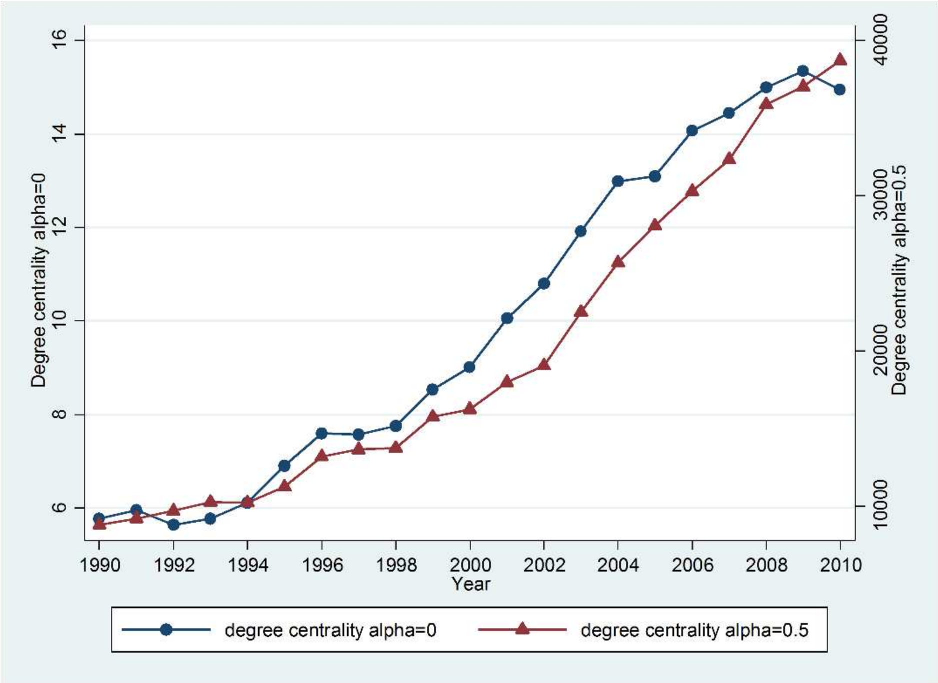
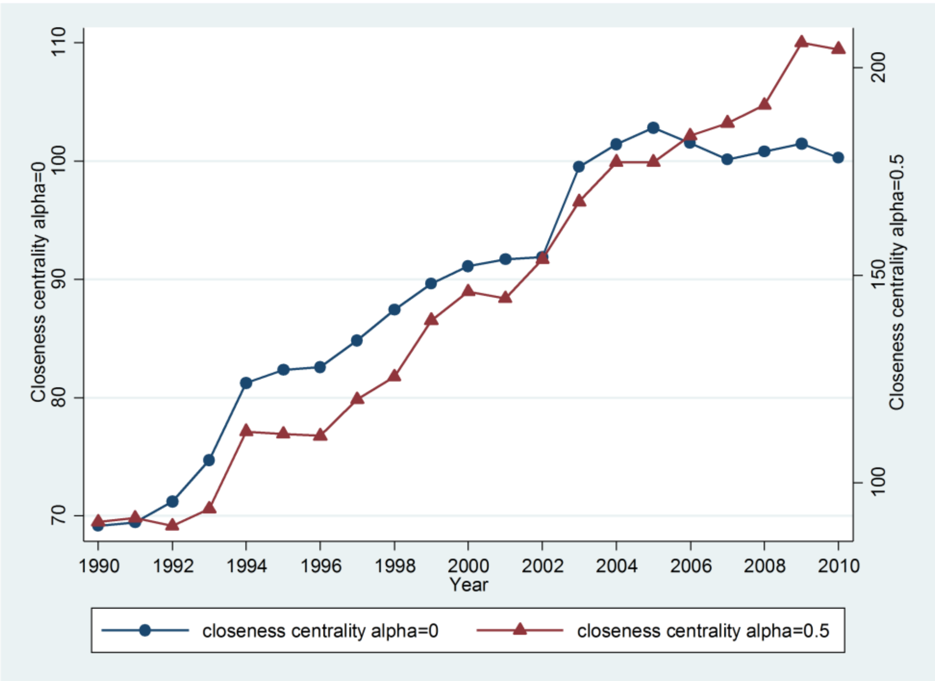


Figure A4. Closeness centrality by year, average of 110 low and middle income countries, 1990-2010.



Web-Appendix 4. Descriptive statistics and multicollinearity diagnostics

Table A3. Descriptive statistics (variables before transformation).

Variable	Obs	Mean	Std. Dev.	Min	Max
Under-5 mortality	2264	78.92	60.10	4.30	300.20
Degree centrality (α=0)	2264	9.72	6.19	0	27.00
Degree centrality (α=0.5)	2264	19618.02	21310.43	0	139839.90
Closeness centrality (α=0)	2264	86.19	22.46	0	112.33
Closeness centrality (α=0.5)	2264	140.05	68.80	0	391.63
GDP per capita	2142	1817.23	1899.38	50.04	11533.82
Health aid per capita	2165	3.33	5.74	0	124.41
Trade as % of GDP	2133	74.37	37.21	0.31	220.41
Urbanisation	2264	44.56	19.84	5.42	93.31
Polity2 score	2201	1.39	6.25	-10	10
Major political violence	2248	0.95	1.92	0	13

Table A4. Correlation matrix (variables after transformation).

	Degree centrality (α =0)	Degree centrality (α =0.5)	Closeness centrality (α =0)	Closeness centrality (α =0.5)	Under-5 mortality	GDP per capita	Health aid per capita	Trade as % of GDP	Urban-isation	Polity2 score	Political violence
Degree centrality (α =0)	1										
Degree centrality (α =0.5)	0.87	1									
Closeness centrality (α =0)	0.70	0.91	1								
Closeness centrality (α =0.5)	0.79	0.98	0.93	1							
Under-5 mortality	0.28	0.25	0.19	0.21	1						
GDP per capita	-0.35	-0.24	-0.16	-0.20	-0.74	1					
Health aid per capita	0.55	0.51	0.36	0.49	0.23	-0.18	1				
Trade as % of GDP	-0.19	-0.21	-0.11	-0.15	-0.29	0.25	0.15	1			
Urbanisation	-0.31	-0.24	-0.16	-0.18	-0.58	0.76	-0.17	0.18	1		
Polity2 score	0.00	0.01	-0.05	0.00	-0.36	0.37	0.13	0.06	0.31	1	
Political violence	0.06	0.07	0.02	0.04	0.22	-0.19	-0.21	-0.28	-0.22	-0.07	1

Table A5. Multicollinearity tests (variables after transformation).

	(1)		(2)		(3)		(4)	
Variable	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance	VIF	Tolerance
Degree centrality (α=0)	1.71	0.59						
Degree centrality (α=0.5)			1.55	0.64				
Closeness centrality (α=0)					1.21	0.83		
Closeness centrality (α=0.5)							1.43	0.70
GDP per capita	2.66	0.38	2.63	0.38	2.63	0.38	2.63	0.38
Health aid per capita	1.74	0.58	1.68	0.59	1.40	0.71	1.62	0.62
Trade (as % of GDP)	1.23	0.81	1.26	0.79	1.19	0.84	1.22	0.82
Urbanisation	2.42	0.41	2.42	0.41	2.42	0.41	2.41	0.41
Polity2 score	1.24	0.81	1.24	0.81	1.25	0.80	1.24	0.81
Political violence	1.20	0.83	1.20	0.83	1.19	0.84	1.20	0.84
Mean VIF	1.74		1.71		1.61		1.68	

Web-Appendix 5. Logarithmic transformation of variables

We use the logarithm of all dependent and independent variables (except political violence and the Polity2 score) in the estimations. This is for three reasons. First, we are examining low and middle income countries and these variables are more likely to be skewed. Second, some variables have large absolute values (e.g. GDP pc and centrality scores), and taking logarithm can effectively bring down the ranges of these variables and therefore reduce the sizes of their coefficients. Third, taking the logarithm facilitates interpretation, as the coefficients can be interpreted as elasticity, i.e. 1% increase/decrease in the independent variable will lead to x% increase/decrease in the outcome. This interpretation is particularly convenient for centrality scores, as they do not have a natural unit. We did not take the logarithm for the Polity2 score and political violence because they are discrete variables and they are less likely to follow a normal distribution. Instead, we changed them into dummy variables to facilitate interpretation (e.g. York, Rosa, & Dietz, 2003).[6] As noted in the text, we followed the convention stated in the Polity IV codebook and defined partial democracy and full democracy as having a Polity2 score between +1 and +6 and between +7 and +10 respectively. The coefficients reported in the article and in these Web-Appendices refer to the effect of partial democracy and full democracy compared to the baseline category of autocracy (a negative or zero Polity2 score). We classify a country as suffering from political violence if it has a score larger than zero in the variable "actotal" from the Major Episodes of Political Violence (MEPV2012) database.

To assess the implications of our decision, we plotted the distribution of our variables to show their original distribution and logged distribution. Using the 'gladder' command in

[6] We are grateful to an anonymous referee for suggesting this.

STATA, the variable of interest is transformed in 8 different ways and a graph is generated showing the distributions of the original variables and 8 transformations (the graphs are available upon request). We find that taking the logarithm worked well for under-5 mortality, GDP pc, trade, degree centrality (alpha = 0.5). It improved the distribution for health aid pc, and it did not worsen the distribution of the other variables.

Web-Appendix 6. The estimation strategy

The paper uses a two-step robust *generalized method of moments* (Difference GMM) model to examine our hypothesis. We utilise this estimation strategy to address 1) the self-dependence in child mortality over time; 2) the potential endogeneity of some independent variables; 3) country-specific fixed effects; and 4) possible heteroskedasticity and autocorrelation in the error terms.[7] Moreover, the Windmeijer finite-sample correction is also made by specifying a robust covariance matrix in the two-step estimation.[8] We estimate the short-term impact of all independent variables by using their one-year lags (except political violence and year dummies) in the equation. This is also an effective way of reducing their endogeneity to the system. As one-year lagged centrality, GDP per capita, health aid per capita and the interaction terms among them (used in the additional analysis) are likely to be predetermined, we instrument them using their own lags starting from the second. The impact of network centrality and other influential factors over the longer term is captured by including two lags of child mortality into the model. Therefore, current mortality is explained not only by the independent variables at t-1, but also those values at t-2 and t-3 as reflected by the dynamics of child

[7] Arellano and Bond (1991); Roodman (2009).

[8] Roodman (2009).

mortality itself. This lag length achieves the desired property of the error terms according to the diagnostic tests of GMM models. By construction, the lags of child mortality would be correlated with the error terms through time-invariant country-specific characteristics. Taking the first difference would not completely remove such simultaneity problem. Hence, we also instrument the dynamics of child mortality using its own lags starting from the second.

There are two main points to note regarding the GMM estimation. First, the number of instruments is quadratic in the time dimension T, and finite samples may lack of adequate information to well estimate the elements of the variance matrix when many instruments are used.[9] Moreover, the Sargan/Hansen over-identifying restrictions could be weakened and generate a p-value equal to 1.[10] Mindful of the "rule of thumb" of not letting the number of instruments exceed the number of cross-sectional units,[11] we estimate models that instrument with one lag only (lag 2) and thus keep the number of instruments below the number of countries. We then check the robustness of our findings by estimating models that instrument with two lags (lag 2 and lag 3) and thus use more information. Consistency across the two sets of results strengthens our confidence in them. The second point worth noting is that the asymptotic of the GMM model is based on the "large N and small T" assumption. Our data set contains 110 countries, which is not exactly "large" when it is compared to the time span of 21 years. This limitation should be kept in mind while interpreting the results.

[9] Roodman (2009).

[10] Andersen and Sørensen (1996).

[11] Kimura, Mori, and Sawada (2012); Roodman (2009).

Web-Appendix 7. Degree centrality

As noted in the main text, closeness centrality is the SNA concept that has the closest fit with the mechanisms highlighted in our argument. It may nonetheless be useful to compare the effect of closeness centrality with the effect of degree centrality, which has been discussed in Web-Appendix 2 and which considers only direct links. Table A4 shows that the correlation between the degree and closeness measures is quite high and Table A6 shows that the beneficial effect of centrality persists when closeness is replaced by degree.

Table A6. Estimated effect of degree and closeness centrality in the health aid network on under-5 mortality, 1990–2010. GMM models instrumenting with one lag (lag 2).

	(1)	(2)	(3)	(4)	(5)
Degree centrality (α=0)	-0.021**				-0.013*
	(0.009)				(0.007)
Degree centrality (α=0.5)		-0.003**			
		(0.001)			
Closeness centrality (α=0)			-0.006***		
			(0.002)		
Closeness centrality (α=0.5)				-0.004**	
				(0.002)	
Degree centrality (α=0) *GDP per capita					-0.001
					(0.005)
GDP per capita	-0.087**	-0.114***	-0.145***	-0.114***	-0.058*
	(0.037)	(0.035)	(0.044)	(0.034)	(0.033)
Health aid per capita	-0.008	-0.007	-0.010	-0.007	-0.006
	(0.005)	(0.007)	(0.008)	(0.007)	(0.005)
Trade (as % of GDP)	-0.014	-0.018	-0.021	-0.019	-0.017
	(0.014)	(0.018)	(0.023)	(0.022)	(0.011)
Urbanisation	0.045	0.057	0.045	0.052	0.099
	(0.042)	(0.043)	(0.050)	(0.039)	(0.075)
Partial democracy	-0.001	-0.002	-0.001	-0.002	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
Full democracy	-0.001	-0.002	-0.001	-0.001	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Political violence	0.005*	0.005*	0.005**	0.005*	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
Lag 1 of under-5 mortality	0.583***	0.627***	0.611***	0.684***	0.733***
	(0.175)	(0.159)	(0.174)	(0.159)	(0.175)
Lag 2 of under-5 mortality	0.261	0.209	0.188	0.173	0.135
	(0.162)	(0.150)	(0.156)	(0.151)	(0.163)
Country-specific fixed effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
No. of observations	1,743	1,743	1,743	1,743	1,743
No. of groups	102	102	102	102	102
No. of instruments	95	95	95	95	113
AR(1)	-1.225	-1.257	-1.260	-1.340	-1.315
AR(1) p value	0.221	0.209	0.208	0.180	0.189
AR(2)	-0.030	0.275	0.342	0.506	0.665
AR(2) p value	0.976	0.783	0.733	0.613	0.506
Hansen stat	56.10	61.37	76.25	64.92	66.12
Hansen p value	0.826	0.671	0.205	0.549	0.925

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Web-Appendix 8. Robustness check with two lags

For the reasons stated in Web-Appendix 4, as a robustness check we re-estimated each model using two lags (lag 2 and 3). The results are presented in Table A7 and are consistent with the results reported in the main text. The robustness of the findings across the two instrumentation choices increases our confidence in them.

Table A7. Estimated effect of centrality in the health aid network on under-5 mortality, 1990–2010. GMM models instrumenting with two lags (lag 2 and 3).

	(1)	(2)	(3)	(4)
Degree centrality (α=0)	-0.020***			
	(0.006)			
Degree centrality (α=0.5)		-0.004***		
		(0.001)		
Closeness centrality (α=0)			-0.007***	
			(0.002)	
Closeness centrality (α=0.5)				-0.006**
				(0.003)
GDP per capita	-0.057***	-0.069*	-0.075**	-0.067***
	(0.021)	(0.038)	(0.034)	(0.022)
Health aid per capita	-0.006	-0.005	-0.008	-0.006
	(0.004)	(0.006)	(0.006)	(0.006)
Trade (as % of GDP)	-0.017	-0.016	-0.014	-0.012
	(0.012)	(0.012)	(0.014)	(0.011)
Urbanisation	0.083	0.046	0.027	0.037
	(0.078)	(0.063)	(0.080)	(0.086)
Partial democracy	-0.003	-0.001	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Full democracy	-0.000	0.001	0.001	0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Political violence	0.005*	0.004	0.004*	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Lag 1 of under-5 mortality	0.553***	0.544***	0.550***	0.558***
	(0.056)	(0.058)	(0.048)	(0.045)
Lag 2 of under-5 mortality	0.309***	0.319***	0.321***	0.333***
	(0.044)	(0.030)	(0.036)	(0.038)
Country-specific fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
No. of observations	1,743	1,743	1,743	1,743
No. of groups	102	102	102	102
No. of instruments	167	167	167	167
AR(1)	-1.437	-1.419	-1.421	-1.397
AR(1) p value	0.151	0.156	0.155	0.163
AR(2)	-0.660	-0.874	-0.836	-0.902
AR(2) p value	0.509	0.382	0.403	0.367
Hansen stat	67.75	78.60	78.07	76.17
Hansen p value	1	1	1	1

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Web-Appendix 9. State capacity as moderating variable

It is possible that governments do not benefit equally from the information flowing through the aid network. Two contrasting expectations can be formulated. On the one hand, management research on knowledge networks indicates that units with little absorptive capacity do not necessarily benefit from network centrality, since the cost of maintaining numerous links can exceed their benefits in terms of knowledge acquisition.[12] A similar effect is possible in the domain of health policy. For instance, Beesley, Cometto and Pavignani report that, when an international and multi-agency team co-ordinated by WHO produced a costly large-scale survey of human resources working in the health sector in southern Sudan and formulated recommendations, the Ministry of Health failed to make use of the findings and recommendations in developing a human resource plan. According to former members of the consultant team, "the institutional environment of the Ministry of Health was not ready to absorb and use the findings of a large scale (or, perhaps, any) survey".[13] In his study on the adoption of eHealth legislation, Lang finds that private-public partnerships lead to more legislation through knowledge transfer in countries that have relatively high level of government capacity in the health sector.[14]

On the other hand, is also possible that the knowledge benefits of centrality are higher in countries with weaker domestic state capacity, since the ability to tap into global information

[12] Tsai (2001).

[13] Beesley, Cometto, and Pavignani (2011, 6).

[14] Lang (2014).

flows allows policy-makers to offset the scarcity of endogenous knowledge creation and evaluation.

These two expectations suggest that network centrality and domestic state capacity can be *complements* as well as *substitutes*. Since both high-capacity and low-capacity government units may benefit from network centrality, although for slightly different reasons, we check whether the effect of network centrality is moderated by the level of state capacity. To do so, we estimate models with an interaction term between each of our centrality measures and four commonly used indicators for state capacity: GDP per capita, the Bureaucracy Quality score of the International Country Risk Guide, and two variables from the Relative Political Performance Data Set: Relative Political Extraction, which gauges the ability of governments to appropriate portions of the national output, and Relative Political Reach, which gauges their capacity to mobilize populations under their control. [15]

The interaction terms between centrality and our various measures of state capacity (GDP per capita, Bureaucracy Quality, Relative Political Extraction and Relative Political Reach) are generally not statistically significant at conventional levels. This suggests that the benefits of network centrality are not conditional on the state capacity of recipient countries.[16] Table A6 only shows the interaction between one centrality measure (degree centrality with $\alpha=0$) and one measure of state capacity (GDP per capita), but other combinations of centrality and state capacity measures lack statistical significance as well. The exception is the interaction term

[15] Kugler and Tammen (2012); PRS Group (2010).

[16] Kam and Franzese (2007, 49). In Model 5 of Table A6 only, the Centrality and GDP per capita variables are centred on their sample means in order to facilitate substantive interpretation, as recommended by Kam and Franzese (2007): the coefficient for Centrality indicates the variable's effect when GDP per capita is at its sample mean rather than at the substantively meaningless value of 0. The interaction term is statistically insignificant regardless of whether the variables are centred or uncentred.

between closeness centrality (α=0.5) and Relative Political Reach, which is significant at the $p < .10$ level.

Web-Appendix 10. The role of donor coordination

We checked if our results hold if we exclude health aid that is highly coordinated among multiple donors. It could be argued that centrality may have beneficial effects when donors coordinate their efforts and detrimental effects if they fail to coordinate or are in a competitive relationship with one another. Donor coordination is a multidimensional phenomenon, which is difficult to quantify for the purposes of cross-national analyses. A proxy measure of coordination among donors is support given a recipient country's health-sector budget, for instance in the context of a sector-wide approach (SWAP) in health, as opposed to funding directed towards specific projects or addressing specific diseases. Table A8 shows the percentage of global DAH given to health sector programme support, which is broken down by channel (bilateral, multilateral, private).[17] We also break down the percentages by period, before and after the 2005 Paris Declaration on Aid Effectiveness, by which donors committed themselves to increasing the coordination of their aid. As shown in the table, only a small percentage of DAH is directed towards health sector support, but it increased in the years after the Paris Declaration.

[17] Data on disbursements for health sector program support come from Ravishankar et al. (2009).

Table A8. Percentage of global DAH given to health sector programme support

	Bilateral DAH	Multilateral DAH	Private DAH
1990 - 2010	6.35%	2.30%	0%
1990 - 2004	2.35%	1.04%	0%
2005 - 2010	9.48%	3.45%	0%

To assess whether the effect of centrality depends on donor coordination, we test whether network centrality continues to have a negative and statistically impact on child mortality after disbursements for health sector program support (our proxy for coordinated aid) are subtracted from the total flows of health aid. Table A9 shows the results. We find that the effects of centrality in the health aid network excluding coordinated aid are very similar to those of the overall health aid network. This suggests that the beneficial effect of health aid network centrality does not depend on high levels of coordination among donors.

Table A9. Estimated effect of centrality in the health aid network (uncoordinated aid only) on under-5 mortality, 1990–2010. GMM models instrumenting with one lag.

	(1)	(2)	(3)	(4)
Degree centrality (α=0)	-0.021**			
	(0.009)			
Degree centrality (α=0.5)		-0.003**		
		(0.001)		
Closeness centrality (α=0)			-0.006***	
			(0.002)	
Closeness centrality (α=0.5)				-0.004**
				(0.002)
GDP per capita	-0.089**	-0.113***	-0.145***	-0.109***
	(0.038)	(0.035)	(0.044)	(0.034)
Health aid per capita	-0.008	-0.008	-0.010	-0.007
	(0.005)	(0.007)	(0.008)	(0.006)
Trade (as % of GDP)	-0.014	-0.018	-0.021	-0.019
	(0.014)	(0.018)	(0.023)	(0.022)
Urbanisation	0.046	0.057	0.045	0.051
	(0.042)	(0.044)	(0.050)	(0.040)
Partial democracy	-0.001	-0.002	-0.001	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)
Full democracy	-0.001	-0.002	-0.001	-0.001
	(0.004)	(0.003)	(0.003)	(0.003)
Political violence	0.005*	0.005*	0.005**	0.005*
	(0.003)	(0.003)	(0.003)	(0.003)
Lag 1 of under-5 mortality	0.584***	0.630***	0.612***	0.692***
	(0.175)	(0.158)	(0.174)	(0.157)
Lag 2 of under-5 mortality	0.259	0.208	0.188	0.169
	(0.164)	(0.150)	(0.156)	(0.151)
Country-specific fixed effects	*Yes*	*Yes*	*Yes*	*Yes*
Year dummies	*Yes*	*Yes*	*Yes*	*Yes*
No. of observations	1,743	1,743	1,743	1,743
No. of groups	102	102	102	102
No. of instruments	95	95	95	95
AR(1)	-1.231	-1.263	-1.263	-1.351
AR(1) p value	0.218	0.207	0.207	0.177
AR(2)	-0.020	0.287	0.347	0.532
AR(2) p value	0.984	0.774	0.729	0.595
Hansen stat	56.26	62.71	76.37	63.72
Hansen p value	0.822	0.626	0.203	0.591

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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