Networks and Economic Policy

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Abstract[§]

Over the past two decades, economists have made significant advances in understanding how networks affect individual behaviour and shape aggregate outcomes. We argue that insights from network economics can play an important role in the design of economic policy. Focusing on six policy domains, we show that network economics not only deepens our understanding of existing policy concerns but also suggests a number of new policy questions. In each of these policy areas, we evaluate the availability of data and assess the suitability of the network economics toolkit for policy work. We conclude with a discussion of challenges to the adoption of network-based methods in economic policy along with strategies to overcome them.

Introduction

Economic activity takes place in an interconnected world. People are linked to each other by familial, social, and business ties. Firms are connected by competing in similar markets, by using each other's inputs and outputs, and by participating in joint ventures. Governments are tied by alliances, by geographical proximity, by trade, by their openness to migration, and by cross-border capital flows.

As economic activity involves interaction, individual behaviour is shaped by choices made by proximate agents, i.e., our *neighbours*. However, the (unpriced) effects of these neighbours on our behaviour – externalities – depend on the strength and the pattern of ties between us and our neighbours, on our neighbours' ties with their neighbours, and so on. To understand how these externalities affect behaviour, we must therefore consider not only the direct contacts of an agent but also the more general structure of the connections in which all agents are embedded. We use the term *networks* to describe the overall structure of connections.

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Over the last two decades, the study of networks has emerged as an important field of research in economics, complementing tools such as game theory and general equilibrium theory. Game theory is well-suited for the study of behaviour in small exclusive groups while general equilibrium theory provides a sophisticated approach for analysing large anonymous systems. Networks offer us a framework for understanding how local interactions affect large interconnected populations. In general, taking a networks approach can be thought of as moving to having a broader, system-wide perspective as opposed to a narrower focus that only takes smaller subjects (individuals, firms, or sectors) as the unit of analysis. Thus, networks help fill an important gap in the economists' toolkit.

The key methodological innovation offered by network economics is the systematic introduction of graph theory (and related concepts from discrete mathematics, probability theory, statistics, and linear algebra) into economics. Tools from network analysis allow economists to embed familiar concepts of strategy, information, prices, and competition into models of network-based interactions. These models are being applied to address an increasingly ambitious range of questions in economics.

Networks serve different purposes. Some networks are functional: they allow us to communicate, to transact, or to transport; other networks, such as social networks of family and friends, also have inherent value. Networks also overlap: people are embedded in social and organisational networks. Firms are tied via production and lending networks while their owners and executives are themselves socially connected. Moreover, networks are dynamic and evolving: they change and adapt according to the decisions of network participants and due to shocks. Some friendships fizzle out, but new ones take their place; suppliers go bankrupt, but firms replace them with new ones. As the government expands social insurance, informal insurance arrangements within communities may weaken; but as governments open up to foreign trade, ethnic groups may be able to use cross country community ties to facilitate long-distance transactions strengthening social ties.

Connections can matter in different ways depending on the economic circumstances. For instance, a consumer seeking information about a new brand will probably do less personal search if he has many friends who are also searching. On the other hand, a firm may invest more in research if it has more collaborators to make better use of the fruits of its own research. Thus, the presence of connections may lower effort in some settings and increase effort elsewhere.

In many settings, however, simply knowing the number of connections may not be enough to gauge relevant economic insights. For instance, consider a classroom with pupils from two ethnic communities and suppose that every pupil has two friends. Consider two possible networks. In one network, every pupil in a given ethnic community has all of their friends within the same community. In another network, each pupil has an equal number of friends from the two communities. Clearly, the flow of information and the interaction in the classroom would be very different depending on which of the two networks obtain. Thus, the overall structure of connections is important—over and above the number of connections. These observations suggest that understanding human behaviour in networks will require both a knowledge of the specificities of the economic circumstances—the content of interaction—as well as the knowledge of the structure of the network.

As the structure of interaction matters, purposeful individuals and economic actors will strive to create networks that are productive and advantageous: This insight underlies theories of *network formation*. In these theories, individuals form connections with others based on a comparison of their costs and benefits. The returns from linking will again depend on the specific economic circumstances. Network formation theories can therefore deliver predictions of which network structures are likely to arise (i.e., *stable* networks) and which network structures might be desirable (e.g. from an efficiency point of view) in different situations. If individual and social preferences are aligned, stable networks can efficient. However, since externalities in linking are widespread, stable networks are typically inefficient (see, e.g., Jackson and Wolinsky (1996) and Bala and Goyal (2000)).

At a high level, network economics has delivered three insights: first, it has shown that empirical networks exhibits heterogeneity (e.g., in the number of connections as well as in other individual network characteristics such as *centrality*). Two, the heterogeneity of networks has a profound effect on individual behaviour and aggregate outcomes across a range of economic environments. A key observation is that differences in network location – measured by the number of connections, closeness to others, and centrality within the network – can dramatically affect economic outcomes. Three, the theory of network formation has shown that individual linking choices can give rise to networks with very striking macroscopic features, (e.g., a core-periphery architecture in banking networks, fat tails in the distribution of the number friendships people have, and the small-world property in social networks whereby two agents have few degrees of separation).

Now is a good time for network economics to become a standard part of economic policymaking. By many measures, our world is becoming more interconnected. People can keep in touch with all their high-school friends for the rest of the lives and foster new online relationships with hundreds of others around the world. Supply chains span the whole globe and people are able to travel more cheaply and safely than ever before. Satellite and communication technologies that underpin the shared economy allow people to enter into new kinds of economic networks. News, true and fake, as well as data, travel faster and further than ever before. At the same time, new protectionist policies could undo some of these changes, and a networks perspective can facilitate a better understanding of the trade-offs.

We therefore argue that insights from network economics can play an important role in economic policy. We illustrate where network economics has already had some success in policymaking, and suggest other fields in which network economics could fill important policy gaps. Specifically, we consider the role of network economics in six areas of economic policy making:

1. Financial markets
2. Competition policy
3. Macroeconomic (sectoral) policies
4. Development
5. Labour, and
6. Crime.

We suggest necessary conditions for network economics to enter into the heart of economic policymaking: first, the abundance of relevant policy questions; second, the availability of cost-effective data; third, the presence of usable tools; and, finally, the political will for a paradigm shift towards network economics in policymaking. We review these conditions and use them to provide a lens on finding the policy areas where networks might have more of an impact in the near term.[5]

The policy areas we cover use rather different network data: the first three areas mainly use firm-to-firm (or sector-to-sector) interconnections while the latter three rely on social network data. Increasing interconnections driven by globalization, digitisation, and the Internet are generating vast amounts of data. Smartphones record many of our transactions. Online platforms serve us recommendations on the basis of our friends' preferences. Policymakers need to carefully consider what data are already available and what are the costs and benefits of collecting more data.

In order to know what to make of all these data, we need a way of grappling with networks. Network economics uses a variety of methodologies in the policy areas we consider. These range from applications of graph theory to identify key network statistics that can be applied to shed new light on old questions in antitrust, through randomised controlled trials used in development to better understand the diffusion of technologies and information spread between social connections in poor communities. We are discovering new tools and technologies to meaningfully process huge datasets in order to make good public policy decisions. These tools range from applying advanced econometric techniques on social network data to find the most influential early adopters to the use of the newly reported data on financial connections between banks for running simulations that stress test the

[5] Our list of six policy areas is not meant to be exhaustive; there are, of course, other fields – such as health, trade, and cybersecurity – in which an understanding of networks is likely to be central to the design of public policy.

financial system. The groundwork for network economics to have a lasting impact in these policy areas has been laid by decades of sociological research, together with recent insights from network economics. Allied with the new opportunities provided by new data, network economics is ready to be added to the toolkit of policymakers in these areas.

The transition to network-based approach in all areas economic policy is unlikely to be immediate and smooth. Policy frameworks are highly path-dependent so it will take both time and political will to shift the paradigm away from economic policy-making based either on partial equilibrium models or on highly aggregated general equilibrium analysis.

The rest of this paper proceeds as follows. In Section 2, we consider a set of important policy questions which have or could have benefited from economic network analysis. In Section 3, we look at different sources of network data. In Section 4, we briefly describe the tools available to policymakers to process and interpret network data. Finally, in Section 5 we point to political obstacles faced by policymakers. Section 6 is a conclusion.

Questions

Any field of inquiry is judged by its ability to answer existing questions and ask new questions. Network economics is no different: without new answers to existing questions and without its ability to open new lines of inquiry the network economics approach would be redundant to academics and policymakers alike.

New answers to existing questions

Let us begin with six typical questions in economic policymaking:

1. **Bank regulation**: How strictly should the government regulate the financial sector?
2. **Competition policy**: Is a merger anticompetitive?
3. **Macroeconomic and sectoral policy**: How would a proposed macroeconomic policy impact different sectors of economy?
4. **Development policy**: How can widespread adoption, among subsistence farmers, of a new more productive technology be achieved?
5. **Labour market policy**: Do Job Centres increase employment?
6. **Rehabilitation policy**: Does social worker support prevent criminals from reoffending?

Economics has, of course, tried to address these policy questions. A traditional approach to these questions might proceed as follows:

1. Evaluate the solvency of banks on a case-by-case basis and, if required, intervene on a case-by-case basis.
2. Conduct the SSNIP (small but significant and non-transitory increase in price) test to identify the smallest relevant markets within which a firm might have market power and evaluate the impact of the merger on competition in these markets.
3. Analyse the costs and benefits of government policies on a sector-by-sector basis.
4. Study the introduction and adoption of a new agricultural technology by farmers to better understand whether take-up is inefficiently slow, and thus whether government intervention may be merited.
5. Stagger the introduction of Job Centres and study the change in area-by-area employment.
6. Use variation in the provision of social worker support across time and space to study its comparative effectiveness on reoffending rates.

However, seen through the lens of network economics, these answers appear partial and potentially insufficient. Let us compare the traditional approach with a networks perspective in each policy domain.

Banks do not simply lend to households and to firms, but borrow and lend to each other. A bank that fails might not only cause other banks to fail in turn: even the perception of insolvency of a bank can have a dramatic effect on the willingness of other banks to transact with each other. Such illiquidity can cause panic and create runs on solvent banks. Therefore, evaluating the regulatory requirement on an individual bank without stress-testing the effect of the bank's failure on the whole financial system can mislead the regulators: a system that seems "robust" to small market fluctuations, might be "fragile" in the face of the failure of systemically important banks (Gai and Kapadia, this issue).

SSNIP tests are the bread and butter of competition policy. However, focusing on a narrow definition of a market can miss the bigger picture: price changes in one market can cause firms in adjacent markets to respond strategically and adjust their prices. A networks perspective can allow out-of-market constraints to be directly incorporated into calculations informing antitrust investigations in order to give a more refined view about the likely competitive impact of a merger. Elliott and Galeotti (this issue) show that ignoring these out-of-market effects can substantially bias estimates about the impact of a merger on competition.

When an industry is in trouble, the government is often under pressure to take action to save or to cut off support to the industry. However, the effect of shocks in one industry can have far larger aggregate effects than the impact on the industry itself. The reason is that industry-level changes propagate through the inter-sectoral network changing prices, profits, and labour demand throughout the economy (Grassi and Sauvagnat, this issue). Moreover, large shocks can often result in hysteresis effects: dramatic and permanent changes in output that are not corrected by price adjustments. A prominent example is the executives of Ford and Chrysler who lobbied the Obama administration to bail out their *competitor* General Motors during the financial crisis, as they feared that GM's collapse would destroy the supply chain that both companies relied on (Acemoglu et al, 2015; Baqaee, 2018). Therefore, industrial policies cannot simply focus on individual industries; rather they must take the input-output structure of the economy carefully into account.

Many governments support the adoption of new technologies. In a development context agriculture is often important and new technologies can have the potential to lift farmers out of poverty. Innovations are often adopted following word-of-mouth recommendations from those we trust: technological diffusion is a network-based phenomenon (Grilliches, 1957; Coleman, 1966). For example, in early work Foster and Rosenzweig (1995) investigate technological diffusion for the case of the adoption of high-yield crops in India during the agricultural revolution. Network economics provides a rich framework that can help development researchers to get a deeper understanding of such diffusion. By collecting data on social relationships, the role of individual connections in diffusion can be properly modelled and analysed. Although the idea that the identity of early adopters might matter has been around in the development literature for a while, the network-based features of such "influentials" are still poorly understood. Policymakers need appropriate network-based theories for the given context to decide whom to "seed", and for deciding whether leveraging the network structure is worthwhile (Breza et al., this issue). Finally, in the context of field interventions, there is a need to elicit relevant network measurements as economically as possible.

Active labour market policies try to match people to jobs by, for example, offering them training and information. However, a large proportion of jobs are found through distant social contacts i.e. *weak links* (Granovetter, 1973). Improving information about jobs in one area can spill over to other areas through social contacts that bridge these regions obfuscating and underestimating the impact of the policy. But virtually no active labour policy helps people build and leverage social connections in the labour market to facilitate these spillovers (which is helpful to those finding jobs thought not the researcher assessing the impact of the policy!). Enacting policies that complement the spillovers should help make active labour market policies more effective (Topa, this issue).

Since the seminal work of Becker (1968), crime has been viewed by economists in the context of the incentives and opportunities that people face. This perspective on crime has led economists to consider how, in particular, good behaviour can be encouraged and bad behaviour discouraged with appropriate incentives. But behaviour is heavily influenced friendships so people often coordinate on types of behaviour and social norms that reflects their social networks. For example, connections formed in prison are likely to be important for both encouraging reform and removing opportunities and incentives to reoffend. Moreover, people also form their friendships in a way that reflects their preferences and reinforces their behaviour. Understanding patterns of social influence and social network formation can therefore be crucial in reducing delinquency and crime (Lindquist and Zenou, this issue).

New questions

There are two themes that run through questions asked by network economists:

How does the pattern of connections affect individual behaviour and shape aggregate outcomes?

When an agent takes an action, other agents in the network will respond by changing their actions. The strength and direction of the response will depend on their position in the network. For example, when an industry becomes less competitive thereby raising its prices, it affects the input prices and the profits not just of its immediately downstream sector, but also of *all* the downstream sectors in the economy (e.g., Grassi (2017)).

To understand effects of changes in incentives or of a shock on an individual entity, we need to a theory of how changes in an individual's behaviour spread through connections and alter the incentives of others and in turn come back to influence the originally affected individual. Depending on the context, different aspects of individual connections and the overall network structure will matter. Network economics proposes general methods to understand how the content of interaction and the structure of the network jointly shape behaviour. In particular, network economics highlights the role of classical network measures – such as centrality, connectedness, clustering, and the cohesiveness of the network.[6]

What are the incentives of individuals to create/dissolve ties and how does this formation process shape the architecture of networks?

Perhaps the most innovative aspect of the network economics research programme is the study of network formation. A range of models have been developed to examine how individual incentives shape the formation of networks and how the externalities inherent in the formation process create social costs and benefits. As networks are often complex and overlapping, changes in one network can have a dramatic impact on other networks. This is probably the least well-understood and the most challenging aspect of applying network economics to policymaking. For example, after the

[6] For an overview, see Goyal (2007) and Jackson (2008); for a recent survey of the literature, see Bramoullé, Galeotti and Rogers (2016) and Jackson, Rogers and Zenou (2018).

introduction of microfinance in a village, villagers may sever not only their risk-sharing relationships, but also their social ties (Banerjee et al., 2018). On the other hand, after the opening of international trade, social ties within an ethnic group spread across different countries may be reinforced.[7]

These two themes set the stage for a statement of the central question on the role of networks in the design of economic policy:

How can networks be used to design effective policy interventions?

To get an answer to this question, the policymaker must (i) understand how the networks mediate the actions of each agent; (ii) appreciate the relative importance of individual or groups of agents as determined by their network positions, and (iii) estimate how the network forms and be able to anticipate how the network will evolve in response to policy changes. The answer comes with a prize: the policymaker can greatly expand her set of cost-effective interventions. Indeed, a policymaker trained in network economics can not only seek new network-based answers to the questions posed in the previous section, but also ask more nuanced questions that reflect her understanding of the importance of networks:

1. Is a bank "too connected to fail" and should such a bank be subject to additional regulation?
2. How does a firm's position in the industry competition network confer market power on it?
3. Which sectors should the government target in reviving an economy during a recession?
4. How would word-of-mouth communication spread information about a new technology?
5. How large are the spillovers from active market policies within and across neighbourhoods?
6. Do past and present social connections affect the efficacy of rehabilitation policies?

Ideally, policy implementation results from a meticulous examination of basic empirical phenomena in conjunction with the creation and refinement of theories, leading to careful policy design. Urgent banking regulations following the financial crisis, however, often became policies before comprehensive theoretical and empirical underpinnings had been established, and, as a result, many of these policies are still being revised and fine-tuned. On the other hand, network-based competition, development, and macroeconomic policies appear somewhat overdue since policymakers are already sitting on growing body of theoretical and empirical tools that can help design new regulations. Finally, the latter two questions on our list are, thus far, the subject of more intense inquiry by academics than by policymakers and practitioners, but hold considerable promise for successful policies in the future.

[7] For an overview, see Bramoullé, Galeotti and Rogers (2016) and Goyal (2017).

We now briefly examine what network data and methodological tools are available to policymakers to tackle policy questions before examining each of the six questions in greater detail.

Network Data

Policy must be based on evidence and evidence requires data. Clearly, in order to use insights from network economics for policy, the policymaker is required to have the relevant network data. Although in some cases these data need to be purposefully collected, often network data already exists. Since data collection carries not only benefits, but also costs, it is crucial to understand how useful data collection will be for evaluating policy interventions.

Repurposing existing network data

Policy-relevant network data often already exist and they simply need to be repurposed for network analysis. One example is infrastructure and locational data. Governments typically keep records of roads, railways, public transport links, pipelines, and electricity networks. Proximity data based on transport links and locations can be a valuable proxy for social or economic connections. For example, municipalities in Colombia that were well-connected by the road network experienced greater spillovers from state capacity investments (Acemoglu et al., 2015). Proximity data can be helpful in understanding neighbourhood effects and can help target active labour market policies (Topa, this issue). In a similar vein, prisons often keep digital records of prison inmates allowing crime agencies to estimate a network of social contacts among former convicts that could help target rehabilitation interventions appropriately (Lindquist and Zenou, this issue). Finally, sectoral input-output tables are important sources of data for network-based macroeconomic policy.

Network data as a by-product

The emergence of online social networks and digitalisation of many services has created a rich source of network data. For example, recorded interactions between users on Facebook, Twitter, LinkedIn and other social platforms have resulted in rich troves of social network data. Many companies are collecting locational data in order to serve location-based advertisements, but these data also paint a picture of social contexts in which individuals live. In addition to transaction-level data collected by credit card companies and lending data from peer-to-peer lending platforms, there are now also many public ledgers of anonymised cryptocurrency transactions, such as Bitcoin. While transaction-level data has been carefully guarded by private firms, governments are stepping in too. For example, governments are digitising VAT records in order to improve tax collection thereby keeping a record of the network of firm-to-firm and firm-to-consumer transactions (Spray, 2017).

Data created for academic purposes

In order to study the importance of networks in different contexts, academics have often tried to collect bespoke datasets that could be made available to researchers around the world. The most famous example of a large-scale academic effort to collect social network data is the National Longitudinal Study of Adolescent to Adult Health (Add Health) which collected individual characteristics and social connections of thousands of American adolescents. This dataset has been accessed by over 30,000 researchers, generating over 2,600 research articles. Among other things, these data have allowed researchers to understand the impact of social connections on delinquency and obesity (Lindquist and Zenou, this issue). The second notable example of publicly available social network data is the Indian microfinance diffusion data. Banerjee et al. (2013) collected two waves of social network data in 75 remote Indian villages in order to help an NGO spread microfinance more effectively. The researchers mapped out social networks in each village by asking more than a dozen specific questions about the villagers' social connections. These are now hundreds of field experiments which are now studying the impact of networks on economic outcomes: As of August 2019, the AEA RCT Registry alone returned 186 experiments which mention "networks".

Network data collected explicitly for conducting policy

Network data is also being collected by policymakers precisely because such data can already be used in policy decisions. For example, large companies are required to report on their largest suppliers and owners. Such data allows policymakers to assess the impact of bankruptcies on supply chains and assess the true nature of market competition. Border agencies also collect data on shipping containers in order implement tariffs and regulations thereby mapping out the network of world trade. Finally, since the Global Financial Crisis, many countries, including the US and the UK, have required banks to report data on their counterparties. Financial network data allows central banks to create a rough picture of the entire financial system and more accurately assess the systemic importance of financial institutions (Gai and Kapadia, this issue).

Innovations that reduce costs of collecting data as well as techniques that enable partial network data to be used for inference are likely to be extremely valuable. One such technique is Aggregated Relational Data (ARD) that consist of responses to questions of the form "How many of your social connections have trait *k*?" Breza et al. (2018) estimate that aggregate relational data approaches can be 80% cheaper than standard surveys of social networks (see also Breza et al., this issue).

Data for network-based policy questions

We now return to the examples of networks-based policy questions we outlined previously and consider the data available and required for successful policy implementation.

Is a bank "too connected to fail" and should such a bank be subject to additional regulation?

Following the financial crisis major, legislation, such as the Dodd-Frank Act in the US, Basel III, Basel IV and the European Market Infrastructure Regulation (EMIR) in Europe, have been implemented to help make banks' financial interdependencies more transparent and to avoid the need for future government bailouts of systemically important institutions. As an example, the EMIR requires that both parties involved in a derivatives trade report the transaction (although one party may designate the other to report on its behalf). These reporting requirements have furnished central banks with the data required for a network based analysis of financial stability. However, counterparty reporting requirements do not cover the entire network of financial transactions. The legislation typically focuses on banks rather than financial institutions more broadly defined. In particular, unlike commercial banks, financial institutions that do not take deposits are subject to less stringent regulations. These "shadow banks", such as hedge funds, broker-dealers and money market funds, provide similar services to the banking sector but largely lie outside of reporting regulations. As a result, a policymaker might be concerned that their view of the financial network is not only partial but also potentially systematically biased.

How does a firm's position in the industry competition network confer market power on it?

Under existing frameworks, a first step in an antitrust investigation is to define the market of interest. Doing so requires understanding to what extent products or services within the market are substitutable with those outside the market. Thus, elasticities of substitution are estimated between the relevant products. In some instances, a network approach can be adopted *without collecting any additional data*. This is true for the main application of supermarket competition discussed in Elliott and Galeotti (this issue): the scope of the enquiry is national but markets are defined to be local, data to estimate substitutability between adjacent regions will necessarily be collected anyway, and these data can be redeployed to inform a network-based approach.

However, in other instances, while data is available on some substitute products and services (typically such data on prices and product/service sales is routinely collected by businesses), data might not be available for *all* the weak and possibly long chains of interaction. For example, to analyse competition in bus transit markets, data on taxis might currently be collected to determine whether taxis should be considered to be in the same markets as buses. On the other hand, a policymaker might not collect data on chauffeur-driven private hire vehicles since their elasticity of substitution with buses is likely to be very low. However, since chauffeur-driven private hire vehicles might substitute *directly* for taxis, they can still *indirectly* impact the bus market. As a result, a policymaker informed by network economics might also be interested in price and quantity data on chauffeur-driven private hire vehicles for her bus market inquiry, if these are expected to directly compete taxis which in turn might directly compete with buses. A comprehensive network-based approach can require gathering more data than would be collected when using more traditional methodologies.

Nevertheless, even when additional data is required for a full networks approach, a partial networks approach might still add value. For example, in the 2011 Competition Commission Local Bus Services Market Investigation, substitution between buses and both car travel and taxi travel was investigated, but both cars and taxis were found to be outside of the market. The (weak) competitive constraints imposed by these alternative modes of transportation could be incorporated into a partial network analysis without more data being collected.

Which sectors should the government target in reviving an economy during a recession?

Aggregate data on the interlinkages between different sectors of the economy has long been available through well maintained input-output tables. However, while analysing these aggregated connections directly provides some interesting insights on which sectors are important (see, for example, Acemoglu et al. 2015), the devil is often in the detail which is lost in the aggregation. Firm-level connections aggregate up into sector-level connections, and heterogeneity in the firm-level connections matters. For example, the exact structure of firm-level connections affects competition in the supply chain, which in turn can affect the transmission of shocks. Moreover, firm-to-firm networks amplify the effect of microeconomic wedges on the economy's total factor productivity (Baqaee and Fahri, 2019).

More disaggregated and more detailed data is becoming available each year. While the reporting requirements of companies about their largest suppliers have long given us some partial information about business-to-business transactions (for example, through the Compustat database), governments are starting to collect much more detailed information. In several countries, new value added tax (VAT) data collecting systems are being introduced that record all business-to-business transactions by using VAT numbers (for example, Spray (2017) makes use of such data to analyse the Ugandan economy). Firm-level tax data therefore provides new opportunities for identifying key firms within an economy which may help in the design of more finely targeted policies.

How would word-of-mouth communication spread information about a new technology?

In order to understand how an agricultural innovation diffuses, two types of data need to be collected. First, the policymaker requires data on the timing of each adoption decision: we need to know not just who adopts, but who adopts when. Adoption data can be collected using surveys by relying on the recollections of participants about timing. For many digital technologies collection can also be done more precisely using mobile phone data. There are key events that occur prior to adoption that can be useful to document. The "discovery", "intention-to-adopt", "experimental adoption" and “actual adoption” steps can involve different timings which might be crucial to understand in order to evaluate successful adoption. For example, a farmer might first hear about a technology; then talk to several friends about it; then buy the seeds (which could be traced via an order placed on a mobile phone); plant the seeds to see if they will catch on, and only then finally switch to a new seed. The second type of data that need to be collected is the social network data that guides each step of technological adoption process. For example, the policymaker might need to understand different types of social (e.g. religious or familial) and business relationships as well as the intensity of interaction of various farmers. Some of the connections might be well captured by proxies: for example, castes or surnames could trace familial, social, or religious links while geodesic distance or mobile phone data could approximate the frequency of interactions.

How large are the spillovers from active market policies within and across neighbourhoods?

In the traditional analysis of the labour market, policymakers look at unemployment, vacancies, as well as new and filled positions within industries and across the whole economy. Typically, however, policymakers have no ability to observe one of the main job-seeking and hiring strategies: social connections. In the past, these data were unavailable, however, there are now many digital services, such as LinkedIn, in which allow workers to display their resumes, record social connections, and make job recommendations. There are also dozens of other job-search websites---which are not social network platforms but where workers voluntarily upload their resumes---which can track the movement of workers between firms and across industries over time. Since privacy might be less of a concern for public job profiles than for personal social media accounts, the social connections data could in principle be used directly in public policy. Governments can also recreate much of the firm-to-firm worker movement data via personal tax returns, social security contributions, and firm reports and match them to education records. However, tax record data often comes with long lags thereby being an imperfect substitute for much of the social network data.

Do past and present social connections affect the efficacy of rehabilitation policies?

Different social behaviours are affected by social networks. For example, the likelihood of delinquency might not only increase due to current associations with delinquents, but also by past connections in prisons. Therefore, in order to use networks for improving rehabilitation, data on past and present social networks might need to be collected and analysed. For example, past school connections, links in prisons, links with co-offenders, hierarchical relationships within criminal organisations, as well as family links to crime might all need to be examined. Law enforcement agencies, of course, collect a lot of such data on criminal, but using such data for social policies may create substantial privacy concerns. However, it is worth noting that some of the social network data—such as school, co-offending, and prison links—are often a matter of public record. Coarse and partial social networks could be constructed in order to understand which groups of individuals are most *central* allowing agencies to target policies that would have the largest impact on the network of delinquents (rather than simply going after the most egregious offenders).

Analytical toolkit

If network economics is to help economic policy, having vast amount of network data and a set of pressing policy questions will not suffice. A rigorous analytical toolkit is required to interpret the data. This toolkit has two components: econometrics and economic theory.

Since networks capture interdependencies in decisions, they should create anxiety for any policymaker wants to evaluate an intervention. As we argued above, an intervention targeted at one agent in a network might not only affect all agents in the network to a different degree but could also alter the network itself. But if everything affects everything else, how can one possibly establish cause and effect? In input-output networks and financial network analysis, the standard approach is calibration: matching the observations of the inter-sectoral to parameters in a theoretical model (Grassi and Sauvagnat, this issue). But, in recent years, network econometrics has started to develop techniques for isolating causes and effects in complex, interconnected systems. Network econometrics can help policymakers interpret the empirical findings, know where causal relationships have been found, and provide caveats where interpreting the data.

Field experiments and natural experiments play a key role in identifying the importance of connections on economic outcomes. For example, by using random allocation of students to dorm rooms, Sacerdote (2001) estimates strong effects of peer on education outcomes. Algan et al. (2019) find that "integration groups" that freshmen are randomly assigned to have long term impact on students' political opinions. In a similar vein, Bayer et al. (2009) find that former inmates' probability of reoffending is strongly affected by the prison peers.

However, while it might be feasible to identify the importance of *individual* connections, it becomes much harder to identify the importance of *whole* network structure. Broadly, there are two possible approaches. One approach is to look for exogenous variation within networks in order to identify peer effects. For example, if agent *A*'s only friend *B* is connected to *C* then agent *C* can only be affected by *A* via *A*'s effect on *B* (Bramoullé et al., 2009). However, the accuracy of these instrumental variable approaches depends heavily on accurate knowledge of the network (Blume et al., 2013). Another approach might be to exploit variation across network structures. For example, individuals with different network characteristics could be randomly targeted across different networks. However, this approaches relies on networks–e.g., social networks of remote villages—to be sufficiently isolated. In practice, most networks are not completely isolated so one can instead experiment by targeting agents who are "sufficiently far" from each other in the network (Aral et al., 2009). However, in social networks, many individuals are only separated by only few degrees of separation and as a result experimental treatments may be "contaminated" by interference. Understanding how to perform randomised controlled trials in networks is becoming an active area of research (see, e.g., Jagadeesan et al., 2019).

Identification is further complicated if agents can change the network. If the researcher does not fully understand the cost and benefits of network formation, they might misattribute the effects of a changing network to agents' actions in the network. Econometric tools for estimating effects of interventions in the presence of network formation have only recently been developed, and are still in their infancy (Chandrasekhar, 2016). Theories of network formation can guide identification but different identification methods are often difficult to carry across settings. Suppose a policymaker tries to identify the effects of financial regulation. They might face the following problem: How do banks respond to new regulations that target systemically important banks? Since regulation changes banks' incentives to maintain existing and form new links, it is crucial to understand how the banking network will reorganise itself into a new equilibrium after regulation. Without a theory of link formation, the policymaker is likely to miss a key effect of regulation. However, the theory of link formation for banks is likely to be quite different from the theory of link formation for subsistence farmers, which means that different econometric approaches might be required.

More generally, however, economic theory can also play an important role in *interpreting* data findings. Suppose that the policymaker has collected data on all business-to-business VAT transactions in order to reduce tax evasion. While such data certainly serves a purpose, what else can be done with it? Looking at the pattern of connections might in principle identify bottlenecks—businesses that sit at key junctions in network and, through these network positions, command market power. But how can such bottlenecks be found? What is the right network statistic to focus on? Here, theory, particularly the combination of graph theory and economic theory, is crucial. Naturally, existing theories might offer different predictions, but when delving into network data analysis it is important to be armed with theoretical predictions to avoid looking for policy needles in a network data haystack—or, more worryingly, mining the data for correlations that may be spurious and misinform policy decisions.

Finally, economic theory can only help focus on the important forces that will determine whether a policy intervention will be successful. For example, models of information diffusion in networks reveal that the relevance of a network characteristic depends on the specific type of innovation being considered. In some cases, the key constraint is information availability: here, it may be desirable to target individuals based on their number of connections. By contrast, in other contexts, adoption involves coordination of actions with neighbours, and it may be desirable to target groups of connected individual based on the level of interconnectedness of the group (i.e., their cohesiveness). The data required to implement innovation enhancing policies in these contexts would differ accordingly (Banerjee et al., 2013; Galeotti and Goyal, 2009; Reich, 2016). Similarly, in the context of macroeconomic policy using input-output tables, economic theory helps in identifying the network measures that are relevant for policy interventions (Grassi and Sauvagnat, this issue).

Tools for network based policy questions

We now return to the examples of networks-based policy questions we outlined previously and consider the analytical tools required for successful policy implementation.

Is a bank "too connected to fail" and should such a bank be subject to additional regulation?

Nowadays, as a matter of routine, central banks undertake stress tests in which they simulate different shocks to the economy to identify any fragilities. A stress test is typically based on a model of financial contagion in which loss in the value of assets in one bank affects the value of the assets as well as the borrowing and lending decisions of the other banks. In Europe, these stress tests also help identify systemically important banks that subsequently become subject to tighter capital requirements (under Basel IV). A consequence of the regulation is that banks have incentives to avoid being classified as systemically important. Regulation avoidance might influence the network structure of financial transactions i.e. which banks transact with which other banks. If regulators can run stress tests perfectly and the banks can anticipate the stress test, then they have an incentive to rewire their connections to make themselves and the entire system robust. However, if the regulator runs imperfect stress tests, then the rewriting incentives might instead lead to a financial system that is *more* fragile than before: there might be "unknown unknowns" not accounted for in the stress tests and as the system become more robust to those things being tested for, it may also become more fragile with respect to these "unknown unknowns". More concretely, stress tests could lead to the tighter regulation of banks, causing shadow banks to become more prominent players in the financial system, ultimately making the system as a whole more fragile. Regulators are, of course, aware of these problems and attempt to disclose only the relevant information about stress test that would limit strategic transaction rewiring. However, better understanding how banks will react to the regulations and change their financial interdependencies can be aided by a better understanding of the incentives underlying the network formation process—an active but as of yet underdeveloped area of theoretical and empirical research.

How does a firm's position in the industry competition network confer market power on it?

A network-based analysis of competition across as well as within markets can build immediately on the tools from standard competition policy. From a theoretical perspective, off-the-shelf IO tools (such as Cournot or Bertrand games) that have been refined over the last three decades just need to be combined with tools that have more recently been developed in papers on games in networks (Ballester et al., 2006; Bramoullé et al., 2014). The underlying approach described by Elliott and Galeotti (this issue) can already be adapted on a case-by-case basis to arising regulatory antitrust questions such as merger. The econometric ingredient needed for network-based models is the estimation of well-studied statistics—in particular, elasticities of substitution among products and services. Advanced tools have already been developed for this purpose and can also be put to use in a networks context. While academic work will continue to push the state-of-art in these settings and provide improved tools over time (e.g., by going beyond linear models, e.g. Parise and Ozdaglar, 2019), policymakers already have an arsenal of applicable tools at their disposal.

Which sectors should the government target in reviving an economy during a recession?

An underlying tool of the macroeconomic networks literature is competitive equilibrium which provides a well-studied and well-understood benchmark into which inter-sectorial linkages are embedded. Price-taking models are also amenable to the introduction of imperfect competition and frictions in a reduced form (e.g. through exogenous mark-ups or taxes) which can provide a lot of realism and flexibility to these models (see, for example, Liu, 2017; Baqaee, 2018; Acemoglu and Azar 2019; Baqaee and Fahri, 2019; Grassi and Sauvagnat, this issue).[8] Importantly, these theoretical foundations also make these rich models relatively easy to take to data. A typical approach here is to start with parameterised model, calibrate it, and use the calibrated model it to shed new light on patterns in the data and glean new insights about, for example, how shocks propagate through the economy and are amplified by this transmission process. Such a calibrated model can also be used to run policy counterfactuals thereby helping inform policy-making.

How would word-of-mouth communication spread information about a new technology?

Classic studies of technological adoption have found that technological diffusion typically follows a *logistic* curve: initially, there is a slow process of adoption, followed by a rapid acceleration in the take-up, and ending with adoption slowing down. Moreover, new technologies appear to spread via social contacts based on friendships or geography. However, since the initial set of adopters in observational studies is endogenous, the characteristics of initial adopters might be systematically different from non-initial adopters. For example, initial adopters might be all risk-takers with relatively poor

8 Recently an input-output-based approach has also been used to integrate imperfect competition. See, for example, Grassi (2017) and Grassi and Sauvagnat (this issue).

connections (at least in terms of the influence they can exert on others). Therefore, if a policymaker is interested in persuading some initial farmers to adopt a new technology in the expectation that their friends will also adopt and so on, she should not simply use target the people who have characteristics similar to initial adopters that encouraged wider spread uptake of a technology from previous observational studies. Field experiments have recently become widely used by researchers to help overcome this limitation with observational data. By targeting individuals at random to initially adopt and tracking the spread of adoption, it is possible to learn which characteristics, including their network positions, make people better initial adopters.

Since there are many network-based individual characteristics (e.g., centrality measures), it is important to organise data using theories of diffusion in order to test and refine the relevant model of diffusion in a particular context. There are many such theories and models: for example, the *independent cascade* model in which each adopter informs all of his friends about a technology with a certain probability; or the *threshold* model, in which each agent adopts a technology as soon as a certain fraction of his friends have adopted the technology. With appropriate data, a horse race can then be run between the various theories to determine which model best fits the data.

How large are the spillovers from active market policies within and across neighbourhoods?

Most theoretical search-and-matching models that are used in policymaking ignore two crucial features of the labour market: the importance of social connections and the relationships between industries and individual firms. Both of these features matter for the likelihood that a worker gets a job in particular firm and for the chances that the worker moves to another firm or transitions for another industry. The labour market is therefore a *dynamic* network: in every time period, there are flows of workers into firms and flows of workers out of firms (either into unemployment, different firms, or self-employment). Dynamic network models are typically analysed in a steady state equilibrium in order to understand long-run patterns that are expected to emerge. Such models might not only allow policymakers to identify early signs of recessions, but also test and target policies more effectively. For example, one could test whether older workers with a lot of connections in the community are effective at helping young workers into employment. If so, then due to a social network multiplier effect, an active labour market policy that targets the retraining of older workers to get them into work could be much more cost-effective at getting young workers into jobs than targeting the young workers directly.

Do past and present social connections affect the efficacy of rehabilitation policies?

Networks with many types of connections between agents are typically represented by *multigraphs*. If rehabilitation policy is sensitive to different types of social connections, it is important to understand how different types of links affect one another. For example, a network formation model might build in a complementarity or a substitutability in the effort required to maintain each type of social link (see, e.g., Joshi et al., 2017). Randomized controlled trials that shock the incentives to form links can then examine whether the disappearance of one type of link causes breaking other types. For example, Banerjee et al. (2018) showed that the disruption of lending relationship by the introduction of microfinance reduced the fraction of connections based on social activities, such as attending religious services. At present, multigraph models of network formation are still in their infancy and poorly understood by network economists. Moreover, as with banking regulation, any policy that targets individuals based on their links can change their incentives for link formation in unexpected ways.

A paradigm shift in policymaking?

Even if policymakers are convinced that network economics would allow them to ask important questions and have the data and the tools to answer them, network analysis might not enter into the heart of policymaking in the near future. Network economics gives policymakers the ability and confidence to look for and to understand granular causes of many larger-scale economic phenomena. But network economics also requires policymakers to become familiar with new tools to evaluate evidence, new types of data, and recognize new pitfalls in evaluating causes and effects. Making changes to “best practice” in policymaking sets a high bar for any new approach.

Nevertheless, network analysis has already entered several areas of policymaking. A considerable focus in macroeconomics is on how different parts of the economy interlink and affect each other. Intersectoral linkages, as captured by input-output tables, have been recorded and used to inform economic policy since the 1940s. Network tools have improved our understanding of such data, and its implications for shock propagation and stabilisation policy (by, for example, permitting more a detailed micro-to-macro approach). Similarly, while the role of social networks in diffusion of information and innovation was recognized in the early work of sociologists in the 1950’s, recent research has clarified the importance of differences in types of diffusion processes and how they interact with different dimensions of networks. This theoretical work has been supplemented with the collection of very detailed data on social networks. Together, the theory and data collection has helped create a more nuanced taxonomy of types of diffusion problems and the corresponding appropriate interventions. The success of using social network data in development contexts might well give confidence to governments to experiment with using social network analysis in other contexts, such as for labour market policies, public health measures, and fighting crime. An important obstacle is using social network data for policy is privacy; citizens might also act very differently if they knew that the government was using their social network data to target their unemployment benefits.

Another way in which network economics could enter policymaking is in a paradigm shift manner: as a response to a major crisis in which network economics is much able to explain important phenomena. During the Global Financial Crisis, standard macroeconomic models failed spectacularly and network economics offered a coherent perspective that could both explain financial contagion and offer ways for governments to respond to the crisis. As a result, network analysis has now firmly entered into the policy toolkit in central banking and financial regulation.

In antitrust, network economics is likely to be the most disruptive. Network economics challenges the accepted definition of a "market" and could fundamentally change not only how antitrust is done and but also how firms protect themselves from antitrust legislation. However, given the weight of precedents and existing laws, antitrust reform is likely to be slow. Network economists might well end up having to argue that network analysis is crucial for antitrust in front of a judge.

Ultimately, as Kuhn (1962) argued, the main debate about a network economics paradigm shift (if there were one) will not revolve around whether network economics is better than the current paradigm at answering *current* problems, but rather whether network economics is adequately equipped to deal with problems that *future* policymakers will face.

Conclusion

In conclusion, we suggest a number of steps that different actors -- academics, policymakers, judges, regulators and other public institutions – can take to facilitate the use of insights from network economics for the design of economic policy.

A key challenge for academics and regulators will be to further develop the network economics toolkit. New econometric innovations to help separate cause from effect in network based data would be welcome. Econometric innovations also complement theoretical ones. Empirical testing can help us understand which theories of network economics are most informative in which situations while further development of the theory can help organise the data. Policymakers will also have a role to play in gathering new network data. Along with regulators and other governmental institutions, policymakers can legislate policies that require the disclosure of new information and of some publicly-shared social network data, run well informed trials of potential policies to help discern their effectiveness, and experiment with new policies in ways that can help evaluate their impact.

But the principal role for policymakers and judges will be in implementing reform. In the most extreme cases policymaking may extend to creating new legal frameworks in which economics policies grounded in network analysis can be implemented. As with all reforms like this, there will be short-term losses that must be compared to potential longer-term gains. New regulations can create unanticipated loopholes regulated agents might exploit. New approaches also bring uncertainty: they undo precedents and create ambiguities. Since a network-based approach is by its nature systemic, resulting policy choices can be more subtle and harder for agents to anticipate. Therefore, network-based regulation could potentially be opaque and difficult to follow. For example, banks might not fully understand which positions and interdependencies contribute most to their being considered systemically important. Under network-based antitrust regulation, firms may be less able to anticipate which mergers will be blocked. While case law and the experience will eventually help agents adjust, the inherent complexity of a network-based regulation means that there are likely to be short-term adaptation costs. Therefore, patience and a long-term view will be essential for a transition towards effective network-based economic policies.

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