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Abstract

We argue that the increasing availability of digital trace data presents substantial opportunities for researchers and policy makers to better understand the importance of social networks and social interactions in fostering economic opportunity and resilience. We review recent research efforts that have studied these questions using data from a wide range of sources, including online social networking platform such as Facebook, call detail record data, and network data from payment systems. We also describe opportunities for expanding these research agendas by using other digital trace data, and discuss various promising paths to increase researcher access to the required data, which is often collected and owned by private corporations.

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1. Introduction

Social networks facilitate much of modern economic activity. Workers use them to find jobs and investors to learn about new investment opportunities. Social networks can serve to spread information, enforce social norms, and sustain collaboration, trade, and lending. The tangible and intangible resources that individuals can access through their social networks—that is, the social capital available to them—are central to fostering their resilience to a range of economic shocks, from recessions to health emergencies to environmental disasters.

Understanding the relationships between social interactions and economic outcomes is therefore of central importance to policymakers. For example, in 2020, the European Commission's first annual Strategic Foresight Report prominently identified the concept of resilience as a central compass for EU policymaking. Increasing the resilience of communities involves strengthening their abilities not only to "withstand and cope with challenges," but also to "undergo transitions in a sustainable, fair, and democratic manner." Investing in social capital is crucial to achieving these objectives. However, policymakers who hope to increase resilience and economic opportunity by fostering social networks face challenges, in part due to a number of important gaps in the academic literature that studies the economic effects of social networks. To close some of these gaps, researchers need to better understand which features of social networks—for example, their size, connectedness, homogeneity, or geographic spread—contribute to the resilience of communities and their access to economic opportunities. Similarly, it is unclear how resilience and economic opportunity are affected by different types of social connections, such as connections among family members, friends, neighbors, or colleagues. As we discuss in this chapter, computational social scientists are in a strong position to answer such questions about the role of networks and social capital in fostering community resilience and economic opportunity.

While policymakers are naturally interested in the economic effects of social networks, fostering strong networks might also be a direct policy objective. For example, following the large increase in immigration to Europe from refugees fleeing violence in Syria and Afghanistan, many European governments are highly concerned with the question of how to best achieve the social integration of these refugees (European Commission, 2020). While social integration has multiple aspects, including labor market attachment and language acquisition, a central aspect is the formation of ties of camaraderie between immigrants and natives. Such ties are desirable in themselves, independent of their positive economic effects, and researchers are increasingly interested in measuring and explaining the formation of such links between different groups (Bailey et al, 2022).

The primary objective of this article is to discuss a number of approaches and data sources that hold promise for computational research studying the economic effects of social networks. In particular, we focus on opportunities to use the recent explosion in digital trace data—the footprints produced by users' interactions with information systems such as websites and smartphone apps—to make progress on questions of policy interest (see also Lazer et al., 2009; 2020). Compared to traditional survey instruments to measure social networks, digital trace data offers a host of advantages: with it, researchers can observe social interactions as they organically occur, circumvent response biases, and measure social networks at unprecedented scales. But while some sources of digital trace data have recently become more accessible to researchers, others have not. In this sense, and in the spirit of this volume, our discussion of future research avenues will be partly aspirational.

2. Current Progress

The role of social networks and social capital in creating economic resilience, exchange, and opportunity has been the focus of research across several fields, including sociology and economics. While it is impossible to do justice to this wide-ranging literature in the few short paragraphs available here, we next describe several research papers that have worked with particularly new and promising datasets. We encourage readers who are interested in obtaining more comprehensive overviews to start with recent review articles. Readers interested in more theoretical treatments could start with Jackson (2011) and Jackson et al. (2017), who discuss various economic applications of social networks, and Jackson (2020), who provides a formal typology of measures of social capital and their interactions with network measures. Readers who are looking for an overview of empirical work on the economic effects of social networks might start with Kuchler and Stroebel (2021), who review the role of social interactions in household financial decision making, and Jackson (2021), who summarizes the evidence on the interaction between social capital and economic inequality. In addition, several chapters of the *Handbook of Social Economics* (edited by Benhabib, 2011) summarize the evidence on peer effects across a wide range of settings. Finally, for discussions of identification challenges in the peer effects literature, see Bramoullé et al. (2020) and Kuchler and Stroebel (2021).

One takeaway from these reviews is that much of the existing empirical research into the economic effects of social networks has measured networks either by using data from a few relatively small surveys (e.g., the National Longitudinal Study of Adolescent Health) or by defining networks according to individuals' memberships in observable associations (e.g., groups of neighbors or work colleagues). However, in recent years, the increased availability of digital trace data has led to a surge of interest in using tools from the computational social sciences to better understand economic activity. (An earlier literature has studied the topological structure of social graphs across a variety of online social networking services, but without explicitly linking the structure of networks to economic outcome variables of interest; see Magno et al., 2012; Ugander et al., 2011). We next discuss some data sources that have the ability to push forward the frontier of this field of research.

2.1. Online Social Networking Services. The appeal of working with data from online social networking services is clear: these widely-adopted services record social links between many individuals and even, in some cases, the strength of these ties. The scale of the most successful online social networks is astonishing. As of the second quarter of 2021, Facebook had 2.9 billion monthly active users—nearly 40 percent of the world's population—and as of their last reports, Twitter and LinkedIn each had over 300 million active users. WeChat, a China-based online platform that includes a substantial social networking element, had 1.25 billion users. The enormous user bases of these platforms dwarf the sample sizes traditionally studied by economists and social scientists, and provide researchers not only with sufficient statistical power to detect granular patterns, but also with data that is difficult or expensive to obtain directly via surveys.

Already, a number of researchers have worked with anonymized (individual-level) microdata from Facebook to study a broad range of economic and social outcomes. For example, Gee et al. (2017) explore the extent to which weak and strong ties might help individuals find new jobs. Similarly, Bailey et al. (2018a; 2019) study the role of social interactions in driving optimism in housing and mortgage markets. Bailey et al. (2019) use data from Facebook to study the role of peer effects in product adoption, and Bailey et al. (2020a) study the role of information obtained through friends on individuals' social distancing behaviors during the COVID-19 pandemic. Bailey et al. (2022) use data from Facebook to explore the determinants of the social integration of Syrian migrants in Germany.

Data from online social networking platforms can also be a rich record of cross-country and cross-regional connections. Using more aggregated data from Facebook—data we describe in more detail in Section 3.2—researchers have explored the historical and cultural drivers of social connectedness across European regions (Bailey et al., 2020b), as well as the relationship between social connections and international trade flows (Bailey et al., 2021), migration (Bailey et al., 2018b), investment (Kuchler et al., 2021), bank lending (Rehbein et al., 2020), and the spread of COVID-19 (Kuchler et al., 2020).

While Facebook is the largest online social networking platform in the world, other platforms—in particular those that offer different services and therefore measure different types of networks—are also valuable data sources for researchers. Jeffers (2017) uses LinkedIn data on professional networks to study the role of labor mobility frictions in reducing entrepreneurship. Bakshy et al. (2011) quantify the influence of Twitter users by studying the diffusion of information that they post, and Bollen et al. (2011) measure the sentiment of Tweets to predict stock market movements. In a similar vein, Vosoughi et al. (2018) examine the network structure of sharing behavior on Twitter to document that false news often spreads faster and more widely than true news.

As illustrated by these studies, social networking platforms have information on a large set of variables. Besides the connections between pairs of individuals, these services collect data on the personal characteristics that users choose to share—for example, education, employment, and relationship status—as well as the content they produce or engage with (such as posts, messages, and "likes"). With advances in natural language processing (NLP) methods, which extract meaning from text, the latter type of data provides increasing opportunities for researchers to measure opinions and beliefs that are otherwise hard to capture at scale. A recent example is Bailey et al. (2020a), who use Facebook posts to measure attitudes towards social distancing policies during the COVID-19 pandemic. (For a review of text mining and NLP research with Facebook and Twitter data, see Salloum et al., 2017) Moreover, many of these services record a rich set of metadata, including users' log-in times and geographic locations. Several recent studies have exploited location data from Facebook to study social distancing behavior during the COVID-19 pandemic (Ananyev et al., 2021; Bailey, et al., 2020a; Tian et al., 2022).

Similarly, most apps record information on the phone type used to log into the apps. Combined with other information, this can provide a proxy of a users' income or socio-economic status (see Chetty et al, 2022a, 2022b). Such data can be very helpful to researchers hoping to study the effects of social capital on outcomes such as social mobility. Indeed, many measures of social capital that the literature associates with beneficial outcomes relate to the extent to which relatively poor individuals are connected with relatively rich individuals—see, for example, the work of Loury (1976), and Bourdieu (1986), and the discussion in Chetty et al. (2022a, 2022b). Measuring the variation of such "bridging capital" across regions or other groups requires information not only on networks, but also on the income or socio-economic status of each individual node.

2.2. Other Communication Networks. The widespread adoption of smartphones has generated a trove of data capturing various aspects of economic and social behaviors. A large body of research has used smartphone location data—available from companies such as SafeGraph, Veraset, and Unacast—to study a range of topics, from the effect of partisanship on family ties (Chen & Rohla, 2018), to the role of staff networks in spreading COVID-19 in nursing homes (Chen et al., 2021), to racial segregation and other racial disparities (Athey et al., 2020; Chen et al., 2020).

Another set of research has used call detail record (CDR) data to understand the economic effects of social networks. This literature includes Björkegren (2019), who uses CDR data from Rwanda to study the spread of network goods (goods whose benefits to a user depend on the network of other users), as well as Büchel and Ehrlich (2020) and Büchel et al. (2020), who use CDR data to analyze how geographic distance impacts interpersonal exchange and how social networks affect residential mobility decisions, respectively.

Other sources of digital trace data suggest further avenues for advancing research on social networks and resilience. For example, researchers who wish to study the relationship between segregation and resilience might follow Davis et al. (2019) in using data from services such as Yelp—a platform that allows users to review local businesses—to test whether people of different racial or socioeconomic backgrounds visit the same parks, restaurants, hotels, stores, or other public places. Email and direct messaging networks can also offer insights into the structure of networks. For example, data on who communicates with whom within a corporation or community can allow researchers to establish how hierarchical organizations are, or how quickly information spreads within a community—both of which can be related to economic resilience and opportunity. For example, the analysis by Diesner et al. (2005) of the Enron email corpus illustrates the patterns of communication within a collapsing organization. Data from other professional communication tools, such as Slack, Skype, or Bloomberg chat, might also offer insights into how the communications of traders and other finance professionals shape trading behavior and asset prices.

2.3. Financial or Business Transaction Networks. One crucial way through which social networks bolster economic resilience is by providing a foundation for the flow of credit and insurance, and a long line of sociological research illustrates this phenomenon in myriad communities. An early example is Geertz's (1962) description of the rotating credit associations of small communities in Asia and Africa, where members periodically contribute money to a fund that can be claimed by each member on a schedule. More recently, Banerjee et al. (2013) document how well-connected individuals in Indian villages—for instance, shopkeepers and teachers—play an essential role in spreading information about a microfinance program.

But the importance of social networks in fostering access to financial resources is not limited to less-developed countries. In Europe, crowdfunding platforms such as GoFundMe and Kickstarter have hosted campaigns to help refugees, rescue small businesses during the COVID-19 recession, and finance individuals' medical needs, educational expenses, or creative ventures. Data from such crowdfunding platforms is thus an interesting and valuable source of information for researchers hoping to measure the strength of social capital across communities. Social networks can also provide essential resources to small businesses. Two classic discussions in the literature are provided by Light (1984), who attributes the entrepreneurial success of Korean immigrants in Los Angeles to social solidarity, nepotistic hiring, mutual support groups, and political connections; and by Coleman (1988), who describes Jewish diamond merchants in New York City exchanging stones with each other for inspection, relying on close ethnic ties, rather than expensive formal contracts, as insurance against theft.

Furthermore, with the growth of online payment platforms (e.g., Paypal, Venmo, WeChat Pay, and Wise) and peer-to-peer lending websites (e.g., Zopa and LendingClub), it is increasingly possible to observe networks of financial transactions among friends and family as well as strangers. An example of work benefiting from such data is Sheridan (2020) who uses data from MobilePay, a Danish mobile payment platform, to measure social networks. Sheridan (2020) shows that individuals' spending responds to their friends' unemployment shocks, thereby documenting that spending and consumption are linked across social networks. In an international context, remittances by immigrants to their home countries are an important economic force in many countries with substantial expat communities. Increasingly, such remittances are sent electronically, allowing for systematic measurement. We view the use of these types of data sources as highly promising directions for researchers interested in studying the contribution of various types of social capital to the resilience of communities.

2.4. Civic Networks. Although sociologists have characterized a central product of social networks—social capital—in various different ways (see the discussion in Chetty et al., 2022a), one influential description by Putnam (2000) emphasizes citizens' participation in civic and community life, their respect for moral norms and obligations, and their trust in institutions and in one another. Digital trace data can be used to provide new ways of measuring these aspects of civic social capital.

A growing body of literature has used digital trace data to analyze the relationship between social networks and political trends, especially polarization. Employing innovative text, content, and sentiment analysis techniques, researchers have quantified patterns in political news and discourse on Facebook and Twitter (e.g., Alashri et al., 2016; Engesser et al., 2017; Moody-Ramirez & Church, 2019). Other work has found that individuals' socioeconomic backgrounds can predict their civic engagement on social media (e.g., Hopp & Vargo, 2017; Lane et al., 2017), and that social media can drive their real-life political opinions and behaviors (e.g., Amador Diaz Lopez et al., 2017; Bond et al., 2017; Gil de Zúñiga et al., 2012; Groshek & Koc-Michalska, 2017; Kosinski et al., 2013). In particular, there has been enormous interest in researching the causes and consequences of "fake news" on social media (e.g., Allcott & Gentzkow, 2017; Guess et al., 2019; Lazer et al., 2018).

Besides Facebook and Twitter, other sources of digital trace data provide further opportunities to measure civic beliefs and behaviors, and to construct measures of civic social capital. An emerging strand of research uses data from e-petition platforms—including governmental sites established by the White House (Dumas et al., 2015) and the Bundestag (Puschmann et al., 2017), as well as commercial sites such as Change.org (Halpin et al., 2018)—to study the forces that motivate citizens' political engagement. Elnoshokaty et al. (2016), for instance, have found that the success of petitions is more strongly driven by emotional elements than by moral or cognitive ones. Combined with records of online and offline social connections, this data offers the opportunity to study attitudes not only towards governmental policies and programs, but also towards those of communities such as universities and neighborhood associations.

3. Paths Forward

Despite the economic and political importance of better understanding the effects of various types of social networks, research has long been hindered by the lack of large-scale data on individuals' social interactions. Moreover, to study how individuals' networks affect their economic outcomes, economists must not only measure connections between individuals, but also match these measurements to data on income, savings, consumption, health, or other variables of interest. The difficulty of obtaining such complex data can pose a serious roadblock to researchers.

3.1. Increasing Access to Microdata

As illustrated in our discussion in the previous section, the richest datasets on social networks are usually not in the public domain, but are instead held by corporations. The digital trace data created on platforms such as Facebook, Instagram, WhatsApp, Twitter, Snapchat, YouTube, WeChat, TikTok (Douyin), Meetup, and Nextdoor hold immense promise for empirical research on which types of people form connections, how and where they meet, and whether their acquaintances and friends shape their future behaviors. As for research on professional networks, LinkedIn, along with its European competitors XING and Viadeo, possesses records that can shed light on important labor market patterns.

While these microdata hold much promise for conducting research of substantial value to policy makers and the academic community, there are obvious challenges to facilitating large-scale data access to researchers. Most importantly, the firms holding the data are responsible for safeguarding the privacy of their users, and have to trade off the benefits of research to the broader public against potential reputational and legal risks from collaborating with researchers on these projects.

There are a number of paths that researchers have followed in navigating the challenge of accessing microdata owned by corporations. On the one hand, some researchers have gained access to proprietary data by working directly with companies as employees, contractors, or consultants. These agreements often involve signing nondisclosure agreements, and companies usually retain the right to veto publication if they are concerned, for example, that their users' anonymity is compromised by the results. Because of the potential for various conflicts of interest in such relationships, some members of the research community have expressed concerns about bias in the questions asked or the results generated by researchers with such arrangements.

On the other hand, researchers may attempt to work independently of the companies whose data they analyze. For example, they might be able to use data that companies publicize through application programming interfaces (APIs) or data purchased from market research firms. However, the former source of data may be unstructured or incomplete, while the latter, collected through methods that are sometimes opaque, might be unrepresentative or prohibitively expensive. (For a longer discussion of the tradeoffs researchers face in accessing proprietary microdata, see Lazer et al., 2020)

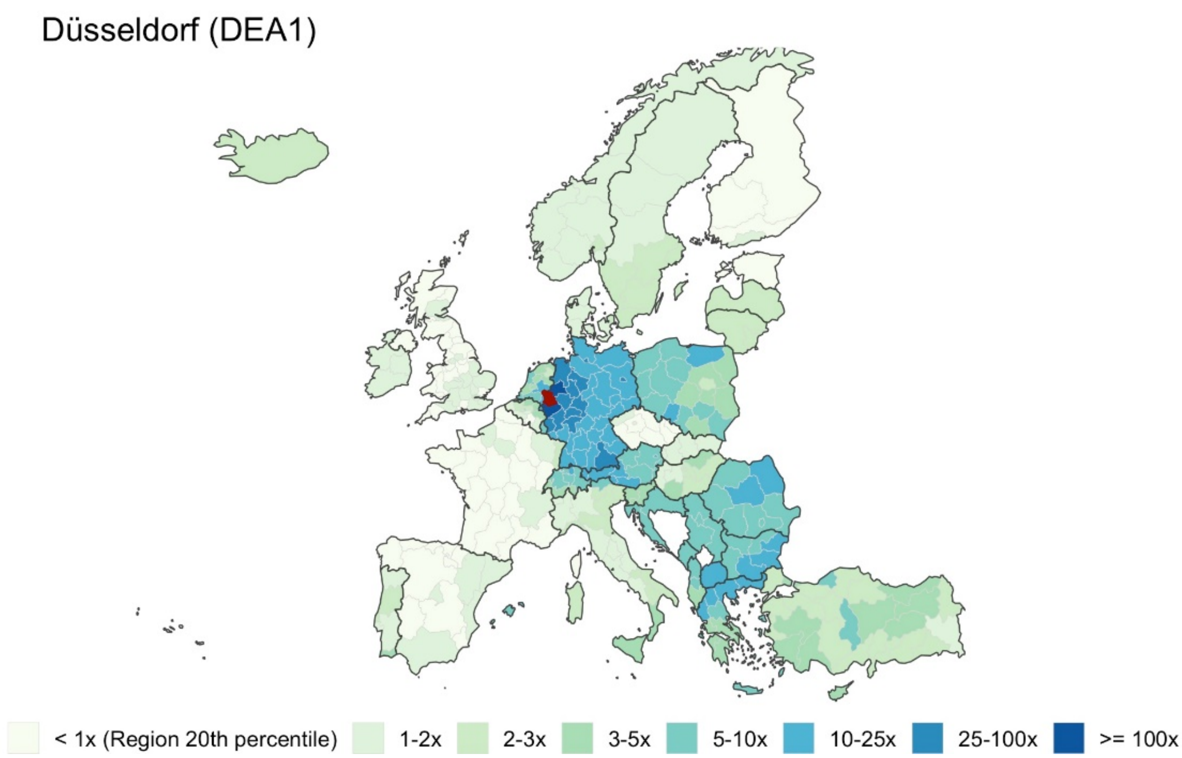
To help navigate these challenges, there have been recent advances in developing models of industry-academic data-sharing collaborations that seek to facilitate researchers' access to anonymized microdata held by firms while guaranteeing their ability to publish findings independent of a final review by the company. Most prominent is Facebook's relationship with Social Science One, launched after the 2016 U.S. elections (see King & Persily, 2020, for details).

We believe that policy makers have the opportunity—and even the responsibility—to play a key role in advancing the various attempts by firms and academic researchers to collaborate on producing publicly accessible research on questions of high social importance. A key aspect of this is to create legal certainty about how academic research would be treated within various privacy frameworks, ideally carving out exemptions for public good research to the frameworks' most restrictive provisions. For example, the U.S. Federal Trade Commission recently highlighted that its consent decree with Facebook "does not bar Facebook from creating exceptions for good-faith research in the public interest." Increasing support from policy makers to facilitate public interest research within the frameworks of other privacy regulations, such as the European Union's GDPR, would be hugely beneficial to the academic research community and broader society.

3.2. Increasing Access to Aggregated Data

While working with individual-level data offers several important advantages for researchers, these collaborations are often hard to scale, in part due to the substantial resources that companies must invest to provide privacy-protected access to their data. In addition, many outcome variables of interest cannot be merged to individual-level data in a privacy-preserving way. On the flipside, there are many opportunities for better understanding the role of social networks and social interactions by using more aggregated data on social networks, social capital, and mobility.

One prominent example of such aggregated data is the Social Connectedness Index (SCI), which was introduced by Bailey et al. (2018). The SCI is based on the universe of friendship links on Facebook and measures the relative probability that a random pair of Facebook users across two locations are friends with each other on Facebook. For example, the map below shows a heat map of the social connectedness to Düsseldorf in Germany to all European NUTS2 regions.



Note: Heat map shows the strength of social connections of European NUTS2 regions to Düsseldorf. Darker colors correspond to stronger social ties. The data source is the *Social Connectedness Index* described in Bailey et al. (2018b)

Importantly, the SCI data is publicly available to researchers through the Humanitarian Data Exchange (HDX). As of February 2022, this data has been downloaded more than 16,000 times, demonstrating that the research and policy communities are highly interested in accessing aggregated data sets, even at such relatively coarse levels of aggregation. We believe that there are many opportunities to deepen the insights from such data sets by further disaggregation—for example, by demographics or by setting. This finer level of information would allow researchers to study questions about how social connectedness varies across individuals of different ages, ethnicities, nationalities, genders, or educational and professional backgrounds.

Other sources of aggregated data also offer opportunities to understand how social networks and social capital affect economic outcomes. For example, LinkedIn could provide aggregated measures of connectedness across geographical locations, allowing researchers to study similarities and differences between the structure of professionalh networks and friendship networks. Similarly, measures of the connectedness between firms could be useful to study the determinants of labor flows.

We believe that policy makers should communicate to firms that such data efforts are perceived as valuable by both the academic and the policy communities, thereby encouraging more firms to engage in similar efforts.

4. Summary

There are many interesting opportunities to work with non-traditional data sources to understand the role of social networks in fostering resilience and access to economic opportunities. Indeed, many of the data sources required to further study these questions already exist or could be collected in a relatively straightforward way. Many of these data sets are owned by private companies. An important question, then, is what can be done to facilitate more broad-based access to such data.

It is critical that the private companies collecting digital trace data, aware of their unique positions to advance important research agendas, continue and expand their engagement with researchers to find paths to improve our understanding of the economic effects of social networks. Our hope is that, over time, we reach an equilibrium where such efforts to engage with academic researchers become the expectation of companies holding unique and important data assets. We are encouraged by the creation of “Data for Good” efforts across a variety of firms such as Meta and Acxiom, as well as by the creation of formal research institutes within many corporations, such as the JP Morgan Chase Institute and the ADP Research Institute. The further expansion of such efforts holds much promise for the future of the computational social sciences.

Policy makers can help this process by creating frameworks that incentivize firms to collaborate with researchers. For firms, collaborations with researchers involve substantial financial costs and can carry reputational and legal risks. In the decision of whether to engage in collaborations that are not directly related to the core business of the firm (as is the case with many of the research questions reviewed in this chapter), these costs and risks are then weighed against potential benefits to the firm, such as positive press and public goodwill.

Policy makers can alter both the perceived costs and benefits to firms from such collaborations. On the cost side, as highlighted above, an important element is the provision of legal certainty about how research for the social good will be treated under data privacy regulations such as GDPR. Policy makers interested in encouraging firms to collaborate with researchers on social good questions should also consider providing explicit carve-outs for these research activities in various privacy regulations. Similarly, policy makers can increase the perceived benefits for firms from academic collaborations, for example, by publicly recognizing that firms' facilitation of such collaborations contributes to the public good.

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