INAUGURAL–DISSERTATION

zur Erlangung der Doktorwürde
der
Gesamtfakultät für Mathematik,
Ingenieur- und Naturwissenschaften
der
Ruprecht-Karls-Universität
Heidelberg

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Tag der mündlichen Prüfung:
10.11.2023

Networks and navigation in the knowledge economy

Studies on the structural conditions and consequences of path-dependent and relational action

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Acknowledgements

Throughout my PhD, I had the pleasure of working with a range of people across a range of projects. The resulting variety of intellectual challenges and interpersonal exchanges has been instrumental in keeping me motivated to push on. My thanks especially go to the members of the Economic Geography Group: First, I want to thank Johannes Glückler, who not only has supported me through his continued guidance, but also has given me the opportunity and freedom to explore a variety of research avenues, and who initially sparked my interest in network analysis and research methodology. I also want to thank all the current and former members of the group, who have assisted me in countless ways and who have contributed to the friendly atmosphere that has made these past years a joy: Thank you, Anna, Claudia, Cristian, Daniel, Denise, Johanna, Katrin, Klara, Lin, Linda, Marius, Michael, Regina, Robert, Ute, Yannick, and Xuan. I furthermore want to thank Emmanuel Lazega for agreeing to supervise this thesis and for many stimulating discussions and helpful recommendations. Finally, I want to thank Anna for her unwavering support and patience over the last years. My gratitude goes to you all!

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September 2023

Abstract

In the wake of a relational turn, economic geographers have begun to scrutinize the relationships and interactions between people and organizations as a driving force behind economic processes at both global and local scales. Through a focus on contingent contextuality and path dependence, relational economic geography and network thinking have provided the necessary conceptual toolbox for untangling the structural effects and drivers of these relationships and their spatial embeddedness. However, despite the conceptual richness of the relational approach, empirical studies have often fallen short of capturing its core tenets: First, there is a prevalence to focus on places, infrastructures, and similarities as aggregate proxies for actors and their socio-economic relationships as the unit of geographical network analysis; While often convenient, this approach misses out on the capacity of networks to represent spatially embedded social contexts as enablers or constraints of economic action. Second, while path dependence is at the heart of evolutionary approaches towards economic geography, few studies actually trace how path-dependent and interrelated innovation shapes the long-term emergence of fields.

Relational processes are especially salient when outcomes are opaque, decisions are interdependent, and when formal rules and roles are weak or absent. In this thesis, I ask how actors navigate such contexts and investigate the structural conditions and consequences of their navigation efforts. In my pursuit of this question, I draw on literatures from sociology, economics, and organization studies and build on novel methods of network analysis capable of empirically capturing contextuality and path dependence to investigate relational processes at three levels of economic activity: The thesis first looks towards a localized and informal trade platform to demonstrate how consumers rely on their former transactions to navigate exchange uncertainty and how such an exchange system can become liable to personal lock-in. It then moves on to show how the geographically and organizationally diversified search for innovation opportunities structures the transfer of knowledge across a globalized and partially informal corporate scouting community. Finally, the thesis shows how the linkage of distinct knowledge domains drives the long-term emergence of heterogeneous technological fields. In its endeavor to trace these processes, the thesis contributes a set of distinct relational research designs that demonstrate how advances in methods and data can be employed to empirically exploit the conceptual richness of relational economic geography.

Zusammenfassung

Im Zuge einer ‘relationalen Wende’ haben Wirtschaftsgeographen Beziehungen und Interaktionen zwischen Menschen und Organisationen als zentrale Treiber globaler und lokaler wirtschaftlicher Prozesse erkannt. Relationale Wirtschaftsgeographie und Netzwerkdenken haben mit ihrem Fokus auf Kontext und Pfadabhängigkeit das notwendige konzeptionelle Instrumentarium für ein solches Unterfangen bereitgestellt. Dem konzeptuellen Reichtum des relationalen Ansatzes steht jedoch eine geographische Netzwerkforschung gegenüber, die dessen zentrale Leitsätze häufig nicht empirisch abbildet: Zum einen untersuchen empirische Netzwerkstudien in der Geographie überwiegend Orte, Infrastruktur und Ähnlichkeiten als Proxys für Akteure und deren sozioökonomische Beziehungen – ein Ansatz, der durch seine Zugänglichkeit besticht, aber häufig die Funktion von Netzwerken als Repräsentation der kontextuellen Bedingungen wirtschaftlichen Handelns übersieht. Zum anderen steht Pfadabhängigkeit zwar im Zentrum evolutionärer Ansätze in der Wirtschaftsgeographie, aber nur wenige Studien untersuchen, wie pfadabhängige und interdependente Innovationen die langfristige Entwicklung von Technologiefeldern prägen.

Relationale Prozesse sind insbesondere im Kontext von Ergebnisunsicherheit, interdependenten Entscheidungsprozessen und schwach formalisierten Regeln und Rollen relevant. In dieser Dissertation beschäftige ich mich mit der Frage, wie Akteure solche Kontexte navigieren, und untersuche die strukturellen Bedingungen und Konsequenzen ihrer Navigationspraktiken. Mit Bezug auf soziologische, ökonomische und organisationswissenschaftliche Ansätze und unter Anwendung neuer netzwerkanalytischer Methoden, die sich für die Abbildung von Kontextualität und Pfadabhängigkeit eignen, befasst sich die Arbeit mit relationalen Prozessen auf drei Ebenen ökonomischer Aktivität: Die ersten beiden Studien zeigen anhand einer lokalen und informellen Tauschplattform, wie Verbraucher auf frühere Beziehungen zurückgreifen um Tauschunsicherheit zu reduzieren, und demonstrieren die Anfälligkeit eines solchen Tauschsystems für personellen Lock-in. Anschließend zeigt die Arbeit, wie die geographisch und organisatorisch diversifizierte Suche nach Innovationsmöglichkeiten den Wissenstransfer innerhalb einer globalisierten und teilweise informellen unternehmerischen Scouting-Community strukturiert. Die beiden letzten Studien zeigen schließlich, wie die spezifische

Verknüpfung verschiedener Wissensdomänen die langfristige Entwicklung technologischer Felder prägt. In ihrem Bestreben, relationale wirtschaftliche Prozesse nachzuzeichnen, trägt die Arbeit zur Entwicklung relationaler Forschungsdesigns bei, die den konzeptionellen Reichtum der relationalen Wirtschaftsgeographie mit Hilfe methodischer Weiterentwicklungen und neuer Daten empirisch ausschöpfen.

Publications

Publication 1

Hoffmann J, Glückler J (2022) Navigating uncertainty in networks of social exchange: a relational event study of a community currency system. *Socio-Economic Review*, mwac066.

Status: Published, 2022, Q1 SCImago Journal Rank

Publication 2

Glückler J, Hoffmann J (2021) Time banks as transient civic organizations? Exploring the dynamics of decline. in Glückler J Meyer H-D & Suarsana L (eds) *Knowledge and Civil Society*, Cham: Springer International.

Status: Published, 2021

Publication 3

Hoffmann J, Panitz R, Glückler J (2023) *From scout to scout: the social network of corporate opportunity search*, Heidelberg: Institute of Geography.

Status: Submitted to the Journal of Knowledge Management, September 2023

Publication 4

Hoffmann J, Glückler J (2023) *Interrelated technology evolution in the field of plastic recycling: A main path analysis*, Heidelberg: Institute of Geography.

Status: Submitted to the Journal of Cleaner Production, September 2023

Publication 5

Hoffmann J, Glückler J (2023) Technological cohesion and convergence: A main path analysis of the bioeconomy, 1900–2020. *Sustainability 15*(16), 12100.

Status: Published, 2023, Q1 SCImago Journal Rank

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Part I

Synopsis

1

A relational perspective on the knowledge economy

Over the past decades, relational thinking and networks have become an integral part of the study of the economy and its spatial manifestation (Bathelt & Glückler, 2003). Networks are valuable tools - both conceptually and methodologically - especially for the study of knowledge-intensive economic processes: They have been used to characterize the interplay of local and global knowledge flow (Bathelt & Li, 2020; Bathelt et al., 2004; Owen-Smith & Powell, 2004) and to study the regional structure of collaborative innovation (Broekel & Boschma, 2012; Cantner & Graf, 2006). They have also proven invaluable in the investigation of personal knowledge exchange in globalized firms (Glückler, 2014; Grabher & Ibert, 2006; Phelps et al., 2012), or the analysis of upgrading dynamics in global markets (Glückler & Panitz, 2016a) and the evolution of technological fields (Nomaler & Verspagen, 2016). While the enormous flexibility of the relational approach has sometimes provoked criticism regarding its consistency (Sunley, 2008), it has nevertheless firmly taken root in economic geography, and references to networks have become ubiquitous across the literature. However, while the use of network concepts to characterize relational phenomena has proliferated, empirical analysis of networks in economic geography has lagged behind and existing studies are often either relatively rudimentary or fall short of representing the ‘social’ in social network analysis (Glückler & Panitz, 2021). This empirical dearth of network studies in geography is contrasted by an explosion of network analytic methods being developed elsewhere, which have led to advances in the study of networks that evolve over time (Butts et al., 2023; Snijders et al., 2010), span multiple levels (Lazega & Snijders, 2016), or which enable the analysis of large relational data sets, such as obtained from bibliographic archives (Batagelj & Cerinek, 2013). The thesis aims to attenuate this discrepancy by contributing a set of empirical studies which draw on the rich methodological toolbox of network analysis to study relational processes at different levels of economic activity, distinguished by their spatial and historical scale as well as their degree of formality. As such, my focus in this thesis is especially on exploring new research designs that exploit advances in methods and tap novel data sources to do justice to the conceptual richness of relational economic geography and to explicitly account for its core tenets of contextuality and path dependence.

The economic processes that I consider in the thesis can be distinguished by the nature of the relationship between knowledge and networks: The first case is an example of networks *from* knowledge: It deals with the structure of exchange under uncertainty, i.e., with the emergence of network structure as a consequence of market knowledge, or rather the asymmetric absence of it. The second case considers an interpersonal network among a corporate community of scouts which facilitates knowledge exchange in their search for innovation opportunities, and thus represents a network *for* knowledge (typically simply referred to as knowledge networks in organization and management studies, Phelps et al., 2012). Finally, I investigate networks *of* knowledge, where the nodes themselves represent knowledge artifacts (represented by patents) and the overall network structure is taken to represent the co-evolution of interdependent knowledge domains. These perspectives are not always distinct: Knowledge flow and the artifacts produced by it both shape and are shaped by networks, often at the same time. In these various settings of interaction between networks and knowledge, a major theme pursued by the thesis is *navigation*: From buying a new smartphone or deciding which tool to use for a task, up to consequential strategic decisions that determine the fates of firms, uncertainty permeates most facets of economic life. Both people and organizations are confronted with interdependent decision-making in fast-paced innovation landscapes and market environments fraught by information asymmetries. This is the case in consumer markets, where consumers are increasingly susceptible to information overload from an overwhelming range of quality and price signals (Glückler & Sánchez-Hernández, 2014), but also in high-tech innovation environments, where firms face consequential technology adoption and investment decisions in the wake of broad market shifts (Katz & Shapiro, 1986). Given these conditions, what are the processes by which individuals and organizations navigate such uncertain environments? How does navigation interact with sometimes dispersed and sometimes localized spatial settings? And what are the patterns that emerge at the field level as a consequence of collective navigation efforts? I contribute to these questions by studying the network structures that arise as a consequence of individuals' and organizations' navigation efforts and, vice versa, the processes by which networks create and constrain navigation opportunities. As such, I am concerned with the structural conditions and consequences of firms' and individuals' navigation practices, which the thesis pursues at different levels of economic activity and with special attention to the considered practices' relational nature and path dependence.

Owed to this PhD being realized in the context of multiple distinct research projects, the thesis is characterized by heterogeneity in terms of the cases it is concerned with. The next section will refine the broad questions outlined above and relate them to the contexts they are studied in, starting with socially embedded exchange in small-scale, localized, and alternative economic communities and moving up to aggregate economic output at the level of globalized technological fields.

2

Networks and navigation at different levels

Networks and navigation in alternative economies

This thesis departs in the setting of informal, alternative economies, which - driven by global crises and rising inequality - increasingly challenge the status quo of mainstream capitalism (Castells et al., 2017; Leyshon et al., 2003). Alternative economic practices contrast global value chains with locally sourced goods, arms-length markets with community-based trade, and profit maximization with sustainable production and consumption (Gibson-Graham, 2008; Seyfang, 2006). Because such alternative economies often spring from local, grass-roots initiatives, there is no standardized template they follow. As a result, they vary in their interaction with the formal economy and with respect to the regulatory responses they elicit, ranging from supplementation to substitution or competition (Sánchez-Hernández & Glückler, 2019). A particular example of alternative economic practices is given by community currency systems, which provide a platform for the trade of goods and services via an alternative, usually community-specific, currency. In an effort to embody egalitarian economic principles, these currencies are sometimes bound in value to the time used to provide a good or service (Collom et al., 2012). Due to their informality and their emphasis on social cohesion, these platforms differ from 'conventional' market economies not only in their motives and goals, but also in terms of the nature of economic exchange and decision-making: While *homo oeconomicus* might be a reasonable assumption for modeling stylized, anonymous markets, regarding economic decision-makers as endowed with all relevant information and thus independent of each other obfuscates the uncertain and social nature of economic decisions in more informal situations. Conventional markets that are liable to information asymmetries often suffer from information overflow due to a multiplicity of sometimes opaque quality signals, such as online rating systems or detailed technical product information (Glückler & Sánchez-Hernández, 2014). Alternative trade platforms, such as community currency systems, can instead be difficult to navigate for participants because knowledge about alternatives and their quality is only tacitly embedded into the exchange system. This is amplified by high variability in the quality of offered goods and services (Aldridge & Patterson, 2002) and the fact that such systems often do not implement rating systems, either due to resource constraints or to not discourage participants from engagement in exchange (Whitham & Clarke, 2016). In the face of sparse information about alternatives and exchange that is strongly embedded into social communities, assumptions about informed and independent decisions are rendered inadequate. The first research question pursued by this thesis is, then:

How does transactional uncertainty shape economic decision-making and the structure of exchange in localized, community-based economies?

Faced with institutional and transactional uncertainty, participants can rely on their own experiences, powered by trial and error, but can also draw on the social embeddedness of exchange to guide their own decisions by the experiences of their peers: A participant's market relations not only indicate the exchange of goods or services but also serve as informational cues for other participants by which they can assess his or her performance and thus inform their own choices through the network of exchanges (inducing a 'prism'-like effect in Podolny's (2001) words). Relying on own and peer experience thus represents relational practices of navigation, i.e. navigation behaviors which are informed by the decision-maker's relationships with other market participants. Such practices have been demonstrated in a variety of settings and forms, such as networked reputation in management consulting (Glückler & Armbrüster, 2003), the tendency to conduct risky exchanges with friends and relatives (DiMaggio & Louch, 1998), or word-of-mouth processes (Bansal & Voyer, 2000). Due to the localized and community-oriented nature of exchange in alternative economic systems, they make for an especially well suited case to study such practices and their structural consequences.

Research has shown that the reliance on such relational practices of navigation increases in settings of higher uncertainty, where search becomes more expensive and past experiences provide an easily available and reliable source of information (DiMaggio & Louch, 1998; Geertz, 1978; Podolny, 1994). Differences in transactional uncertainty can derive from differences in the institutional guardrails framing a market but they can also originate directly from the characteristics of the traded good: While some goods' quality is easily assessed before a purchase (search goods), for others their quality is only revealed after the transaction (experience goods) or remains altogether opaque (credence goods) (Dulleck & Kerschbamer, 2006; Nelson, 1970). While especially many physical goods transactions fall into the former category, services transactions usually exhibit experience or credence characteristics (Ford et al., 1988). Building on this conceptual distinction, I use the variety of goods and services typically traded in community currency systems to investigate the associated differences in a set of exchange structures which are consistent with different relational practices of navigation.

Networks and navigation in multinational organizations

While the last section has discussed how individuals navigate transactional uncertainty in informal consumer markets, this section concerns itself with the processes by which organizations, and in turn their employees, navigate uncertainty in globalized and fast-paced innovation landscapes. Contradicting the conventional wisdom that innovations primarily spring from organizations' R&D activities (Von Hippel, 1988), researchers have turned to the question of how organizations acquire new knowledge from the external environment and to the processes by which they make productive use of it. Based on the premise that one of the core functions of the firm is the integration and application of knowledge (Grant, 1996), this question has become central to the field of organizational research but has also spilled into neighboring disciplines and economic geography (Bathelt et al., 2004; Maskell, 2001). The capability of organizations to successfully identify, integrate, and apply new knowledge has been referred to as their absorptive capacity, which is argued to depend critically on compatibility with knowledge already existing within the organization (Cohen & Levinthal, 1990). Absorption thus involves two steps, both of which are necessary conditions for its ultimate success: On the one hand, it requires the identification and acquisition of new knowledge that is relevant to the firm from the external environment. On the other hand, externally sourced knowledge will ultimately only be valuable when it is directed to where it can be put to productive use within the firm.

Regarding step one, there are many ways in which organizations engage with their environments, either with the direct goal of external knowledge sourcing or with it being a byproduct of the pursuit of some other goal: Firms attend global trade fairs or conferences, which allow them to observe the competition and to assess the general trajectory of the field (Bathelt & Schuldt, 2010; Lampel & Meyer, 2008; Schüssler et al., 2015) or to rewire their networks (Panitz & Glückler, 2017). Firms are also known to involve their users or customers into the innovation process (Foss et al., 2011; Von Hippel, 1976) or to cooperate with startups to enrich their own knowledge base (Weiblen & Chesbrough, 2015), summarized by the paradigm of open innovation (Chesbrough, 2003). And finally, firms set up listening posts (Gassmann & Gaso, 2004; Maskell, 2014) and designate innovation scouts (Klueter & Monteiro, 2017; Monteiro & Birkinshaw, 2017), with the explicit task of hunting for external knowledge relevant to the firm's goals and processes. Combinations of such practices lead to different levels of breadth and depth of external search and have been found to positively influence innovative performance (albeit only to a certain threshold, beyond which search cost becomes prohibitive, Laursen & Salter, 2006).

Regarding step two, the internal distribution, communication, and application of external knowledge is complicated by the intrinsic features of knowledge exchange but also by the organizational and geographic structure of the firm. This is especially the case in large, multinational corporations (MNCs), which operate in markets all over the world and are the main drivers of the globalized knowledge economy. As indicated above, one of their core capacities is their ability to tap into localized knowledge pools across the world (Gassmann & Gaso, 2004; Malecki, 2010; Maskell, 2014; Monteiro & Birkinshaw, 2017), which they recombine to innovate. However, the same reach which grants this capacity puts them continuously at risk of (a) reinventing the wheel by acting on the same external impulse in multiple parts of the organization or (b) missing out on opportunities because they have not been recognized as useful and thus have not been forwarded to the right context of application within the organization. While formalized knowledge management systems (Alavi & Leidner, 2001) have received increased attention from both academia as well as practitioners, these are often not a one-size-fits-all solution as they clash with the personal and social nature of tacit knowledge (Grant, 1996; Nonaka, 1994; Polanyi, 1958) and are faced by public goods dilemmas (Cabrera & Cabrera, 2002). These issues are likely amplified in the context of externally sourced knowledge which is characterized by high degrees of uncertainty but also by disruptive potential. The challenge of knowledge exchange in such contexts gives rise to the second research question pursued by this thesis:

How do organizations mobilize and integrate externally sourced knowledge in the face of organizationally and geographically dispersed entry points?

In line with the abovementioned shortcomings of formalized communication systems, one of the main contributions of the literature on organizational networks has been in uncovering the 'company behind the chart' (Krackhardt & Hanson, 1993), i.e., the ways in which networks of informal relationships among employees supplement, enhance, or even overrule formal organizing structures. Such organizational networks are notoriously hard to assess and are often misjudged in their structural properties by participants (Kilduff et al., 2008; Krackhardt, 1987, 1990). They also often deviate considerably from formal reporting structures (Glückler & Panitz, 2014), both of which make them difficult to actively manage. Effective knowledge exchange critically depends on such networks (Phelps et al., 2012), which however often are shaped by social processes untethered to the efficient distribution of knowledge, such as homophily (McPherson et al., 2001), Matthew effects (Barabási & Albert, 1999; Merton, 1968), competitive dynamics (Burt, 1992; Lazega et al., 2016), status inconsistencies (Lazega, 2001, 2016), or relational turnover (Lazega, 2017; Panitz & Glückler, 2020). These networks are also susceptible to organizational and geographical constraints arising from the dispersed nature of multinational corporations, which have led researchers to pay special attention to issues of boundary spanning (Pedersen et al., 2019; Rosenkopf & Nerkar, 2001; Tushman & Scanlan, 1981). Boundary spanners, i.e., individuals that establish ties to individuals in other organizational or geographic (and in extension functional, institutional, or cultural) contexts, are in a position to recognize redundancy and forward opportunities across geographical and organizational 'pockets'. As such, they are able to link dispersed 'receptors' (Cohen & Levinthal, 1990, p. 132) of externally sourced knowledge and thus occupy central roles in building absorptive capacity.

However, while the advantages of boundary spanning are well understood, still relatively little is known about the individual characteristics, organizational roles, and organizational locations which promote individuals' boundary spanning activities (Schotter et al., 2017; Tushman & Scanlan, 1981). Using the case study of a corporate scouting community consisting of both formally designated innovation scouts as well as individuals engaged in scouting only informally, I contribute to this stream of research by investigating how the formality of scouting status affects the propensity to engage in geographic and organizational boundary spanning and how that propensity varies across the different units of the firm. As before, the network analytic approach allows for an assessment not only of individual level relational outcomes, but also of the network as a whole, which enables a combined assessment of how organizational structure and formal roles shape the overall structure of knowledge exchange across the firm.

Networks and navigation in technological fields

Firms' efforts to navigate fast-moving innovation landscapes depend on their ability to pick up on new technologies, practices, and markets. As discussed in the last section, absorptive capacity conceptualizes a firm's ability to take in new knowledge as critically dependent on the compatibility of such new knowledge with the firm's existing stock of knowledge (Cohen & Levinthal, 1990; Nooteboom et al., 2007). The last section of the thesis builds on the cumulative nature of innovation implied by this process. Cumulativeness describes the degree to which existing knowledge fosters the development of new knowledge, or, in Dosi et al.'s (2010, p. 73) words, the degree to which "success breeds success". It is at the core of some of the most prevalent theories of economic growth and change: Because cumulativeness implies that a large stock of existing knowledge does not decrease the utility of obtaining new knowledge but rather increases it, it is the main justification for increasing returns in Romer's (1986) endogenous growth model. And because accumulation of knowledge implies a process akin to inheritance, it is a centerpiece of evolutionary theories of economic change (Breschi et al., 2000; Freeman, 1991; Nelson & Winter, 1982). Tacitness (Polanyi, 1958) and partial excludability (Cabrera & Cabrera, 2002) often bind the exchange of knowledge to social relationships, which has been the focus of attention of the last section. As ideas mature they sometimes can however be formalized (Nonaka, 1994) or embedded into organizational structures and routines (Nelson & Winter, 1982), decoupling them from their specific social origins. In many organizational contexts, this decoupling is a critical step for knowledge to accumulate, since passing on knowledge through 'oral tradition' (i.e., along informal, personal relationships) is easily disrupted by high relational turnover and is a difficult process to manage strategically. Accordingly, evolutionary theories (Dosi & Nelson, 2010) but also theories of organizational learning (Argote, 2012; Levitt & March, 1988) put much emphasis on organizational processes and patterns that achieve this decoupling of knowledge accumulation from interpersonal relationships.

Irrespective of the precise social or organizational mechanism of accumulation, "cumulativeness and its effect on expectation formation imply that [...] development is domain-specific and is path-or history-dependent" (Cohen & Levinthal, 1990, p.136), i.e., that future options are conditioned on the current state of the art. Dosi (1982) captures path dependent technological change in his framework of trajectories and paradigms: A technological paradigm represents a general solution approach towards some problem, such as, e.g., the use of combustion technology in vehicle engines. In the context of such a paradigm, incremental progress is made (e.g., regarding fuel efficiency) without deviating from the general approach, resulting in relatively stable technological trajectories. With enough accumulation of knowledge about a paradigm and the associated incremental improvements, an inferior technology can dominate a superior one for long periods of time. Combined with network effects and high switching costs, path dependence accordingly leads technologies and the firms that produce them to be equipped with a degree of persistence that is not merely due to their superiority over competing alternatives (Arthur, 1989). This is often exemplified with the dominance of the arguably suboptimal QWERTY keyboard (David, 1985), although this example is not uncontested (Liebowitz & Margolis, 1990). Notwithstanding this often observed longevity, disruptions of technological trajectories can occur through paradigm shifts (Freeman, 1991; Freeman & Perez, 1988), i.e., changes to the fundamental solution approach. This can for example be observed in the recent widespread switch to electric drive technology, which led to a far-reaching disruption of the automotive industry and its supply sectors. Next to path dependence, Cohen and Levinthal highlight a second point in the quote above: Cumulativeness along specific trajectories is usually domain-specific, i.e. accumulation occurs in some well-defined body of knowledge; In the same vein, paradigm changes are often domain-crossing in that they build on the application of a hitherto unrelated body of knowledge to a new problem. While paradigm shifts are often disruptive for the industries they occur in, borrowing knowledge from a different domain does not necessarily lead to creative destruction, but can also spawn completely new fields of application or invigorate lagging ones. In this vein, studies have shown that regional and technological characteristics affect the Schumpeterian unfolding of innovation (Malerba & Orsenigo, 1996). However, how the interplay of stable, path-dependent development and potentially disruptive paradigm changes shape the overall evolution of heterogeneous technological fields is not yet well understood. Motivated by increasingly cross-disciplinary knowledge recombination (Rosenkopf & Nerkar, 2001; Strumsky & Lobo, 2015) and recent calls for more historical approaches towards field evolution (Argyres et al., 2019; Martin & Sunley, 2022), the third research question pursued by this thesis is:

How do cumulativeness of knowledge and interdependent development across technical domains shape the long-term structural evolution of technological fields?

Originating as the tenet of evolutionary economics (Dosi & Nelson, 2010), path dependent technological change has received much attention also in economic geography (Boschma & Frenken, 2006; Martin & Sunley, 2006), where it promises to shed light on the linked fates of regions and the technologies they specialize in (Nomaler & Verspagen, 2016; Schamp, 2005). While approaches following the dominant stream of evolutionary economic geography typically investigate patterns of technological diversification at the regional level (Castaldi et al., 2015; Frenken et al., 2007), their focus on the optimal level of technological variety usually brushes over interdependencies in the development of different technologies. These can however be decisive for the fates of firms and in turn for regional development, as can be seen, e.g., in the decline of combustion technology and its impact on the automotive supply sector in southern Germany (Altenburg, 2014). With their focus on regional innovation activities, they also usually do not account for the impact of extra-regional developments (Bathelt & Storper, 2023; Content & Frenken, 2016), which however can be substantial when technological development is strongly interdependent across domains. Similarly, approaches from technology studies often focus on individual technological trajectories (Fontana et al., 2009; Magee et al., 2018; Verspagen, 2007) without accounting for their intersection with trajectories from other domains. In an attempt to remedy some of these shortcomings, I here take an explicitly structural and historical approach that aims to identify patterns of (inter)dependence and convergence across heterogeneous technological fields.

3

Novel data and methods for relational research

The studies in this thesis address research questions at different levels of economic activity and accordingly they build on different data sources and employ different methods. However, they all share a relational approach, i.e., they are interested in how economic agents or the traces of their activities are connected, using networks as a formal representation that lends itself for structural analysis. Most of the studies are furthermore interested in the evolution of structure (except for paper three, where the case did not allow for dynamic analysis). The thesis strives for empirical contributions based on research designs which are supported by recent methodological advances or untapped methodological potential in these areas. In this vein, I explore recent or little known methods, which I have adapted, extended, or recombined to fit the needs of the specific papers' research goals. I also have developed software implementations when they were not at hand, some of which have found their way into open source libraries. In its effort to trace relational processes in different economic contexts, the thesis makes use of primary, publicly available, and private secondary data. Regarding the used data sources, I here restrict myself to more general discussions without going into the details of the studied cases, which are covered in the summaries further below.

Exchange networks, relational event models, and sequence analysis

Exchange structure in observational settings. Papers one and two are concerned with the structure of exchange in contexts of social embeddedness and transactional uncertainty. Studies on the structure of social and economic exchange have traditionally focused on experimental settings (Kollock, 1994; Molm et al., 2000), not least owed to the difficulty of observing such exchange systems in the real world. The two studies presented here use the unique empirical opportunity provided by a community currency system to observe transactions in a self-contained exchange system over an extended period of time. Community currency systems are (usually localized) platforms for exchange of goods and services among admitted members, facilitated by a community-specific alternative currency. Because they need to administer members' accounts, these systems often collect complete lists of time-stamped exchanges, each containing the sender, the receiver, a description of the provided good or service, and the currency amount; This high-resolution data in turn enables longitudinal structural analysis of exchange behavior. In paper one, I use relational event models to investigate how the choice of an exchange partner is conditioned by past exchanges and how the degree of conditioning varies across different kinds of goods and services transactions. While this approach makes use of the temporal structure in the data to identify history-dependent patterns in provider choice, it does not study the overall development of the system. In paper two, I accordingly turn to structural evolution at the network level over an observation period of eight years, relying on stochastic block models and sequence analysis to disaggregate different types of membership trajectories.

Relational event models for temporal network analysis. While many approaches towards temporal network analysis, such as the stochastic actor-oriented model (SAOM, Snijders et al., 2010) or the temporal exponential random graph model (tERGM, Leifeld et al., 2018), rely on panel data obtained from observing the full network at multiple time points, the data described above carry a time stamp for each edge. Instead of representing 'relational states' (as in, e.g., friendship networks), these data thus constitute a history of discrete relational events (Butts, 2008). Compared to models using aggregate panel data, the high resolution of relational event sequences allows for even more flexible modeling of social processes while simplifying statistical estimation: Instead of simulating change trajectories between time points, as is for example done in the SAOM approach, relational event models (REMs) can directly use the observed sequence of events. Modeling flexibility comes especially through the construction of statistics representing different kinds of dependence on previous events, which can represent fundamental social phenomena, such as inertia, reciprocity, or triadic closure, but which can also be adapted to more context-specific metrics. Guided by theoretical deliberations on relational mechanisms for the reduction of transactional uncertainty, the paper relies on five such statistics: The first three, product repetition, partner repetition, and reciprocity, capture the tendency of consumers to pick exchange partners whom they are already familiar with, either with respect to their ability to provide the specific good or service at choice (product repetition), or as an exchange partner more generally (partner repetition and reciprocity). Formally, these are defined as indicator functions over a one-year time window preceding a transaction at time point t:

$$\text{product repetition}_{ij} = \mathbb{I}_{E_t}(e : i_e = i \wedge j_e = j \wedge c_e = c)$$

$$\text{partner repetition}_{ij} = \mathbb{I}_{E_t}(e : i_e = i \wedge j_e = j \wedge c_e \neq c)$$

$$\text{reciprocity}_{ij} = \mathbb{I}_{E_t}(e : i_e = j \wedge j_e = i)$$

Here, E_t refers to the set of all events in the window preceding time t and $\mathbb{I}$ is the indicator function which returns 1 if any event e in E_t satisfies the specified conditions and zero otherwise. To capture patterns of networked reputation (Glückler & Armbrüster, 2003) manifested in peer referral, I furthermore develop a product- and timing-aware transitive closure statistic:

$$\text{transitive referral}_{ij} = \mathbb{I}_{E_t}(e : j_e = j \wedge c_e = c \wedge i_e \in \{k : (k, i) \in E_{t_e - t} \vee (i, k) \in E_{t_e - t}\})$$

Similar to the statistics above, this specifies a dummy variable which in this case equals one when the consumer i had a previous exchange with a peer k that had already received the good at choice c from provider j before. Finally, I define product activity as the number of times provider j has delivered product c before time t:

$$\text{product activity}_j = \sum_{e \in E_t} \mathbb{I}(j_e = j \wedge c_e = c)$$

The analysis also makes use of an interaction term between product repetition and transitive referral to capture the conditional nature of the usefulness of indirect product-specific experience when direct experience is available.

Based on these statistics, the paper investigates the degree to which they shape provider choice and the structure of exchange in the community currency system, and assesses the degree of variation across exchanges of different types of products. To achieve this, I extend the Dynamic Network Actor Model (DyNAM, Stadtfeld & Block, 2017, a variant of the relational event model introduced by Butts, 2008) to accommodate a hierarchical model architecture, which allows coefficients to vary by type of product while still making efficient use of all data (Gelman & Hill, 2007). Building on softmax / conditional logit regression, the model specifies a probability distribution over the set of potential providers available at any time point (denoted A_t), where the probability of i choosing j as a provider of good c is a function of their common exchange history:

$$p\left(i \xrightarrow{c} j | E_t, \beta_c\right) = \frac{\exp(\beta_c^T s(i, j, c, E_t)}{\sum_{k \in A_t} \exp(\beta_c^T s(i, k, c, E_t)}$$

Here, $s(.)$ denotes a vector containing the above statistics and β_c is a vector of coefficients specific to product c. The elements of the latter indicate to what degree a given summary of two participants' common exchange history increases or decreases their likelihood of exchange and are subject to estimation. The model is fit using Bayesian statistical methods and implemented in the probabilistic programming language Stan (Carpenter et al., 2017). I here forego a more detailed discussion of Bayesian methods and hierarchical models here and instead refer the interested reader to the next section, which goes into more depth on these topics.

Positional sequence analysis. While paper one operates at the level of individual choices and is guided by considerations of decision-making under uncertainty, paper two uses the case study of the community currency system to study the long-term evolution of an exchange system that is characterized by high relational turnover (Lazega et al., 2017) and generational stagnation. Its primary goal is in developing a disaggregated image of the types of membership trajectories that are common to the system to provide more refined evidence to the claim that localized community systems often lack durability (Seyfang & Longhurst, 2013). To achieve this goal, I combine positional network analysis (Glückler & Doreian, 2016) and methods from sequence analysis (Abbott, 1990) to identify typical positional trajectories of participant involvement. Positional methods, such as generalized (Doreian et al., 2005) or stochastic (Snijders & Nowicki, 1997) blockmodeling, identify groups of actors that are similar in terms of their relationships to members of their own and the other groups. Applications include, e.g., the identification of core-periphery structures in organizational networks (Lazega et al., 2011) or the disentangling of new divisions of labor in markets (Glückler & Panitz, 2016b). Sequence analysis, on the other hand, is used to identify (families of) typical temporal sequences of events or states, e.g. in career paths or organizational lifecycles, and is thus a core tool of process-oriented analysis (Abbott, 1990). The paper combines these two approaches by first aggregating transactions into yearly networks for each of the eight years in the observation period. For each of these networks, a stochastic blockmodel is used to assign all active participants to either a core or a periphery position. This results in a length-eight sequence for each participant that was active at some point, where inactivity is a third state option next to the two positions. These sequences are in turn clustered using an optimal matching distance metric and hierarchical clustering to identify typical trajectories, such as a stable core, a stable periphery, and short-term exits and entries. In contrast to a static, aggregated approach, the combined use of positional and sequence analysis is able to distinguish, e.g., between participants with ephemeral bursts of exchange activity and those forming the long-term, stable backbone of the system. As such, the dynamic-positional approach proposed here is a suitable method to disentangle individual contributions to the overall evolution of the system.

Limitations. The data and methods outlined here also carry some limitations. First, while the data available from the records of the community currency is rich in detail for transactions, it does not contain any information about the participants. Sociodemographic factors and motivations for participation are likely to imprint on exchange behavior and accordingly such data would be invaluable for a more comprehensive analysis. Second, paper one treats relational behavior as informed by the past but in itself static. Given the different participant trajectories identified by paper two, a combined approach that investigates how exchange behavior changes as a member becomes more familiar with the exchange system seems a worthwhile research project. Third, while paper two identifies different trajectories of participation, it remains largely silent on what might cause such differences. Here, a mixed-methods approach that goes into more depth regarding the organizational context of the system and the motivations for participation might prove valuable.

Snowball sampling and Bayesian hierarchical models

Mapping a latent corporate scouting community. Paper three studies the network of knowledge exchange in a corporate community of innovation scouts. Because the paper builds on a generalized definition of scouting that also allows for informal scouts, i.e. scouts that do not carry scouting in their formal job description but still practice scouting activities, the extent of this community was not known a priori. Accordingly, one of the core tasks of the study was to identify the population of formal and informal scouts in the organization. This was achieved with a snowball sampling approach that departed from a large initial seed list of known formal scouts and likely informal scout candidates, which was provided by managers of the scouting programme. These known and potential scouts were sent a survey invitation that contained a definition of formal and informal scouting asking them to indicate their involvement in scouting activities, if any. The survey then asked them to identify other individuals they deemed to be involved in scouting, who were added to the list of participants in a next round of surveying. This was repeated for a total of five waves, at which point the rate of newly identified informal scouts was deemed low enough to have captured the majority of the scout population. This process resulted in the identification of 136 formal and 295 informal scouts, for a total of 431 scouts in the community. More generally, the survey and its design were carried out as outlined by the SONA (Situative Organizational Network Analysis) process (Glückler et al., 2020): As such, it involved the initial identification of key problems and metrics together with management representatives, which served as a foundation for survey design, and the validation of results in the context a workshop concluding the study.

Mapping intraorganizational knowledge networks. One of the primary goals of the study was an assessment of how formal and informal scouts are integrated through a network of knowledge exchange and to what degree that network is shaped by the organizational and geographic structure of the firm. Recently, more and more studies interested in mapping intraorganizational knowledge flow have been relying on secondary data sources, such as patent-based co-inventorship networks (Grigoriou & Rothaermel, 2017; Paruchuri & Awate, 2017). Such an approach is considerably easier to implement and more scalable compared to primary data collection, as it does not require concerted efforts involving the studied organization. However, it also comes with a series of drawbacks: First, it is not obvious to what degree the relationship obtained from co-inventorship involves explicit collaboration and knowledge exchange; For example, whether R&D managers will be included in the list of inventors, irrespective of their direct contribution, is largely a matter of an organization's IP culture. Direct, survey-based querying requires active acknowledgement of the relationship and the implied flow of knowledge by the survey participant and thus is more transparent and robust. Second, it is unclear whether all individuals that participate in the circulation of knowledge in the organization will be included by an approach relying on patent information or whether there is systematic exclusion of relevant groups. This is especially true for the partly informal population of scouts studied here, and we accordingly rely on a survey-based network generator to capture knowledge exchange in the scouting community. Next to questions about their scouting activities, the survey thus included the following name generator: "Who of your colleagues have helped you to carry out your scouting activities successfully over the past two years?" This yielded a total of 1033 ties among the 431 scouts, spanning a global network of knowledge exchange among scouts across all divisions of the firm.

Hierarchical models for context-aware statistical analysis. Large multinational organizations, such as the one studied here, are characterized by heterogeneity with respect to goals, organizational forms, and culture: A research unit is organized and staffed for knowledge circulation and idea generation while a production unit will more likely be geared towards efficiency (Stabell & Fjeldstad, 1998). Such contextual heterogeneity is likely to also imprint on the role of scouting across the different units of the firm and accordingly needs to be reflected in the research design. Traditionally, statistical approaches either assume uniform effects across nested data (reffered to as complete pooling), or they split the data and estimate models separately (no pooling). Both of these strategies have conceptual and statistical disadvantages: While the first brushes over differences between groups and risks biased results, the second treats groups as completely independent and mutually uninformative. This paper makes use of hierarchical (or multilevel) models, which allow for variation in effects over the organizational units of the firm while taking into account the data in other units through a mechanism called partial pooling (Gelman et al., 2014). This is achieved through modeling unit-level effects as drawn from a higher-level prior distribution, the parameters of which are themselves subject to estimation and capture the combined information from all units. As such, hierarchical models can be more flexible while also providing more precise estimates and guarding against overfitting through regularization of extreme estimates via their hierarchical prior structure. This is especially important in settings where some groups have only little data, as is also the case here.

More formally, and here exemplified by the boundary-spanning outcomes modeled by a binomial distribution (where y_i is the number of boundary spanning ties of scout i and n_i refers to the total number of ties), the models used in the study include unit-specific intercepts ($\alpha_{U[i]}$ denotes the intercept for the unit hosting scout i) and unit-specific scout coefficients ($\delta_{U[i]}$):

$$
\begin{aligned}
y_i &\sim \text{Binomial}(n_i, p_i) \\
p_i &= \text{logistic}(\alpha_{U[i]} + \delta_{U[i]}\text{informal}_i + X_i\beta)
\end{aligned}
$$

As such, the overall propensity to span boundaries as well as the differential propensity of formal and informal scouts to span boundaries can vary between different units in the firm. The $X_i\beta$ term captures control variables that do not vary by unit. The unit-level intercepts and coefficients are then modeled as drawn from a hierarchical prior represented by a bivariate normal distribution with mean 0 and covariance matrix Σ, which is decomposed into a standard deviation component (σ) and a correlation matrix component (Ω). Both of these receive their own respective priors, with the exponential distribution as a natural option for the standard deviation components and an LKJ prior for the correlation matrix:

$$
\begin{aligned}
(\alpha_u, \delta_u) &\sim \text{MvNormal}(0, \Sigma) \\
\Sigma &= \text{diag}(\sigma)\Omega\text{diag}(\sigma) \\
\sigma_\alpha, \sigma_\delta &\sim \text{Exponential}(1) \\
\Omega &\sim \text{LKJ}(3)
\end{aligned}
$$

Accordingly, intercepts and scouting-status coefficients can be correlated across units.

Hierarchical models are most easily expressed and estimated using a Bayesian computational approach, which provides general algorithmic frameworks for the flexible estimation of complex models, such as Markov Chain Monte Carlo (MCMC) procedures. Beyond modeling flexibility, Bayesian statistics also has some conceptual advantages as it builds on the direct representation of uncertainty about unknown quantities, such as regression coefficients, with probability distributions. This contrasts with classical ('frequentist') approaches, which regard unknown quantities such as model parameters as fixed, and randomness as arising from repeated sampling from some population (McElreath, 2020). As such, the Bayesian framework is often more intuitive for two reasons: First, the notion of a repeated experiment is hard to justify in many observational settings, which are the norm in the social sciences. Second, direct expression of uncertainty about unknown quantities via the language of probability is usually more intuitive than appeals to a hypothetical resampling procedure. As such, Bayesian interpretations of statistical uncertainty are often more natural, while also being easier to propagate to derived quantities of interest. A Bayesian approach allows for easy checking of model behavior based on posterior predictions while accounting for both systemic and estimation uncertainty. As such, it is especially well suited for approaches towards exploratory data analysis that compare model expectations to patterns in the observed data, often using visualization techniques (Gelman, 2004).

Limitations. While the hierarchical models presented here allow for differences between organizational contexts, they don't go into the 'why' behind this variation. In principle, the outlined methodological approach allows for the inclusion of unit-level information in the analysis of scout-level outcomes; however, such contextually qualifying information was not available here. Many organizational networks are furthermore characterized by high degrees of relational and membership turnover (Lazega et al., 2017; Panitz & Glückler, 2020). Especially in light of the largely informal nature of the studied community, this is likely also the case here; However, a dynamic study able to capture processes of integration or disintegration among formal and informal scouts was not feasible due to the already complex nature of conducting network surveys in large organizations. Combinations of primary and secondary data on knowledge networks might be able to provide a remedy here, as such an approach could draw on the robustness of network surveys to provide a basis for more scalable uses of longitudinal co-inventor or co-publication data.

Patent citation networks and main path analysis

Patent data. Papers four and five are concerned with knowledge accumulation and path-dependent technological development over long time periods and across heterogenous technological fields. Building on a long history of patent-based innovation indicators (Griliches, 1990; Hall et al., 2005), this thesis uses patent data to trace the structural evolution of technological fields. Patents' usefulness as economic indicators is incidental - first and foremost, they are legal titles that give the owner a territorially bounded exclusionary right to prohibit others from using the patented technology (without payment of licensing fees). A patent is granted when the novelty, inventiveness, and economic applicability of the underlying technology are confirmed by expert opinion throughout an examination of the patent application by a national patent office. When the validity of the patent is confirmed, the holder is granted a temporary monopoly over the use of the patented technology, usually with an upper limit of 20 years but with increasing fees for renewal. Patents can be thought of as both measures of input and measures of output (Griliches, 1990): As measures of input, they represent inventive activity in that they indicate the allocation of resources by economic agents towards specific technologies. Because firms are unlikely to go to the lengths of filing a patent for a technology they deem irrelevant, taking patents to signify activity or attention is a relatively conservative approach. Regarding patents as the output of innovation activities is more contentious, especially since assessing patent value is challenging and its distribution is highly skewed. However, even under more conservative interpretations of their economic meaning, patents are a highly useful data source for pragmatic reasons: they are collected in standardized databases, are available for long time periods and at global scale, and contain a variety of useful content- and metadata.

Technology classification and citation networks. Two pieces of patent information deserve special mention: First, patents are classified by examiners according to sophisticated technology classifications, such as the Cooperative Patent Classification (CPC), which features a hierarchy of five levels with more than 250,000 unique leave nodes. Patent classifications form the basis of many statistical patent analyses because they allow the delineation of industries and technological fields (a mapping which is not always trivial, see the discussion in Griliches (1990)). Following this practice, papers four and five use the CPC to delineate the technological field of plastic recycling and the bioeconomy and its subdomains, respectively. Second, during the prior art search conducted to determine novelty of the patent application, references to related earlier applications are collected. These citations have been put to different uses: On the one hand, forward citations (i.e., citations received by future patents) have been shown to correlate with economic value (Hall et al., 2005; Harhoff et al., 1999; Trajtenberg, 1990), and thus address some of the shortcomings regarding the measurement of patent quality. On the other hand, citations can be aggregated into citation networks which lend themselves to structural-historical analysis (Barberá-Tomás et al., 2011; Verspagen, 2007). This latter avenue is also taken in this thesis. Citation networks have some special properties: Each node has an associated time stamp (the patent application's filing or publication date or a patent family's earliest filing date) and its citations can only point to earlier patents, i.e. back in time. If this is not violated, the citation network forms a directed acyclical graph (DAG). This property enables the use of some efficient algorithms for methods such as main path analysis, (Batagelj, 2003), which is a requirement for networks that can easily grow to hundreds of thousands or even millions of nodes and edges.

Main path analysis. Main path analysis (Hummon & Dereian, 1989; Liu et al., 2019) is a bibliometric, network analytical method which makes explicit use of the time-ordered structure of citation networks. Its goal is the identification of major trajectories of knowledge flow represented by chains of citations. The extracted citation paths can then be taken to represent the 'backbone' of the studied corpus of knowledge. As such, it aligns well with the goal of identifying major trajectories of technological knowledge. Main path analysis represents a family of different methods, which usually however comprise two steps: First, the computation of some flow weight for edges (or nodes), which can be thought of as representing the forward flow or accumulation of knowledge that is funneled through any given edge. A commonly used, easy to interpret, and efficiently computable variant are Search Path Count (SPC) weights (Batagelj, 2003), which count the total number of geodesic paths from source nodes to sink nodes that run through any edge (or node), somewhat akin to the idea of betweenness centrality (Freeman, 1977). Second, the citation network is traversed departing from a prespecified set of start nodes, following the highest weight edges according to the weighting scheme of step one. Traversal can be performed forwards, backwards, or in both directions; Start nodes can be, e.g., source nodes with forward traversal, sink nodes with backwards traversal, or can be selected according to some other heuristic (e.g. high-impact patents in a given domain or period).

Interrelated development and convergence. While most applications of main path analysis rely on qualitative explorations of the extracted main paths for a given scientific or technical domain, this thesis proposes an approach that relies on the quantification of structural properties of main path networks that span multiple domains. For this purpose, papers four and five develop simple measures for capturing interrelated technological development and convergence based on main path representations.

First, in paper four I define the *backwards reachability* for a technology domain i relative to another domain j as as the share of start points in i that lie on forward paths originating from start patents in j in the context of a main path G: $\mathrm{BR}_G(i,j) = \frac{1}{|S_i|}\sum_{t\in S_i}\sum_{s\in S_j} r(s,t)$. Here, S_i and S_j refer to the two sets of start nodes and $r(s,t)$ is equal to one when node t is reachable from node s and zero otherwise. A value of one would indicate that all start patents in domain i have an ancestor in the start set of domain j, which we take as a sign of technological dependence of domain i on domain j. Computed pairwise for a set of technological domains, this index can be used to uncover (asymmetrical) patterns of (inter)dependence in their historical coevolution. In a similar fashion, the paper also makes use of mean geodesic distances between the start patents of two domains to indicate technological interrelatedness and more generally uses simple graph theoretical measures, such as the network diameter, for the purpose of comparing main path networks.

Second, in paper five, I take the reduction of parallel paths in a main path network that occurs in a given time interval as a measure of *structural convergence*. The paper maps this measure over 5-year intervals to identify periods of convergence in a main path network representing 120 years of technological development in the bioeconomy technological field. Keeping track of the technological domains of the patents that emanate outgoing paths for each interval, we extend this approach to capture domain switches, i.e. main paths that shift from one technological domain to another. In combination, the two metrics are used to indicate structural and inter-domain convergence to capture the long-term evolution and the development of a common technological backbone in the context of a heterogeneous technological field.

Limitations. The approach outlined here also has a series of limitations. First, it is liable to the shortcomings of patent data: Not all innovations are patentable and not all innovations that could be patented, are (e.g., because nondisclosure is valued higher or a more feasible strategy, Griliches, 1990). Accordingly, there can be no general claim for completeness or homogeneity across domains in the representation of technological development based on patents. Second, while main path analysis has been in use for a while, its accuracy in detecting major technological trajectories in a field is still contentious. Recent investigations using expert opinion for validation, for example, have shown that main paths can contain failed technologies while not containing some key technologies that had lasting impact (Filippin, 2021). Approaches focused on structural analysis instead of qualitative investigations of the included patents, such as the one presented here, might provide a remedy - a claim which however needs to be checked more carefully in future work. Finally, the degree to which structural properties identified in main path networks are related to shifts in industrial organization or organizational fields has only been assessed anecdotally here. More thorough analysis of this relationship is required to validate main path analysis as a useful and scalable tool in the study of technological development.

4
Publication summaries

Navigating uncertainty in networks of social exchange: a relational event study of a community currency system

Research problem and background. This paper is concerned with the processes by which individuals navigate socially embedded exchange systems in contexts of transactional and institutional uncertainty, i.e., when quality control is weak and quality signals are absent or opaque. In its pursuit of this research objective, the paper combines two literatures: First, it draws on informational economics, which distinguishes product classes based on their inherent transactional uncertainty. In an endeavor to better understand the impact of quality uncertainty on consumer behavior and in turn market structure, economists have distinguished between search, experience, and credence goods (Dulleck & Kerschbamer, 2006; Nelson, 1970): Search goods represent goods whose quality characteristics can be learned by a potential buyer with reasonable search effort and cost prior to the purchase. For experience goods, conversely, quality can only be assessed after purchase. Finally, for credence goods, the buyer cannot even fully know the good's quality characteristics after the purchase and an assessment is fully dependent on the seller's assertions. While many (but not all) transactions in physical goods fall into the former category, most services, such as a haircut or a doctor's diagnosis, are more difficult to assess and belong to one of the latter two (Clark, 1993; Gabbott & Hogg, 1994). As a second field of study, the paper draws on social exchange theory and theories of network emergence. In the face of varying levels of transactional uncertainty, consumers rely on different practices of navigation (Beckert, 1996; Glückler & Sánchez-Hernández, 2014) to inform their choices. The paper studies three such mechanisms that are relational and represent tradeoffs in richness and reach (Evans & Wurster, 1997): First, consumers can build on their previous experiences, which are highly informative but limited by the transactional capacity of the buyer and thus exhibit high richness but low reach. When acted upon, direct experience leads to observable commitment behavior in exchanges (Kollock, 1994; Lawler & Yoon, 1993; Molm et al., 2009). Second, when direct experience is not available, consumers can instead build on the experiences of their peers through a mechanism of networked reputation (Glückler & Armbrüster, 2003). While not as rich as direct experience, recommendations by trusted peers can still be valuable guidance while having higher reach. Finally, consumers can rely on the public reputation of or common knowledge about a provider, which is easily obtained but not as informative direct or networked experience. Based on this conceptualization, the paper studies patterns in the structure of exchange consistent with the above relational navigation behaviors as well as their variation across different types of goods and services transactions.

Case, data, and methods. The paper builds on the empirical case of a community currency system, a localized platform which facilitates the exchange of goods and services among registered participants via a platform-specific currency. Previous research on these systems has, e.g., studied participants' motivations (Collom, 2011; Ozanne, 2010), impacts on local economic development (Dittmer, 2013), or implications for sustainable consumption (Seyfang & Longhurst, 2013). While community currency systems are 'market-like', they usually come with an explicit focus on social inclusion (Collom, 2008; Seyfang, 2004) and often forego formalized quality control. As such, their socially embedded but economically uncertain setting make for a good case to study the relational practices of navigation outlined above, driven by the localized nature of face-to-face experience and reputational effects (Storper & Venables, 2004). The studied community currency system used a time-based currency and was located in a medium-sized city in southern Germany. The analysis builds on transaction records available from 2009 to 2017, a period over which 4,454 transactions among a total of almost 200 members were recorded. Each transaction record includes the sender, the receiver, the time, and a description of the contents of the transaction. Content descriptions were used to classify transactions into 28 categories, which in turn were aggregated into physical goods transactions, object-related services, and person-related services. Based on these data, the paper uses the Dynamic Network Actor Model (DyNAM, Stadtfeld & Block, 2017), a type of relational event model (Butts, 2008), to investigate how the choice of a provider is related to the history of exchanges connecting the buyer and the provider. More specifically, the analysis builds on statistics of product repetition, person repetition, and reciprocity as indicators of direct experience, a customized transitive closure statistic as an indicator of networked reputation, and on a provider's previous product activity as an indicator of public reputation. To allow for variation of effects across different types of goods and services transactions, the DyNAM is furthermore extended to a hierarchical model architecture.

Findings and discussion. Our analysis identifies patterns in the history of exchanges that are consistent with the navigation mechanisms of direct experience, networked reputation, and public reputation. First, there is a strong tendency to repeat transactions of the same type with the same provider, with odds of repeating on a provider of a person-related service at around 60 times those of choosing a new one. This finding also extends to repeated transactions with the same person but for different products, as well as reciprocal exchange, leading to an overall pattern of strong dyadic stability that is consistent with acting on direct experience. Using an interaction effect between product repetition and our transitive referral statistic, we also find support for indirect experience as a source of guidance when direct experience is not available. Since the exchange-based measure for word-of-mouth-based referrals does not capture other relationships and communication channels, there are likely even further opportunities for referral in the system due to its small-scale, community-oriented nature. Pursuing this further, co-evolution of both exchange relationships and other social relations could prove to be a worthwhile future subject of study. Finally, providers that have a rich history of providing a specific good or service are more likely to be chosen than those who do not, indicating an effect of visibility and public reputation in shaping provider choices. There is also some evidence that provider choices are more likely to be embedded into uncertainty-reducing exchange patterns for service transactions and especially person-oriented services than for goods transactions. This ordering is consistent with expectations based on the informational characteristics of the three groups. However, evidence is somewhat ambiguous across the different patterns and there is considerable variation within the respective groups as well as between them. This ambiguity is probably indicative of the inherent difficulty of assessing search, experience and credence characteristics of products (Ford et al. 1988) and likely a consequence of the relatively rough classification of the three transaction groups used here. Furthermore, in the community currency context, financially risky transactions are rare and differences in transactional uncertainty between different products might be less relevant than in other contexts. Accordingly, comparisons with exchange systems with different levels and qualities of uncertainty make for another promising avenue for research. To conclude, this paper has demonstrated how participants of a localized and socially embedded exchange system make provider choices which are structurally consistent with relational practices of navigation in contexts of transactional uncertainty. A better understanding of these mechanisms is an important precondition for understanding the structure and development of localized and socially embedded market systems, as they can be drivers of stability but can also lead to structural lock-in and centralization - structural features which will be studied more closely in the next section.

Time banks as transient civic organizations? Exploring the dynamics of decline

Research problem and background. Paper one has used the case of a localized, community-based exchange system to study relational practices of navigation in the context of uncertain exchange partner choices. Motivated by discussions about the longevity of such alternative economic platforms (Seyfang & Longhurst, 2013; Valor & Papaoikonomou, 2016), paper two studies the same case but focuses on the structural evolution of the system. Community currency systems have been argued to support local labor markets, community development, and social inclusion (Gregory, 2009; Seyfang, 2004; Williams et al., 2001), and have thus been argued to provide suitable local responses to economic and social crises. In line with this, such systems have appeared numerously in many southern European (and especially Spanish) cities and regions which were hit hard by the financial crisis in 2007 (Sánchez-Hernández & Glückler, 2019; Valor & Papaoikonomou, 2016). Yet, they were frequently only relatively short-lived: Studies have shown that community currency systems often struggle to retain the critical mass of people needed for continuous commitment and long-term engagement (Seyfang & Longhurst, 2013), possibly because they fall short of their ambitious economic goals (Dittmer, 2013; Williams et al., 2001). Accordingly, aspects of systemic stability have been identified as a research frontier (Valor & Papaoikonomou, 2016). Because little is known about the structure and dynamics of exchange in time banks, paper two takes a relational perspective and frames the community currency system as an evolving network of social exchange (Whitham & Clarke, 2016) to evaluate its structural stability based on the structure of exchange.

Case, data, and methods. Because the case and data are the same as in paper one, we will forego a detailed description here to avoid duplication and refer the interested reader to the previous section. However, while the previous paper treated the data as a continuous stream of relational events, we here group transactions year by year to construct eight exchange networks. These can vary in size as people enter and leave the time bank over time. As before, transactions in a range of goods and services are distinguished. Based on these data, the paper first relies on simple graph-level indices to capture exchange activity and structure, their development over time, and their differences across different types of transactions. More specifically, total active members, transaction counts, and network density are taken to indicate overall activity and connectivity, while in- and outdegree centralization are used to proxy for supply- and demand-side concentration, respectively. As a second step, the paper combines stochastic blockmodels (Zhang et al., 2015) with methods from sequence analysis (Abbott, 1990) to identify typical membership trajectories. To do so, we first use stochastic block models to assign each member, in each year, to one of three positions: core, periphery, and inactive. The resulting member-specific membership sequences are then clustered using hierarchical clustering and an optimal matching distance measure (Gabadinho et al., 2011) to obtain groups of similar membership trajectories.

Findings and discussion. In line with Seyfang and Longhurst's finding (2013) that time banks often lack durability, aggregate statistics indicate that the number of members and transactions had begun to decline in the second half of the observation period, after several years of initial growth. This downward trend in overall activity is accompanied by a decrease in centralization, i.e., transactions are more spread out and less concentrated on a few highly active members. Disaggregating this overall trend, the approach of positional sequence analysis outlined above yields a total of five typical trajectories. The first three groups constitute the long term backbone of active members in the system: First, a stable core containing 13 actors holding core positions throughout most of the observation period. Second, a fading core composed of members who initially held core positions but moved to peripheral positions over the observation period. Third, a stable periphery of 26 long-term members who however only participate occasionally. Next to these three groups, there are two groups of drop-outs: First, long-term exits, i.e., members who held core or peripheral positions for long periods of time but eventually left the platform. Second, short term exits, i.e., members who left the system only shortly after becoming active for the first time. This last group is also by far the largest and indicates the large amount of volatility and relational turnover (Lazega et al., 2017) surrounding the small stable core of longstanding members. These results indicate a large degree of concentration on a small core of highly active members, which, partly driven by demographic factors, is however in decline. This densely connected core also provides trade opportunities for a group of stable, casual members as well as a volatile group of short-term and perhaps experimental members. Especially the latter is indicative of the fact that recruiting new members in community currency systems is hard (Collom, 2005). Based on this overall disaggregated pattern of membership trajectories, the platform seems to be at risk of fading out with its long-standing core members as it struggles to replenish itself.

From scout to scout: the social network of corporate opportunity search

Research problem and background. Paper three moves to the empirical setting of a multinational corporation, where it concerns itself with the internal structures and processes by which externally sourced knowledge is distributed across large-scale and dispersed organizational settings. In their efforts to navigate fast-moving, globalized, and highly competitive innovation landscapes, firms incorporate external knowledge as a safeguard against lock-in and to promote recombinant innovation (Hargadon & Sutton, 1997; Kaplan & Vakili, 2015; Kogut & Zander, 1992). Accordingly, a firm's absorptive capacity, i.e., its ability to source knowledge from the external environment and integrate it into internal processes, becomes crucial (Cohen & Levinthal, 1990). To enhance this capability, organizations rely on innovation scouting, which has also been studied in the context of R&D globalization: One common scouting strategy involves establishing scouting units or 'listening posts' in remote high-tech clusters (Birkinshaw & Hood, 2000; Gassmann & Gaso, 2004; Gassmann & Von Zedtwitz, 1999; Patel & Vega, 1999), which facilitate the sourcing of localized knowledge and benefit from spillovers (Almeida, 1996; Bathelt & Glückler, 2014; Maskell, 2014). However, despite the benefits of innovation scouting, formal scouts often face challenges in effectively mediating between a firm's external environment and internal operations. According to Decreton et al. (2021), formal scouts may fail to be effective brokers when they are disconnected from a firm's core. This paper seeks to challenge the conventional view of scouting, which confines it to formally defined roles and units. Such a narrow perspective risks overlooking the more organic and informal practices that employees engage in to mobilize innovation opportunities throughout the firm. Instead, the paper applies a more comprehensive approach that recognizes the interrelation between formal and informal scouting activites, i.e., scouting by employees which are not formally designated scouts. Informal practices are often embedded within formal organizational structures, and both aspects are mutually intertwined, a characteristic of knowledge management typical in large multinational corporations but relatively understudied (Foss et al., 2010). Given these considerations, the paper's primary interest is in the differences between formal and informal scouts with respect to their scouting practices and especially regarding their capability to span organizational and geographic boundaries within the organization. Based on this approach, the paper provides an image of how formal and informal scouting integrate to facilitate knowledge exchange across the divisional and regional structure of the organization.

Case, data, and methods. To answer questions regarding the differences between formal and informal scouts as well as differences in the mobilization of opportunities by way of boundary spanning, we study innovation scouts and the internal network of opportunity search at a multinational chemical corporation that employs over 100,000 people at more than 200 sites in more than 90 countries. Due to the nature of informal scouting, the scout population was not known a priori. We accordingly employed a snowball sampling strategy to identify both formal and informal scouts, for a total of five sampling waves. We distinguished formal and informal scouts via self-assignment based on a succinct definition of scouting that was developed together with management representatives. This strategy yielded a total of 431 scouts (distributed across eight divisions and 26 countries), of which 126 reported to be formal and another 295 to be informal scouts. Based on this set of scouts, we constructed the scout-to-scout network of opportunity search with the following name generator: "Who of your colleagues have helped you to carry out your scouting activities successfully over the past two years?" We then measured the scale of scouting based on (i) the amount of time (hours) spent on scouting per week, (ii) whether a scout served as a key contact to external partners, and (iii) the number of internal projects to which a scout provided input. We furthermore measured the scope of scouting using an Ansoff matrix capturing differences regarding the scouted technology and its target market; Based on this representation we used hierarchical clustering to distinguish core and radical scouting scopes. Finally, we measured network activity by out- and indegree centrality and captured organizational and geographic boundary spanning by recording the fraction of a scout's ties that connects them to scouts in other units and other sites. Based on these measures and a set of control variables, we employed Bayesian hierarchical generalized linear models to investigate the differences in scouting scale, scope, and connectivity between formal and informal scouts.

Findings and discussion. In terms of the scale and scope of their scouting work, formal scouts, particularly those in the Research and Support Divisions (RSDs), dedicated more time to scouting, participated in a greater number of projects, acted as gatekeepers to other organizations, pursued more radical innovation leads, and played a more active role within the scouting network compared to informal scouts. This is not surprising, given their formal assignment of tasks and resources. However, informal scouting as a whole greatly augmented the corporate search for innovation opportunities: Informal scouts substantially increased overall scouting time, project contributions, and knowledge exchange, highlighting the importance of incorporating informal scouting into broader innovation strategies.

Instead of unidirectional or hierarchical dependence, we furthermore find that informal and formal scouts are interdependent, with opportunities travelling both ways and producing an interrelated scout-to-scout communication network. This holds two implications for corporate innovation: First, the scout-to-scout network facilitates the efficient redirection of opportunities, whether originating externally or internally, to units within the organization where they hold innovative or productive potential. This process involves identifying and tapping into untapped knowledge reservoirs within the company, thereby supporting peripheral innovation (Glückler, 2014). Second, this mobilization of resources reduces redundant search efforts and fosters the potential for recombining existing knowledge, stimulating novel insights and innovative breakthroughs.

Finally, the analysis reveals how the firm's organizational and regional structure influences the flow of knowledge across the scouting community: The RSDs served as structural bridges that facilitate knowledge flow between the different Business Divisions (BDs), which would otherwise be disconnected from each other. Especially formal RSD scouts, with their strong focus on radical innovation, effectively brought together diverse pools of 'core' knowledge scattered across the BDs. In general, there was no significant difference between formal and informal scouts to bridge organizational boundaries; However, across geographic boundaries, formal scouts displayed a disproportionate tendency to establish bridging ties. A likely explanation for this discrepancy is in the higher degree of visibility and potential functional legitimacy enjoyed by formal scouts due to their status, enabling them to more effectively mobilize and rewire innovation opportunities across the globalized geography of the corporation. The findings of the paper imply that formal scouts should be incentivized to not only source external knowledge but also investigate the easily overlooked internal sources of innovation through the establishment of ties to informal scouts. Due to the nature of their work, informal scouts are more closely involved with the core business and can contribute to the 'grounding' of innovation opportunities. The core task for innovation management is then to first develop a strategy for the identification of informal scouts and then to stimulate integration of informal and formal scouting practices.

Interrelated technology evolution in the field of plastic recycling: A main path analysis

Research problem and background. This paper argues that to understand the emergence and evolution of technological fields it is critical to account for the interrelated nature of technological knowledge and development. Rather than investigating individual technological trajectories, as has been common practice in empirical studies (Fontana et al., 2009; Ho et al., 2014; Magee et al., 2018; Mina et al., 2007; Verspagen, 2007), it proposes to take a broader point of departure by studying bundles of related technologies. This focus on interdependence is founded on two key characteristics of technological development: First, it is path dependent (David, 1985; Dosi & Nelson, 2010) in that the emergence and adoption of technical innovation often depends on existing knowledge embedded into firm histories (Breschi et al., 2003; Makri et al., 2010), with which new knowledge is recombined to create cumulative progress (Kogut & Zander, 1992). This recombination often carries a distinct geographical component in that it is likely to occur in the form of local knowledge spillovers (Jaffe et al., 1993). Second, network effects, standardization, and increasing returns (Arthur, 1989; Farrell & Saloner, 1985; Majumdar & Venkataraman, 1998) turn technology development into a collective action problem where individual adoption decisions are interdependent. These basic premises call for an approach that can identify (inter)dependencies in the course of technological development to uncover structural junctures, such as convergence or divergence, and which allows decision-makers to exploit synergies and identify opportunities for recombination.

Case, data, and methods. The paper develops a method to trace interrelated technological development based on main path analysis, and applies it to the field of plastic recycling, which is characterized by complex, multi-stage processes and distinct technological approaches. To achieve this, the study relies on patent data, which are well suited for identifying path dependence and technological interdependencies due to their long-term availability, their technological breadth and depth, and their inclusion of references to earlier related patents (Verspagen, 2007). To map technological progress in plastic recycling, a selection strategy based on CPC technology classes yields an initial data set of 116,021 patent applications, which reduces to a total of 61,321 patent families. References to earlier related patents can then be used to construct a citation network, which in this case yields a total of 57,956 family-to-family edges. Such a citation network in turn lends itself to main path analysis, which refers to a family of methods that have the goal of extracting chains of citations representing the most 'important' technical developments, i.e., the main path(s) (Hummon & Dereian, 1989; Liu et al., 2019). Main path analysis typically consists of two steps: First, the computation of 'flow' weights for edges (or vertices), such as Search Path Count (SPC) weights (Batagelj, 2003), which are also used here. Second, the traversal of the citation network along the highest weight edges, departing from prespecified start points. The selection of start points is crucial for the structure and composition of the resulting main path, in general, and is also a core component of the identification of technological (inter)dependencies presented in this paper. Here, we use the top k=20 patents in terms of SPC vertex weight for each of three example technologies: First, separation technologies, which are an important foundation for many recycling processes. Second, textile recycling, which is characterized by additional complications compared to the more conventional recycling of packaging materials. Third, enzymatic recycling, which deviates from conventional techniques, such as mechanical recycling, in its use of biotechnological processes to break down polymers. For these three example domains, the paper first performs a comparison of basic structural metrics of their respective main paths to assess their internal cohesion. It then uses backwards reachability and average geodesic distances among the start patents in a combined main path network to identify structural interdependencies (or lack thereof) in the development of the three domains.

Findings and discussion. Based on the approach outlined above, the paper first identifies clear differences across the three example domains with respect to size and maturity, organizational composition, and main path structure. On one end of the spectrum, enzymatic recycling, which relies on biological processes for depolymerization, is characterized by topical homogeneity and a strongly clustered main path structure, and is dominated by a single patent portfolio (belonging to the French biotechnology startup Carbios). Textile recycling, at the other end of the spectrum, is topically more heterogeneous than the other subdomains, which is consistent with its inclusion of distinct fiber-based materials (such as PET for carpets or carbon fibers). This heterogeneity becomes structurally visible through a high main path diameter and long start-to-start geodesic distances, which represent a more 'long-armed' structure of the trajectory. Finally, separation technologies, the most mature of the three domains, lies inbetween the other two in terms of main path clustering and applicant concentration but also exhibits a high degree of topical homogeneity. The paper then investigates structural dependence in a combined main path network and identifies two key patterns across the three example domains: First, enzymatic recycling is largely independent of the other two domains; This finding is plausible because enzymatic recycling relies on a largely different knowledge base (biotechnology) compared to more conventional approaches (relying on mechanical engineering and polymer chemistry) and has so far been applied mostly to packaging applications but not yet textiles. Second, there is a unidirectional historical dependency of more recent developments in textile recycling on earlier advancements in separation techniques. Because textiles are often multicomponent materials which require separation before further processing, this finding is consistent with a solution-driven development pathway, where new applications are spurred by advances in cross-sectional techniques. Here, the importance of individual organizations becomes visible again, with e.g. carpet specialist firm Mohawk Industries being a key driver of separation technologies for textile applications. The paper's main contribution lies in its application of simple graph-theoretical measures to quantify the structure of main path networks, which hitherto have mostly been used as a basis for qualitative analysis in terms of their constituent patents. We demonstrate that these measures relate to the organizational and technological structure of the represented trajectory and show how they can be used to identify and quantify patterns of technological (inter)dependence (or lack thereof) among a set of technology domains. This approach is useful for the identification of bottleneck or bridging technologies and their core providers to inform policy or strategic decision-making.

Cohesion and convergence in technological fields: A main path analysis of the bioeconomy, 1900-2020

Research problem and background. Paper five is a continuation of the focus on interrelated technological development of paper four; It departs from the well established concepts of technological trajectories and paradigms (Dosi, 1982; Dosi & Nelson, 2010) but broadens its perspective to the technological field as a nexus of interdependent technological development across multiple subdomains. Its main interest is in uncovering the long-term patterns of convergence that occur in the evolution of such heterogeneous technological fields (Hacklin et al., 2009; Kodama, 1992). Empirically, the paper explores the structural development of the bioeconomy over a period of more than 100 years. The bioeconomy is a prime example of a heterogeneous technological field: Demarcations often comprise both traditional industries, such as agriculture or forestry, as well as more recent, high-tech sectors, such as the life sciences or biosynthetic materials (McCormick & Kautto, 2013; Staffas et al., 2013); In the same vein, underlying scientific knowledge bases are also heterogeneous and include, e.g., the biological, chemical, and engineering sciences. In this setting, the goal of the paper is to assess structural patterns of cohesion and convergence in the technological field of the bioeconomy. In pursuit of this goal, it follows the following research questions: First, does the bioeconomy constitute a cohesive technological field and what structural positions do its subdomains occupy? Second, to what degree is the bioeconomy connected with outside technologies and does the field close over time? Third, are there patterns of convergence within and across the bioeconomy subdomains and how do these unfold over time? Based on these questions, the paper's contributions are twofold:

It first aims to provide a better understanding of the emergence of the bioeconomy, which has attracted considerable policy and funding effort but remains opaque in terms of its inner structure and development pathway. It second provides a simple method for identifying patterns of convergence based on main path analysis, which can aid future research on the topic of technological convergence.

Case, data, and methods. As for paper four, paper five relies on patent data to trace long-term technological progress. To map the bioeconomy technological field and its subdomains, it builds on previous studies which provide a definition of the bioeconomy in terms of the Cooperative Patent Classification (CPC) (Wackerbauer et al., 2019). We reclassify this collection of technology classes to distinguish a total of six subdomains: Biochemistry (1), Life sciences (2), detergents and dyes (3), foods and tobacco (4), textiles, paper and wood (5), and agriculture and fertilizers (6). This selection strategy yields a total of 4,096,554 patent applications, which reduce to 1,525,980 patent families. The paper then uses two different features of patent data to measure technological cohesion across subdomains: First, it relies on coclassification among CPC technology classes (at the maingroup level), i.e., the tendency of two technology classes to appear together in patents' classification records. Second, and as in paper one, it uses patents' inclusion of references to earlier related patents to build a citation network, which in this case contains close to 6 mio. edges. Based on these measures, the paper first relies on simple descriptive statistics and visualization techniques to explore the aggregate cohesion of the field. Second, it again uses methods of main path analysis (Hummon & Dereian, 1989) to trace long-term chains of knowledge flow across the six subdomains. As in paper one, the paper uses Search Path Count (SPC) edge weights (Batagelj, 2003) and initializes a forward-backward traversal at the top 10% of nodes in terms of SPC vertex weight in each of the six domains. Based on the obtained main paths, the paper develops a simple measure of structural convergence, which for a given period inspects the reduction in parallel paths as well as the share of outgoing paths that accrues to each domain. This method is applied to each of the six domains to explore patterns of both structural as well as inter-domain convergence.

Findings and discussion. Based on the methods and data outlined above, the paper first investigates the overall cohesion of technologies in the field based on coclassification and identifies two structural characteristics: First, it is not closed with respect to other technologies but integrates strongly with technologies outside of the scope of the bioeconomy, and increasingly so over time. Second, its internal cohesion is not homogeneous across its subdomains: Technologies from the wood, paper and textile domain, for example, are strongly connected to non-bioeconomy technologies but much less so to the other technologies within the field and even to other technologies in their own domain. These findings raise questions regarding the consistency of broad delineations of technological fields that span largely unrelated industries. The paper then uses main path analysis to assess structural and inter-domain convergence. All domains exhibit structural mergers of main paths after an initial phase of path creation. They differ in terms of timing and intensity, with three convergence phases becoming visible: Textiles, paper & wood technologies start to converge throughout the 1940s, detergents and foods start in the 1970s, and life sciences, biochemistry and agriculture domains only throughout the 1990s. Especially for the earlier phases, structural convergence is not yet accompanied by domain switching of main paths; During the second phase, however, most of the application domains converge to biochemistry trajectories, which is in line with the historical rise of biotechnology. This rise is shown to be heavily intertwined with the development of life sciences applications, as indicated by considerable overlap of patents in the two domains' main paths. Both life science technologies as well as biochemistry furthermore share a common origin in food technologies, as indicated by high shares of food patents on the paths in the first half of the observation period. This indicates the importance of high-impact 'carrier applications' (first food technologies and then the life sciences) as vehicles for the development of field-defining, cross-sectional technologies, such as biotechnology. Given the exploratory nature of this study, theoretical models that sketch the conditions under which such cross-sectional technologies can evolve and branch from their origin applications are still underdeveloped and would make for a valuable foundation for more exploratory empirical studies such as the one presented here.

5 Conclusions

Relational processes shape all levels of economic activity, from localized informal exchange to the emergence of global technological fields. While relational economic geography has long advocated a spatial perspective that is sensitive to the ways in which people, organizations, and their outputs are interdependent (Bathelt & Glückler, 2003; Boggs & Rantisi, 2003; Yeung, 2005), empirical research still rarely matches the conceptual richness of this perspective. Accordingly, an overarching goal of this thesis has been to reduce this gap by building on novel methods and empirical opportunities to implement relational research designs (Bathelt & Glückler, 2018). In the pursuit of this goal, the studies contained in the thesis have shown how relational processes condition consumers' localized navigation of exchange uncertainty, structure the transfer of knowledge across globalized organizations, and drive the emergence of technological fields through linkage of distinct knowledge domains. In their combined characterization of a knowledge-based economy, these studies shed light on how actors navigate uncertain environments in a way that is both path-dependent and relational, and how such navigation accumulates to produce long-term development trajectories.

While the focus of this thesis was not on the development of new methods, it is strongly influenced by methodological curiosity. In my search for new and interesting methods, I was especially on the lookout for ways to capture the core tenets of the relational approach: contextuality, path dependence, and contingency (Bathelt & Glückler, 2011): First, this thesis follows a long tradition of capturing *contextuality* through network representations (Granovetter, 1985). While networks are uniquely capable of linking individual behaviors and outcomes to structural conditions and processes (Raub et al., 2011; Stadtfeld et al., 2020), geographical uses of network analysis have overwhelmingly not taken stock of these capabilities: Most geographic network analyses operate at an aggregate level, treating places not as contexts for economic action but themselves as the unit of analysis (Glückler & Panitz, 2021). I here instead treat geographical context as enabling or constraining social cohesion and knowledge flow. Next to networks, the thesis furthermore builds on multilevel models which quantify the degree to which effects of interest vary across different contexts and thus represent a step away from universalist statistical modeling (Gelman & Hill, 2007). While they could prove to become a valuable tool for providing a quantitative equivalent to the calls for 'rich description' (Gibson-Graham, 2014) and have been known to geographers for a while (Jones, 1991; Srholec, 2010), multilevel methods don't seem to have widely caught on, so far. Second, the presented studies use two sets of methods to explicitly capture *path dependence* from two different perspectives: Paper one uses relational event models (Butts et al., 2023) to investigate the micro-structural mechanisms which link past choices to current choices in the emergence of an exchange network. This micro-level perspective is useful to identify the potentially self-reinforcing social and economic behavioral mechanisms that lead to aggregate structural features such as centralization or lock-in. Papers four and five, on the other hand, use main path analysis to get a bird's eye view of the flow of ideas over extensive periods of technological development. This macro-level perspective captures the large-scale structural features of field emergence and convergence produced by cumulative and thus path-dependent innovation. Third, while *contingency* is a more difficult to capture concept, it can be loosely related to a Bayesian approach that takes seriously the probabilistic nature of inference about non-deterministic social processes while incorporating a mechanism to consistently update probabilistic beliefs held about the world in the face of new evidence. Based on these considerations, I hope to show how novel methodological approaches can unleash the potential of the paradigm of relational economic geography.

I want to close this synopsis by highlighting some of the limitations of the work presented here and by offering what I believe to be a plausible way forward to remedy them. First, my treatment of geographical context and space is often only cursory or implicit and more weight is put on social and economic factors. While this negligence is generally supported by the relational view, which maintains that space provides the context in which social and economic processes occur but should not itself be the primary object of study (Bathelt & Glückler, 2018), there is also no fundamental reason why geographic context could not take a more prominent role in some of the research designs presented here: The approach of paper one could for example be extended to a comparative design by also considering exchange patterns in 'footloose' platforms, thus being more explicit about what kinds of relational navigation mechanisms are exclusive to face-to-face-enabled trust and social cohesion (Storper & Venables, 2004), and what mechanisms might be more generally applicable. Developing a better understanding of the relationship between relational practices of navigation and space would be valuable not only for academic purposes but also as a foundation for network design and management.

Second, while the thesis relies on a variety of methods, these are almost exclusively quantitative in nature. While such an approach sacrifices depth for breadth, it was largely driven by necessity arising from the nature of the studied cases: For example, investigating the evolution of networks over years or even decades naturally limits the feasibility of a qualitative approach. Nevertheless, qualitative research is invaluable for developing the theoretical foundations of relational patterns and for providing meaning to structure (Glückler & Panitz, 2021; Pachucki & Breiger, 2010), which mixed-methods designs such as the SONA method (partially employed in paper three, Glückler et al., 2020) aim to facilitate. Looking forward, increasingly sophisticated tools for assisting qualitative content analysis (e.g., transcription and coding) (Hoxtell, 2019) and new sources of textual data will likely blur the lines between qualitative and quantitative research. This will only increase the appeal of approaches able to integrate the two paradigms, such as sequential methods like SONA, or more formal methods, for which Bayesian analysis can form a basis (Humphreys & Jacobs, 2015).

Third, in its theoretical characterization of how individual or organizational practices of navigation get stabilized into distinct structures, the thesis has mostly relied on economic arguments, founded, e.g., in transactional uncertainty due to information asymmetries or the cumulativeness of knowledge as a factor of production. While these are undoubtedly important, they tend to overlook the institutionalized nature of much of economic life. This has not gone unnoticed in the field of economic geography, where institutional theory has recently attracted considerable attention (Bathelt & Glückler, 2014; Lenz & Glückler, 2021; Rodríguez-Pose, 2013). With its focus on stable patterns of interaction based on mutual expectations (Bathelt & Glückler, 2014), institutional theorizing is highly compatible with network approaches: Positional (blockmodeling) and micro-structural (relational event models) approaches, for example, are well suited to investigate stabilized interaction patterns, their drivers, and the relational role systems arising from them. In the context of geography and institutions, network analysis seems an especially promising avenue to pursue for two reasons: First, institutional approaches have so far either relied on aggregate indicators at the regional level (Rodriguez-Pose & Di Cataldo, 2014) or on in-depth, qualitative studies (Lenz & Glückler, 2021), and network approaches might provide a middle ground or even a link between these. Second, similarly to geography, network analysis is itself relatively scarce in terms of theory, with much of its theoretical foundations being derived from neighboring fields, such as sociology or organization studies. As such, institutional theory could not only enrich economic geography but also stimulate theoretical development in network science, and in the process provide a theoretical bridge between the empirical focus of geography and the methodological toolkit of network analysis. Together, the combination of refined relational methodology, an ever increasing supply of digitized data sources, and deeper theoretical grounding opens up a universe of research opportunities for geographers, if only we can navigate it.

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Part II

Publications

1

Navigating Uncertainty in Networks of Social Exchange: A Relational Event Study of a Community Currency System

Abstract. This paper analyzes the structure of socially embedded exchange under uncertainty in the context of a community currency system in Germany. We discuss three relational and path-dependent mechanisms - experience-based trust, networked reputation, and public reputation - which serve as navigation practices to mitigate uncertainty. We furthermore associate these mechanisms with observable structures of exchange, namely repeated transactions and reciprocity, transitivity, and provider activity, and discuss differences in product-inherent uncertainty as a source of variation in network structure. Based on original observations of more than 4,000 transactions over a period of 8 years, we use relational event models to demonstrate that the history of transactions exhibits structure consistent with the three hypothesized mechanisms, with some variation across different types of transactions. This variation is partly in line with differences in product-inherent uncertainty, but we also discuss alternative sources of variation related to organizational and institutional conditions of the exchange system.

Introduction

Over the last decade, platform (Langley & Leyshon, 2017; Srnicek, 2016) or sharing economies (Ravenelle, 2017) have been arising on national and global scales, but also on the local level of cities and neighborhoods. Community currency systems are one organizational type in the emerging landscape of localized alternative economic practices (Castells et al., 2017; Sánchez-Hernández & Glückler, 2019), organizations (Parker et al., 2014) and spaces (Leyshon et al., 2003). Community currencies are platform organizations that facilitate the exchange of goods and services among their members by relying on a proprietary, localized currency. As such, they however do not usually try to replace the 'regular' market systems they are embedded in. Instead, their goals are mostly in supporting local community building, which they pursue by stimulating generalized reciprocity through "multilateral bartering" (Collom, 2012, p. 7) at the community level. In some instances, such as the case studied here, the currency implemented by the platform is time-based: the value of a good or service is proportional to the time it takes to provide it. Three hours of lawn mowing, for instance, are equivalent in value to three hours of car repairs, house cleaning, babysitting or the provision of health services. Community-based exchange systems have been found to be effective community responses to periods of economic crisis (Carnero et al., 2015; Valor & Papaoikonomou, 2016), to the marginalization of social groups, e.g. the unemployed, poor or elderly individuals (Collom, 2008; Seyfang, 2004), and to a need for access to otherwise unavailable social capital. Academic research so far has especially focused on the motivations to engage in exchange (Collom, 2011; Ozanne, 2010) and the efficacy and impact of these platforms on local economic development (Dittmer, 2013), sustainable consumption (Seyfang, 2006; Seyfang & Longhurst, 2013) or health benefits (Lasker et al., 2011). Here, we examine a less studied aspect of community currencies, namely the structure of exchange. We consider community currency systems to be an interesting real world setting in which to explore the nature of socially embedded, path-dependent and inherently uncertain exchange for three reasons: First, while community currency systems implement 'marketplaces' for the exchange of goods and services, many differ from conventional markets in their strong social embedding of exchange relationships produced by their explicit focus on social inclusion. Due to the personal and social quality of exchange that comes with this focus, they provide a unique opportunity for investigating social mechanisms in the emergence of exchange structure. Second, community currencies support the exchange of a broad range of different types of goods and services, which enables the study of variation in exchange behavior across different types of transactions. And finally, for community currency systems the full list of participants is in principle known due to their membership model, and they often keep time-stamped digital records of transactions for managing accounts, making them one of the arguably scarce instances of a fully observable exchange system.

Building on this empirical opportunity, we revisit extant theory on social exchange and informational economics to (a) link well-known social mechanisms or 'practices of navigation' (Beckert, 1996; Glückler, 2014) – namely experience-based trust, networked reputation, and public reputation (Glückler & Armbrüster, 2003) – to structural features of exchange histories, and (b) to assess variations in the reliance of such navigatory mechanisms across settings of varying exchange uncertainty (Ekelund et al., 1995). Because research on social exchange behavior has largely been preoccupied with experimental research designs (Kollock, 1994; Lawler et al., 2008; Molm et al., 2007; Skvoretz & Lovaglia, 1995), our analysis offers an original opportunity to elaborate on theories of exchange structure by drawing on real-world transactions over long periods of time. To do so, we use relational event models (Butts, 2008; Stadtfeld & Block, 2017) to analyze the structural evolution of the exchange system. Section 2 discusses uncertainty, its sources, and its effects on the social structure of exchange through navigation practices. Section 3 elaborates on the organization and workings of community currency systems, illustrates the research context in general and provides further information on the case at hand as well as the available data. Section 4 gives an overview of methodology and measurement and section 5 discusses findings. Finally, section 6 concludes with a discussion and an outlook beyond the factors that we focus on here.

Theory

Institutional, transactional, and product-inherent uncertainty

One of the most important, albeit still often neglected aspects of economic exchange is uncertainty. We follow Beckert (1996, p.804; cf. Knight 1921) to conceive uncertainty as "the character of situations in which agents cannot [fully] anticipate the outcome of a decision and cannot assign probabilities to the outcome". If the structure of exchange is not fixed by experimental design – as is often done in studies of social exchange – different structures emerge in contexts of varying uncertainty (Kollock, 1994). Similarly, DiMaggio & Louch (1998) use real-world data to show that the more uncertain transactions are, the more likely are they to be conducted within social circuits of family or friends than with unknown third parties. Uncertainty can on the one hand arise from a lack of rules framing a market, e.g. legally enforceable standards of professions, qualifications, certificates or contracts (institutional uncertainty) or it may arise from information asymmetries and the possibility of opportunistic behavior by transaction partners (transactional uncertainty) (Glückler & Armbrüster, 2003). Uncertainty in exchange of goods and services furthermore varies with the informational characteristics of the product[1] and depends on the extent to which a user can assess its quality and the timepoint of a possible assessment (Ford et al., 1988). According to the particular informational characteristics, at least three types of product qualities are prevalent (Ekelund et al., 1995): search, experience and credence. A product is said to exhibit search characteristics if its qualities can be assessed before purchase, with reasonable effort and expertise (Nelson, 1970). In contrast, experience characteristics can only be evaluated after the purchase, either because no prior information is available or because to obtain such information would come with disproportionate cost. Finally, sometimes it will be almost impossible at all to meter the quality of a product even after the purchase (Darby & Karni, 1973; Dulleck & Kerschbamer, 2006). Given

[1]From here on, we use the term product (Lancaster, 1966) to explicitly include both physical goods as well as services into our discussion.

the lack of professional expertise, for example, a patient can hardly know if the treatment prescribed by a doctor is appropriate or even necessary. The perceived quality of such a credence product is ultimately based on the credibility of the provider and the trust between provider and user. Whereas physical goods tend to be characterized predominantly by search and experience characteristics, most services tend to be subject to experience or credence. Hence, services are usually much harder to evaluate than goods (Clark, 1993; Gabbott & Hogg, 1994; Zeithaml, 1981). The distinction of search, experience and credence characteristics then offers the opportunity to, at least conceptually, define a continuum of quality-uncertainty, ranging from search goods (e.g. materials and many household goods) at one extreme to services (e.g. car repair, health services, management consulting) at the other extreme. Given the uncertainty related to credence products, the literature on services marketing has turned to the question of how users choose service offerings from the market, with a strong emphasis on interpersonal mechanisms such as word-of-mouth (Bansal & Voyer, 2000; Freiden & Goldsmith, 1989; Friedman & Smith, 1993). In the context of a community currency system, all of the aspects of institutional, transactional and product-inherent uncertainty are at play. Most community currency systems do not have the size and resources to standardize or certify the contents of transactions or the qualifications of their providers beyond what is regulated by the general legal system. On the contrary, people are often encouraged to provide whatever they can to counteract the widespread notion on behalf of (potential) participants that they have nothing to contribute (Ozanne, 2010), related to the idea that ‘getting is giving’ (Whitham & Clarke, 2016). Accordingly, there are often no quality checks or other restrictive regulations, which would even further spur participants’ self-consciousness regarding their ability to provide something of value (although sometimes these platforms implement rating systems, which was however not the case here). However, the lack of institutional framing of transactions incurs the institutional uncertainty to assess the quality of a specific good or service on the individual members. Similarly, members of the exchange system act in situations of transactional uncertainty whenever the supplier's ability, effort and motivation to deliver quality products remain opaque. This is even more pronounced in situations where actors have difficulties in evaluating a good's quality or when they are unaware of its flaws (Dimoka et al., 2012), such as in the case of experience and credence products. Information asymmetries between supplier and buyer thus induce transactional uncertainty relating to qualities of the specific transactions and issues of product credibility (Erdem & Swait, 2004; Mishra et al., 1998). Such transactional uncertainty is amplified in exchange settings where there is high variability of the quality of offered goods or services, as has been shown to be the case for time community currency services (Aldridge & Patterson, 2002; Lee et al., 2004). Finally, the informality typical for many community-based exchange systems also opens up uncertainty relating to awareness and availability (Savage & Bergstrand, 2013). The case of a community currency system, in which members trade a broad range of goods and services, thus offers a particularly appropriate real-world situation to explore the variation of exchange structure across transactions associated with different levels of uncertainty.

Practices of navigation: trust, networked and public reputation

Navigation describes a user's effort to screen alternatives and make preferred choices from ever-more overwhelming product offerings. The more prevalent experience and credence characteristics are, and the higher the overload of information, the higher is the uncertainty of choosing appropriate products and exchange partners. Hence, "navigation refers to all services [or practices] that collect, filter, qualify, and evaluate information about products to allow users and consumers to attach value to particular products and to make optimal choices among alternatives" (Glückler, 2014, p. 1202). In today's open markets, there is a plethora of services providing consumer guidance, such as test institutes, customer ratings, or certificates. However, these usually are not available in small-scale community exchange platforms, which differ from conventional markets not only in terms of availability of navigation services but also in terms of the motivations to participate in exchange. How, then, do actors in a community currency system choose what to exchange with whom? Building on the navigation practices identified in earlier models of relational provider choice (DiMaggio & Louch, 1998; Glückler & Armbrüster, 2003), we aim to align social practices of navigation with the evolving structure of a transaction network. Such social navigation practices do not only come naturally when more formal alternatives are lacking but also fit the nature of exchange in a community currency system, which often strongly focus on building social bonds among participants that in turn serve as guidance in future exchange. In this context it is useful to distinguish between the reach and richness of information (Evans & Wurster, 1997): Reach refers to the number of users that receive information, whereas richness characterizes the completeness, quality and validity of information on a product. Usually (but not necessarily) there is a tradeoff regarding the reach and richness of information provided by different search mechanisms. Here, we propose the following navigation mechanisms and their corresponding informational and structural features:

Experience: repeating on proven providers. Direct experience with transaction partners is associated with high informational richness: Having (repeatedly) received or experienced high-quality services in a face-to-face setting reduces uncertainty and transaction costs by building trust in the reliability of the provider (Kramer, 2002; Molm, 1994; Storper & Venables, 2004). If existing experience helps to bridge transactional uncertainty, then it is necessary to examine the exchange history of previous transactions among market participants (Boyle & Bonacich, 1970; Koch et al., 2009; Kramer, 2002; Kreps & Porteus, 1978; Perkins & Rao, 1990). Accordingly, one would expect that, where available, direct personal experience strongly conditions current provider choices, resulting in observable commitment behavior (Boussard et al., 2019; Kollock, 1994; Yamagishi et al., 1998) and 'micro social orders' (Lawler et al., 2008). Commitment behavior is furthermore expected to be especially pronounced in the community currency context, where participants often build social bonds through exchange. Such personal experience is however often not available or only available for a select number of cases and therefore has limited reach. Actors, then, have to rely on other means of informing their choices in the absence of direct experience.

Networked reputation and referrals: triadic closure. Under conditions of uncertainty and in the absence of own experience with proven providers, user choice also builds on the experience of their peers: "an actor's pattern of market relations are informational cues on which other market actors rely to make inferences about the quality of that actor" (Podolny, 2001, p. 34). Hence, we conjecture that users will draw on the experience of trusted third parties, whenever direct experience with a proven provider is lacking. Search by credible referrals from trusted contacts describes a mechanism of networked reputation (Glückler & Armbrüster, 2003), which has been found in professional services of management consulting as well as in marketing studies on consumer search [e.g. in the context of 'word-of-mouth' advertising; Bansal and Voyer (2000)]. Networked reputation constitutes a compromise between richness and reach as it taps into 'indirect experience' which generalizes the availability of direct experience through recommendations and in turn increases reach. Structurally, such an uncertainty-reducing mechanism then provides a meaningful explanation for triadic structures in settings of economic decision making based on the mechanism of referral, as have been found e.g. in international trade (Kim & Skvoretz, 2013), the internationalization of service firms (Glückler, 2006) or venture capital investments (Batjargal, 2007).

Public reputation and visibility. Finally, public reputation is opposite to direct experience in the richness-reach spectrum, with high informational reach but low informational richness: It represents a baseline of 'common knowledge' about a provider and thus information that is easy to gain access to. However, this 'common knowledge' is also shallow and thus only has relatively low value for informing provider choices. Accordingly, public reputation creates an overview of offerings and often provides an initial filtering lens rather than shaping final decisions (Glückler & Armbrüster, 2003). Public reputation emerges from high levels of activity and visibility: controllable efforts, such as advertisements, or (partly) uncontrollable processes, such as rumors and hearsay can contribute towards a provider's visibility (both in a beneficial or in a harmful way). The mechanisms discussed here are not new: Trust and reputation have gained significant attention as determinants of exchange structure in the wake of the 'informational revolution' in economics (Gambetta, 1988; Kreps & Wilson, 1982). Commitment behavior has become one of the core structural features in social exchange studies (Cook & Emerson, 1978; Kollock, 1994; Lawler & Yoon, 2006; Lawler et al., 1993). Similarly to Schilke et al. (2017), who study the effectiveness of trust production across goods with different informational characteristics, we here combine the above literatures to build a framework for analyzing the structural evolution of exchange networks. Given varying levels of product-inherent uncertainty and social structures that help mitigate such uncertainty, it is reasonable to expect that transactions involving products with higher inherent uncertainty (i.e. most services) are more likely to be embedded in uncertainty-mitigating structures than lower-uncertainty transactions (i.e. search goods). The next section will first elaborate on the research context and data and then discuss the measures and the statistical methodology utilized to assess the prevalence and variation of the above mechanisms across community currency exchanges.

Research design and context

Research context: A community currency system in southern Germany

Over the past 30 years, community currency systems have become increasingly popular in many countries, such as in Spain (Carnero et al., 2015), Italy (del Moral-Espin, 2017), Great Britain (Lee et al., 2004), New Zealand (Ozanne, 2010), the USA (Collom, 2012) or Japan (Hayashi, 2012). They are seen as an effective response to economic crisis, in particular in southern European countries, where recent economic crises hit particularly hard and a steep rise in newly founded platforms could be observed (del Moral-Espin, 2017; Valor & Papaoikonomou, 2016). However, economic benefits for local labor markets have often not been confirmed in practice (Peacock, 2000; Williams et al., 2001). Especially for time-based community currencies, such as time banks, it has also been argued that these economic benefits are in conflict with the egalitarian principle of 'equal time, equal value' (Collom, 2012), and that they could jeopardize more profitable exchanges in the real economy (Dittmer, 2013). Instead, many scholars highlight the social and ecological role of community currencies in fostering social inclusion and cohesion through reciprocal provision of help (Cahn, 2004; Seyfang, 2004) and in promoting local sustainable consumption (Seyfang & Longhurst, 2013). We here study a German community currency system with a time-based currency (*Zeittauschring*) located in a medium sized city in southern Germany. The studied system was founded in the mid-1990s by volunteers active in local solidarity and sustainability initiatives and was still run by volunteers by the time the analysis was conducted. Regionally, the platform covers primarily the urban area of its focal city but also accepts participants of neighboring cities and villages. Transactions are conducted utilizing a proprietary currency called 'talents' (*Talente*), where one talent corresponds to a time investment of 15 minutes. Before receiving new services from others, new members need to provide services amounting to 14 talents. There are also limits to the balance of a member's account, where the negative balance must not exceed -20 talents and the upper limit is 200 talents. While the system ran an office for administration and consulting services (staffed itself by volunteering members earning talents for their service), the platform did not employ a formal broker to coordinate transactions, as is sometimes the case for community currencies. Instead, transactions were primarily coordinated through a regularly published 'exchange newspaper' (*Tauschzeitung*) containing a register of requests and offerings. Service transactions are usually realized on a peer-to-peer basis but members also use events, such as summer or Christmas parties, to exchange foods and other goods. While utilization of a time-based currency and the emphasis on egalitarian exchange indicates a 'service credits' system akin to a time bank in Seyfang and Longhurst's (2013) classification of different community currency systems, the prevalence of goods exchanges and the central accounting system are more similar to what they term ‘mutual exchanges’, such as e.g. LETS systems in Great Britain (Aldridge & Patterson, 2002; Williams et al., 2001). While the time-based currency works unanimously for services, it is less straight-forward for the pricing of goods. Hence, the trade of goods is often subject to bargaining between buyer and seller. Generally, the many ‘gifts’ and ‘satisfaction bonuses’ recorded in the payments suggest that members have been relatively generous with their ‘earnings’. Regarding demography, the platform had experienced two trends that are quite characteristic for many community currency systems (Collom, 2008; Valor & Papaoikonomou, 2016): demographic ageing and feminization. While most members were in their thirties or forties in 2009, the average member is in their fifties or sixties today, and about 75 percent of the members were women at the point of conducting the data collection.

Data: Time-stamped transactions

While the platform was founded in the 1990s, it was formalized as a registered association in 2008 and implemented an online accounting system for transactions in 2009, which made possible the ex-post collection of data. Our analysis uses transaction data for a period of eight years, between 2009 and 2017. The initial set of raw data contained more than 6,000 transactions. We excluded all transactions related to member exits, clearance of accounts etc. to identify a total of 4,454 peer-to-peer product transactions. Each transaction includes a record of (i) the ID of the provider, (ii) an ID of the user, (iii) a timestamp (day-month-year) of the transaction as well as (iv) a verbal content description of the product[2]. Regarding the overall exchange activity, Figure 1.1 (bottom) illustrates a rather steady number of transactions, with a peak around the fourth year of the observation period and

[2]In principle, a further element of each transaction is given by price. However, while the analysis of pricing seems promising in its own right, we here restrict ourselves to the analysis of the structure of transactions, i.e., who exchanges with whom, to stay in line with the theoretical and methodological approach of the paper. Given the highly social nature of exchange in the observed community, pricing seems to be more a ‘part of the game’ than an essential driver of exchange structure, making the focus on exchange structure a reasonable restriction, in our view.

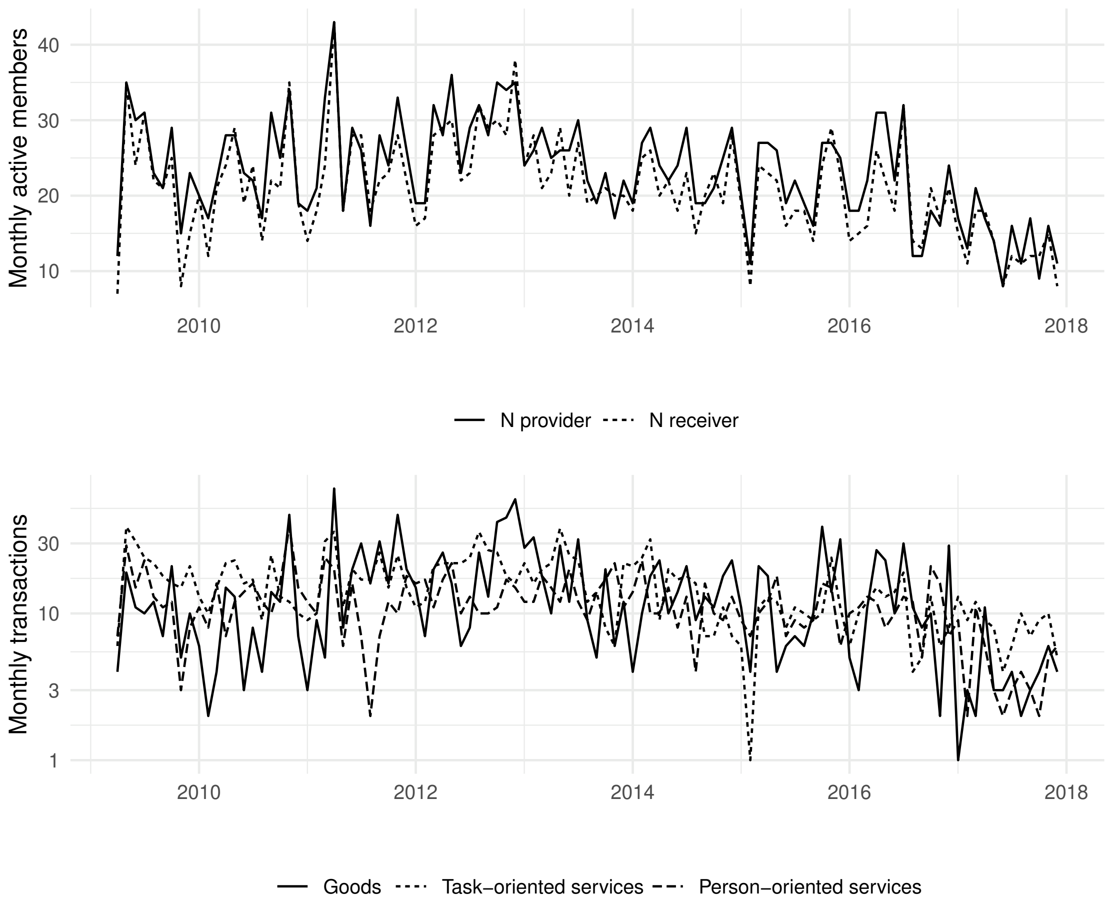


Figure 1.1: Number of monthly active members and transactions, 2009-2017 (log scale for monthly transactions).

a slight decline towards the end. The count of monthly active members varies between 10 and 40 during most of the observation period but shows signs of decline during the last 3 to 4 years of the observation period. Monthly active members represent around 40 percent of registered members for most of the observation period, with this ratio also decreasing to around 25 to 30 percent towards the end. This pattern confirms reports of a spokesperson of the organization who reported to have had trouble in canvassing new members while simultaneously having to deal with an ageing population and membership decline. There is some slight seasonality in the data, with, e.g., a relatively persistent low in august, which is likely related to summer holidays. Sharp upward spikes in activity could furthermore be related to community events, which are often used to trade foods and other goods.

Participants recorded the type of transaction with unstandardized (free-text) content descriptors. Initially, we built on Collom's (2012) typology which we extended to classify all transactions into a total of 28 product categories (Table 1.2). Among the most frequently traded products were homemade or homegrown foods, IT-related services, as well as haircuts, massages, alternative medical services and various services related to household and gardening. In a next step, we assigned the product types to three groups that are meant to differently represent search, experience and credence features: physical goods, object-related services (e.g. cleaning or repairs) and person-related services (e.g. massages, tutoring, or socializing), which loosely relate to distinctions made in service research [Lovelock and Yip (1996)][3]. These categories differ in informational characteristics, so that relational transaction behavior can be expected to vary between them. Transaction choice presupposes that there is a sufficient number of alternatives to choose from. We compute the total number of unique providers and users for any given product, as well as the median number of providers and users within the span of a year preceding any transaction event (cf. Table 1.2 in section 4). Across all transactions, the weighted mean of this statistic is at roughly 11 different providers and 14 consumers during the preceding year. In the case of smaller product categories, such as lodging, lectures and entertainment or language tutoring, the median of providers or users goes down to 1 person, only. Such variation in supply or demand concentration needs to be considered when investigating choice behavior. Finally, because we lack information on actor attributes, a problem commonly known in relational event data (e.g. Stadtfeld & Geyer-Schulz, 2011; Vu et al., 2015), our analysis focuses solely on the relational conditions of transactions through time.

[3]Note that we refrain from directly assigning search, experience, or credence labels. This is because the well-known issue of one product potentially being characterized by multiple characteristics (Ford et al., 1988). Trades in physical goods, person-related services, and object-related services facilitate a less ambiguous classification while still differing in ease of evaluation and uncertainty.

Methods: A hierarchical relational event model of provider choice

Models for relational event data (Butts, 2008) have been developed for relational data which describe discrete interactions observed through time rather than relational 'states', such as friendship. We employ this approach to model the socioeconomic mechanisms behind the evolution of exchanges. More specifically, we use the Dynamic Network Actor Model (DyNAM Stadtfeld & Block, 2017), a particular variant of relational event model. The DyNAM models relational event dynamics via two conditionally independent sub-models (Stadtfeld & Block, 2017): a rate model, which determines when/the rate at which an actor becomes active, and a choice model, which determines to whom an active actor sends a tie. We here omit the explicit modeling of individual activity rates (Stadtfeld et al., 2017) as we are more interested in the structure of choice behavior and the modeling of rates would arguably be more fruitful when data on personal attributes were available (e.g. on the amount of available time due to employment or family status). The DyNAM choice model is specified by the conditional logit model originally developed in econometrics (McFadden, 1973). In the context of relational events, the model evaluates the observed partner choice against the range of potentially available actors either in terms of actors' individual characteristics, or in terms of the joint history of the chosen target with the 'choosing' actor through past interactions or other relations. In the present case of community currency transactions, we specify a model to reflect how user i chooses a provider j for the delivery of a product. Drawing on additional data containing information about the dates of members' entries and exits, we construct a 'choice set' of potential transaction partners that varies in time to not misrepresent the choice scenario by including individuals who have either already left the organization or who have not yet joined. We furthermore extend the DyNAM choice model to accommodate comparisons over different types of transactions as discussed in section 3.2 by utilizing a hierarchical model structure (DuBois et al., 2013; Gelman & Hill, 2007). For model estimation, we rely on Bayesian methods as implemented by the probabilistic programming language Stan (Carpenter et al., 2017). The Bayesian approach allows for a straightforward implementation of the hierarchical model structure and comes with other benefits, such as arguably more intuitive interpretations of statistical uncertainty and, given the right choice of priors, regularization of extreme estimates as a guard against overfitting (Gelman et al., 2014). A more technical description of the model specifications is available in the appendix to this paper.

Measures of exchange behavior

Our data do not allow for direct observation of the social institutions and underlying beliefs of trust and networked reputation because we have no information on the communication or social relationships between the members of the platform. Yet, we can conceive the pattern and history of transactions that trust and networked reputation (i.e. word-of-mouth and interpersonal referrals) would produce. We use the following measures for the navigation practices discussed in section 2:

Trust and experience. To capture the structural trace of transactions embedded in buyer-supplier relations based on trust and positive experiences, we rely on three separate statistics: product repetition, partner repetition, and reciprocity. (i) *Product repetition*[4] is a dummy variable which equals one if provider j delivered the same product c (the good at choice) to consumer i previously during the past year[5] (Table 1.1) . (ii) In a similar fashion, *partner repetition* is a dummy variable which equals one if provider j delivered any other than the good at choice) to user i over the past year . Whereas partner repetition reduces transactional uncertainty by offering experience about the commitment and quality of a partner, product repetition reduces the uncertainty of both relational risk attached to the partner, and quality or performance risk attached to the product (Das & Teng, 2001). (iii) Finally, *reciprocity* is a dummy variable which indicates whether user i provided any product to provider j before seeking a product from j over the past year .

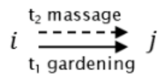
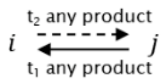
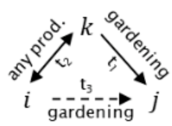
[4] The technical literature also refers to the notion of repeating on a previous transaction relation as an inertia effect (Butts, 2008; Stadtfeld & Block, 2017).

[5] For a more detailed discussion of windowed effects, see (Stadtfeld & Block, 2017). In the case studied here, a time window of 1 year seemed to adequately reflect the flow of activity in the studied system.

Reciprocity has a key role in establishing trust between transaction partners and can lead to the development of stable emotional bonds beyond mere exchange of goods and services (Molm et al., 2009; Simpson et al., 2018). Reciprocity furthermore also resembles the notion of partner repetition in that it reduces the relational risk attached to a provider by giving information on their general conduct in former transaction scenarios .

Networked reputation. Networked reputation refers to situations where a buyer is referred to a supplier by a third party. Whereas we cannot observe actual incidents of social referrals in the data available here, we can observe the transaction structures that referrals would generate. Based on the assumption that exchange of goods or services may serve as situations where information on former transactions is exchanged or recommendations are made and that users incorporate such information into their future exchange decisions, we investigate transitive patterns of referral. We measure such *transitive referral* as a dummy variable indicating if the good at choice c was received from provider j by former trading partners k of choosing actor i. To make sense as an indicator for situations of referral, the ordering and content of the elements of the triad are relevant (Table 1.1): First, an intermediate actor k needs to have received good c from j. Then, k interacts with the focal actor i, where direction and content are irrelevant as the interaction is just seen as a proxy or opportunity for exchange of information about their experiences. And finally, i may or may not choose j as a provider of good c. As for the other statistics, we utilize a one-year time window. Furthermore, in section 2, we indicated a conditional logic of direct and indirect experience (Bansal & Voyer, 2000). As an illustration, consider the likelihood of choosing a restaurant after reading a negative online review. The chances to still visit the restaurant are different for those who have not yet visited this restaurant compared to those who have made positive first-hand experience. In the first case, the restaurant is likely to be discarded as an option while in the second case the first-hand experience (high richness) might outweigh the negative review (low richness). To account for this conditionality, we include an interaction term of transitive referral and

Table 1.1: Network statistics

Statistic	Schematic Example	Formula
Product repetition$_{ij}$		$\mathbb{I}_{E_t}(e: i_e = i \wedge j_e = j \wedge c_e = c)$
Partner repetition$_{ij}$		$\mathbb{I}_{E_t}(e: i_e = i \wedge j_e = j \wedge c_e \neq c)$
Reciprocity$_{ij}$		$\mathbb{I}_{E_t}(e: i_e = j \wedge j_e = i)$
Transitive referral$_{ij}$		$\mathbb{I}_{E_t}\big(e: j_e = j \wedge c_e = c \wedge i_e \in \{k: (k,i) \in E_{t_e-t} \vee (i,k) \in E_{t_e-t}\}\big)$
Product activity$_j$		$\sum_{e\in E_t} \mathbb{I}(j_e = j \wedge c_e = c)$

Note: The consumer is denoted as i and a potential provider as j. E_t refers to the set of all events in a time period 1 year prior to the current event at time t and i_e and j_e refer to the consumer and provider of a past event e, respectively. In the transitive referral statistic, E_{t_e-t} refers to the set of events between the event e and the current one. $\mathbb{I}(.)$ denotes the indicator function which returns 1 if its argument is true and 0 otherwise.

product repetition. With the inclusion of the interaction effect, the transitive referral main effect relates to the change in likelihood of an exchange given no prior direct experience and the combined effect of both direct and indirect experience is given by the sum of the main effects and the interaction effect.

Public reputation. Public reputation refers to situations of widely available 'common knowledge' about an actor as supplier of a certain good. Apple, for instance, enjoys high visibility through its public reputation as a supplier of top-end smartphones, with the iPhone being one of the most sold devices in the market. As an indicator for public reputation, we accordingly include product activity. This counts the number of times actor j provided the good at choice c during the last year (i.e., a product-specific indegree statistic). High product-specific activity can be argued to indicate higher visibility and popularity in the system, thus serving as a measure of public reputation. Furthermore, it also serves as a control for specialization or supply concentration which would otherwise be captured by transitive referral: If someone regularly provides a product which is not provided by many others, this information would only be reflected in the transitivity statistic when excluding product activity, leading to overestimation of the transitivity effect. We scale product activity by subtracting the mean and dividing by twice the standard deviation of each of the product types, respectively, to make the coefficients more comparable to those for the dummy variables and to aid computation (Gelman, 2008). Data preparation and preprocessing of model statistics were performed with the R programming language (R Core Team, 2017).

Results

To investigate the structural characteristics of the exchange network unfolding over time, we rely on two different relational event models as well as descriptive statistics (Table 1.2). Of the two models, the first (M1, Figure 1.2; see also Appendix) varies the coefficients for the relational choice statistics discussed in section 3.4 over the three transaction groups of physical goods, object-related services and person-related services. The second model (M2, Figure 1.3) varies the coefficients over the lower-level classification of the 28 product types. Model coefficients can be interpreted in terms of relative probabilities (odds) on a log scale (Stadtfeld & Block, 2017): E.g., a coefficient of 2.0 for person repetition would indicate that a transaction $\exp(2.0) \approx 7.4$ times more likely to be conducted with a person with whom an exchange has taken place before than with a person with whom no exchange has been conducted before. Conversely, a negative coefficient would indicate a decrease in the likelihood of a transaction being conducted with someone when an exchange had taken place with them before.

Generally, there is a strong tendency to repeat transactions of the same type with the same provider. About 43% of all transactions are such repetitions of earlier

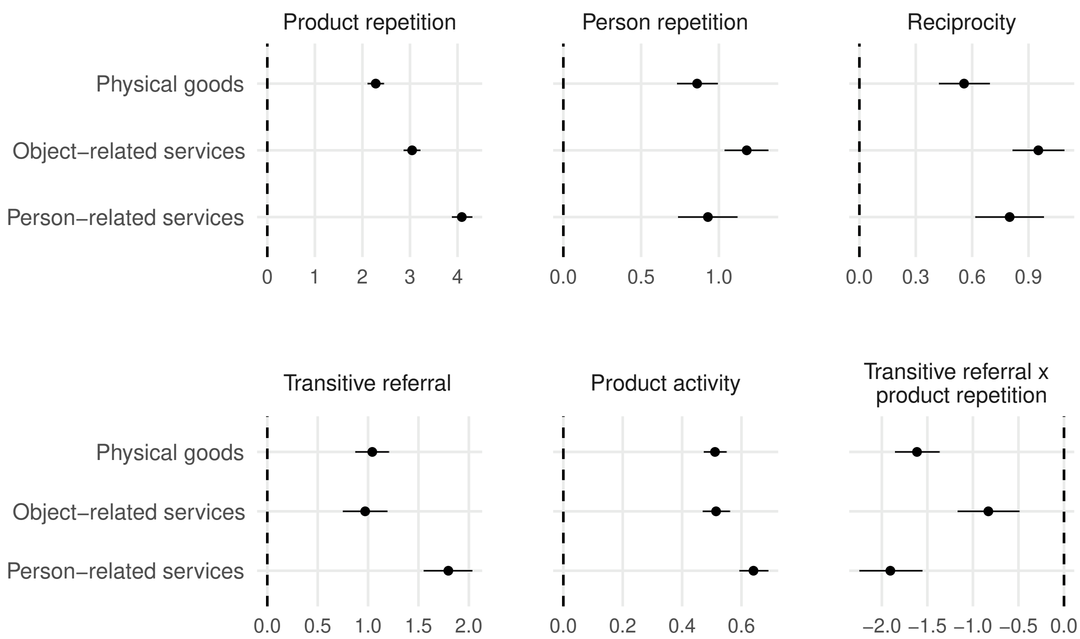


Figure 1.2: Coefficients for model 1 (M1). Coefficients can be interpreted as log-scale relative probabilities (log odds). Points indicate posterior means, error bars indicate 90 percent uncertainty intervals.

transactions (Table 1.2). This is also reflected in the large positive coefficients for product repetition in M1 (Figure 1.2): In the case of person-related services, the odds that a specific service is provided by someone who provided that service to the recipient before are around 60 times higher than for a provider who did not[6]. For goods transactions, this number is smaller but still relatively high, at around 8 to 10 times the odds. Finally, object-related services lie in between, with an odds-ratio of around 20. Generally, this ordering is consistent with expectations based on the differential informational characteristics, with services transactions – and arguably especially person-related services – relying to a stronger degree on direct, personal experience than goods transactions (see also the aggregate counts in table 1.2, which indicate a similar ordering but with less of a difference between physical

[6]Exponentiating the raw coefficient yields the odds-ratio:

$$\frac{P(y_{ij}=1|ProdRep_{ij}=1)/P(y_{ij}=0|ProdRep_{ij}=1)}{P(y_{ij}=1|ProdRep_{ij}=0)/P(y_{ij}=0|ProdRep_{ij}=0)}.$$

In this case, this gives $\exp(4.1) = 60.3$. Note also that this is the effect size conditional on $TransRef = 0$ because of the interaction term.

goods and object-related services). However, regarding the specific transaction types, there is also variability within the three groups (Figure 1.3). Within the group of physical goods, for example, product repetition is more likely for food, craftwork and especially books, and less likely for other non-food goods, such as rummage or clothing.

Within the cluster of person-related services, language tutoring stands out with a very large coefficient yet under conditions of only a small number of actual and median recent providers (13 and 1, respectively). Given in addition that there is no distinction between different languages here, this likely indicates that there is not much of a choice with respect to language tutors. Nevertheless, for the other (and more numerous) types of person-related services, such as haircuts, massages or (alternative) medical services or advice, there is still also a marked tendency towards provider repetition. The data are consistent with the expectation that information about a person's conduct in exchange (i.e. not related to their proficiency in providing a specific service) plays a role in choosing a provider. Structurally, this can manifest as (a) repeated exchange with a provider across different product types or (b) as reciprocal exchange. Looking at the effects for provider repetition (a), we see a positive and significant tendency across all three groups of products, generally though to a smaller degree than for product-repetition. Compared to the latter, differences between the three groups are also smaller and more uncertain, with the largest effect observable for object-related services at around 3 to 5 times the odds of choosing a provider that has been chosen before over someone who has not (for a product different from the good at choice). This effect is somewhat smaller for transactions in physical goods but also for person-related services. Reciprocity generally displays a similar pattern in terms of effect sizes and variation over the three groups of transactions, with positive effects across the board but a somewhat smaller coefficient for physical goods, especially when compared to object-related services.

As for product repetition, there is again some within-group variation. One transaction type that stands out is personal tutoring, with above average effects

Table 1.2: Descriptive statistics for transactions

Type	**Total** N	**Providers** tot. / med. past year	**Consumers** tot. / med. past year	**Product repetition** N / %	**Person repetition** N / %	**Reciprocity** N / %	**New** N / %	**Transitive referral** N / %
Physical goods								
Homemade & processed foods	490	61 / 18	74 / 25	220 / 45	206 / 42	204 / 42	174 / 36	54 / 31
Raw foods	357	41 / 13	57 / 16	183 / 51	195 / 55	132 / 37	101 / 28	48 / 48
Various goods	258	73 / 15	59 / 17	50 / 19	114 / 44	69 / 27	111 / 43	17 / 15
Books & movies	144	46 / 9	47 / 11	39 / 27	43 / 30	21 / 15	68 / 47	9 / 13
Arts, crafts & jewelry	120	33 / 6	48 / 10	28 / 23	37 / 31	20 / 17	61 / 51	20 / 33
Plants	100	29 / 6,5	39 / 10	20 / 20	41 / 41	29 / 29	42 / 42	6 / 14
Clothing & materials	53	32 / 5	24 / 4	5 / 9	21 / 40	16 / 30	26 / 49	2 / 8
Rentals of goods	47	22 / 4	16 / 3	14 / 30	34 / 72	27 / 57	10 / 21	0 / 0
Group total	1569	50.7 / 13.0	45.5 / 12.0	559 / 36	691 / 44	518 / 33	593 / 38	156 / 26
Object-related services								
IT problem-solving & advice	381	58 / 16	59 / 18	223 / 59	204 / 54	216 / 57	96 / 25	26 / 27
Gardening & harvest	178	53 / 14	51 / 11	72 / 40	70 / 39	73 / 41	58 / 33	4 / 7
Office, writing & translation	152	56 / 11	48 / 11	56 / 37	75 / 49	49 / 32	53 / 35	6 / 11
Cleaning, light tasks & errands	150	56 / 10	39 / 10	57 / 38	50 / 33	55 / 37	59 / 39	6 / 10
Craftsmanship & Repairs	149	38 / 11	63 / 14	33 / 22	47 / 32	37 / 25	75 / 50	12 / 16
Transport	133	55 / 11	43 / 9	31 / 23	59 / 44	42 / 32	61 / 46	12 / 20
Trips/Event support & organization	132	45 / 10	52 / 10	21 / 16	42 / 32	43 / 33	62 / 47	9 / 15
Sewing & ironing	131	23 / 5	53 / 11	52 / 40	40 / 31	37 / 28	53 / 40	14 / 26
General advice & problem-solving	118	48 / 9	38 / 7	45 / 38	67 / 57	47 / 40	36 / 31	2 / 6
Heavy tasks	43	20 / 4	23 / 3	10 / 23	16 / 37	18 / 42	16 / 37	0 / 0
Automotive & bike	41	15 / 3	15 / 3	13 / 32	13 / 32	12 / 29	19 / 46	5 / 26
Lectures & entertainment	28	11 / 1	20 / 3	3 / 11	7 / 25	4 / 14	17 / 61	2 / 12
Group total	1636	47.8 / 11.1	49.1 / 11.7	616 / 38	690 / 42	633 / 39	605 / 37	98 / 16
Person-related services								
Massages	321	32 / 10	57 / 15	190 / 59	99 / 31	148 / 46	99 / 31	32 / 32
Haircuts & cosmetics	317	14 / 4	57 / 19	218 / 69	61 / 19	110 / 35	75 / 24	34 / 45
Medical services & advice	314	39 / 11	62 / 13	175 / 56	116 / 37	144 / 46	88 / 28	31 / 35
Socializing	133	21 / 3	39 / 11	65 / 49	37 / 28	39 / 29	43 / 32	26 / 60
Personal tutoring & advice	79	28 / 5	29 / 5	34 / 43	52 / 66	31 / 39	17 / 22	2 / 12
Language tutoring	54	13 / 1	14 / 2	36 / 67	14 / 26	12 / 22	16 / 30	0 / 0
Babysitting & care	22	16 / 3	12 / 2	5 / 23	7 / 32	3 / 14	11 / 50	0 / 0
Hospitality & lodging	9	6 / 1	6 / 1	1 / 11	0 / 0	0 / 0	8 / 89	1 / 13
Group total	1249	26.5 / 7.1	51.5 / 13.6	724 / 58	386 / 31	487 / 39	357 / 29	126 / 35
Summary	4454	42.8 / 10.7	52.7 / 14.1	1899 / 43	1767 / 40	1638 / 37	1555 / 35	380 / 24

Note: 'New' here refers to transactions between actors that had no direct contact before (i.e., no product or person repetition in both directions). For the transitive summary statistics, percentages refer to the shares of all new ties, not the shares of the totals.

for both person repetition as well as reciprocity. This indicates that people tend to get help with personal issues from providers they already know from other exchanges. Somewhat harder to reason about are the differences between different kinds of physical goods, such as lower reciprocity for homemade and processed foods (e.g. cakes) compared to higher reciprocity for raw foods (e.g. homegrown vegetables). Validation of possible explanations of this discrepancy (e.g. related to the circumstances of trade in either peer-to-peer transactions or trade events) would require more in-depth analysis, e.g. based on qualitative, interview-based approaches or additional contextual data. We also find the data to be consistent with the mechanism of networked reputation by way of high positive main effects for the transitive referral statistic. This indicates that new exchanges are more likely to be initiated with providers to whom an indirect connection through intermediate exchange partners already exists than with providers on which no direct or indirect product-specific information is available. While exchanges in physical goods and object-related services are at a similar level (2-3.5 the odds of a transitive exchange vs. a non-transitive exchange), this is especially pronounced for person-related transactions (around 5-7 times the odds). Beyond this baseline effect, the strong negative interaction of transitive referral and product repetition provides support to the conditionality implied by different levels of informational richness inherent in different mechanisms: Given that information on a provider's proficiency with respect to a specific good is available through direct experience, additional indirect information through third parties yields little to no increase in the likelihood of that provider being chosen. However, in the case of physical goods, the interaction effect even surpasses the main effect in absolute size. This might also be an indication of an effect being at play that relates to the distribution of limited resources.

If, say, a provider distributes their (finite) harvest of homegrown vegetables among other members, the information that many of the alters of some 'choosing' actor already received vegetables could also indicate that none or little are left, which would in turn reduce the choosing actor's likelihood of receiving vegetables from that provider. The model and data employed here are limited in disentangling and capturing such aspects of the exchange system more precisely, so we leave a more detailed exploration of these issues for another time. Nevertheless, it is worthwhile to note that the transitivity effect can also be observed for less supply-driven types of transactions, such as harvest help or hairdressing. More broadly, there is some heterogeneity, with some effects – especially in the clusters of physical goods and object-related services – being close to zero, while others remain quite high. It remains speculative to attribute all this variation to differences in product-inherent uncertainty, and we lack additional information to conduct a more systematic analysis here. However, some of the transaction types characterized by weak transitivity (e.g. writing & translation, personal tutoring) show strong effects for person-related direct experience and reciprocity. This suggests that some product types follow a more person- or dyad-specific logic of exchange which, for some reason or the other, is not easily transferred through chains of referral.

Finally, actors are more likely to choose providers that have a rich history of provision in the past. As we have argued, actors can gain a 'public reputation' through frequent activity and growing visibility. Such a pattern is also plausible because many offerings repeat due to, e.g., seasonal availability, or because people specialize in specific contributions while not providing others. Accordingly, this also serves as a control for availability and specialization effects. In terms of type-specific variation, some product types stand out with larger effects, such as, e.g., sewing & ironing services, hairdressing, or plants sales. This indicates a larger degree of concentration on highly active providers in some types of transactions than in others and indeed some of the types with high product activity also show relatively small scores in the median recent providers statistic (Table 1.2; e.g. 4 for haircuts, 5 for sewing services).

To assess how much more information on the variability of relational mechanisms is contained in the idiosyncratic transaction types (M2) vs. the three groups informed by theory (M1), we furthermore compare the two models in terms of out-of-sample model fit. Table 3 provides a comparison in terms of two metrics: ELPD, the expected log pointwise predictive density, and accuracy, the number of correctly

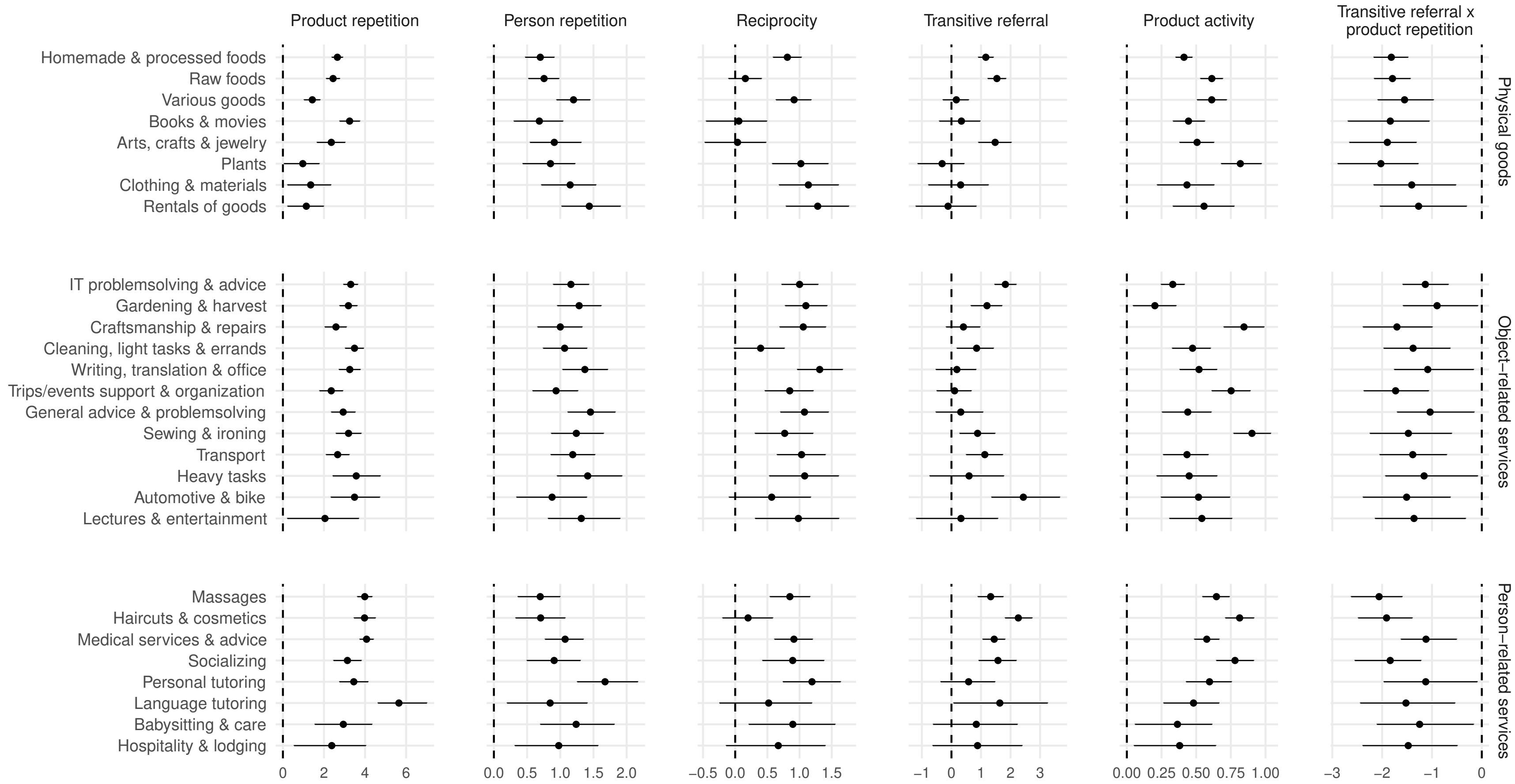


Figure 1.3: Coefficients for model 2 (M2). Coefficients can be interpreted as log-scale relative probabilities (log odds). Points indicate posterior means, error bars indicate 90 percent uncertainty intervals.

Table 1.3: Summary of model fit

Model	ELPD (SE)	Accuracy (%)
M1	-11815.7 (121.4)	34.9
M2	-11206.4 (121.9)	36.5
M2-M1	609.3 (31.4)	1.6

Note: For ELPD, larger values indicate better model fit.

classified provider choices. The former is well justified in terms of statistical theory and makes use of the whole posterior distribution (Vehtari et al., 2017) but is hard to interpret directly. The latter is not as rich but easier to understand. Both values were computed by approximate leave-one-out cross validation to represent out-of-sample fit. Based on the difference in ELPD we see that M2 is significantly better in terms of out-of-sample predictive ability (Table 3). This is generally in line with the strong variation of some of the effects across the different product types we encountered throughout our analysis. However, we also see that the difference in terms of actual classification accuracy is not particularly high.

To conclude, the empirical model captures micro-structures that are consistent with our theoretical model of the navigation practices of repetition (consistent with experience-based trust), transitivity (consistent with networked reputation) and activity (consistent with public reputation). The analysis furthermore captures systematic variation of these structures between different types of transactions, which in part can be explained with product-inherent uncertainty but, as indicated, could also be connected to other institutional or organizational conditions of the exchange system.

Discussion

Our analysis of transactions in a German community currency system supports the literature on social exchange and suggests that structures of repeated exchange, reciprocity and transitivity evolve naturally as a consequence of actors seeking to reduce uncertainty by relying on trust and reputation (Glückler & Armbrüster, 2003; Kollock, 1994; Molm et al., 2009). In our analysis, we found that the structure of the transaction network was strongly shaped by repeated transactions with the same partners on the same products. This dyadic stability also extends to repetitions of the same provider for different products as well as reciprocal exchange. Furthermore, the data are consistent with the navigation practice of word-of-mouth (Bansal & Voyer, 2000) or networked reputation (Glückler & Armbrüster, 2003) in that there is evidence for product-specific transitive closure, taken to indicate indirect experience, when building new transaction relations, i.e. when direct, product-specific experience is lacking. Beyond the presence of these uncertainty-reducing mechanisms, theory on informational characteristics of goods and services furthermore suggests different levels of product-inherent uncertainty, with services transactions often being more uncertain than physical goods. While we found some empirical support that the embedding of provider choices in uncertainty-reducing structures is more pronounced in the case of services than of physical goods, this was not completely unambiguous. Furthermore, the higher resolution model revealed considerable variation between product types beyond the gross clusters of physical goods, object-related and person-related services. In part, these findings probably reflect the known difficulty of assessing search, experience and credence characteristics of products and any classification of products based thereon (Ford et al., 1988). While less ambiguous in terms of product classification, the distinction of services and physical goods utilized here was only a rough indicator of inherent uncertainty, and there are possibilities for overlap. There are also limitations to the approach chosen here, especially with respect to the reliance on electronically collected transaction records, which point towards future research opportunities. Because actor-level information on participants' characteristics, motivations and perceptions was not available retrospectively, the study relied on transaction data alone. There are however many promising research questions that could be addressed by including such data: First, accounting for demography and professions could, e.g., indicate gender asymmetries in exchange behavior or signaling of trustworthiness through qualifications. Second, community currencies purposefully mix social and economic logics. Particular motives for participation, e.g., the degree to which participants care more about social outcomes of exchange (such as building friendships or integrating newcomers) over individual benefit, are likely to imprint on the structure of exchange. As the resulting multiplicity of different sources of uncertainty and rationales guiding exchange behaviors is arguably a feature of many settings of social and economic exchange (DiMaggio & Louch, 1998; Savage & Bergstrand, 2013), direct surveying of exchange motives seems like a worthwhile endeavor. And third, signals of individual satisfaction with an exchange, such as included in many peer-to-peer online exchange platforms, would be valuable for better contextualizing specific exchange structures: product repetition, for example, could both arise as a consequence of positive experiences with an earlier provided service or as a 'fix' for an initially unsatisfactory service, i.e., for conflict resolution. Next to individual participant characteristics, there are also aspects of the organizational context of the exchange system that justify closer attention: First, the small-scale community nature of the studied platform implied that knowledge about specific offerings could spread quickly and along channels other than observable exchange relations, which would not be captured by the (rather crude) exchange-based measure for referrals utilized here. A research design incorporating the co-evolution of both exchange relationships and other social relations suited to capture information flow and the logic of referral could provide a remedy here. Second, high risk transactions (in financial terms) are relatively rare in the community currency context, and, accordingly, differences in the level of uncertainty could be less influential than in for-profit market situations. Accordingly, comparisons across exchange systems with different levels and qualities of uncertainty seem promising. And third, as we discussed in section 4, the studied platform offered opportunities for exchange in both peer-to-peer settings as well as in fair-like marketplaces. Yet, how the organizational circumstances of exchange affect social mechanisms of uncertainty reduction is, to our knowledge, a largely unstudied subject. More generally, these issues highlight the added value of mixed-methods and comparative research designs for the study of community currency exchanges: Additional qualitative data could provide a more comprehensive picture of how exchange structure is conditioned by personal motivations and expectations and comparative cases could provide new insights on how organizational and institutional features of an exchange system affect the structure of exchange. As a final point, the navigation practices discussed here – when viewed from a perspective of structural evolution – provide both mechanisms that consolidate structure (repeat transactions and reciprocity) as well as mechanisms that build structure (transitive referrals). As such they can play an important role in bridging the micro-macro gap (Lawler & Yoon, 1993; Raub et al., 2011; Stadtfeld et al., 2020) in that they help understand the long-term stability and change of exchange systems fraught by transactional and institutional uncertainty. To conclude, we support the debate on uncertainty in social exchange structure by focusing on three social mechanisms, experience-based trust, networked reputation, and public reputation. These mechanisms serve as relational navigation practices, especially in the absence of more formalized navigation systems, as is the case in the studied platform. We have demonstrated that microstructures relating to these mechanisms vary over transactions in different products. This variation was found in part consistent with expectations from theory on product-inherent uncertainty, but we also discussed other potentially influential conditions beyond transactional uncertainty that seem promising in providing a deeper understanding of the nature and evolution of social exchange.

Appendix

This appendix provides some more detailed information on the model specification. The full derivation and justification of the basic DyNAM model can be found in Stadtfeld and Block (Stadtfeld & Block, 2017). We here extend the model to encompass a hierarchical structure (as used in M2). Accordingly, the probability that i chooses j for good or service c and at time point t, conditional on the history of events up to time t and coefficients β, is modeled using conditional logistic / softmax regression:

$$p\left(i \xrightarrow{c} j|E_t, \beta_c\right) = \frac{\exp\left(\beta_c^T s(i,j,c,E_t\right)}{\sum_{k\in A_t}\exp\left(\beta_c^T s(i,k,c,E_t)\right)}$$

Where $s(i, j, c, E_t)$ represents a vector of statistics of the joint history of i and j(such as whether or not i received c from j in the past year) and A_t refers to the set of actors that are active at time t (not including i) The transaction type-specific coefficient vectors β_c are modeled with a multivariate normal prior with mean vector μ and covariance matrix Σ. The covariance matrix Σ is decomposed into a vector of standard deviations τ and a correlation matrix Ω which receive an exponential prior and an LKJ prior, respectively. The mean vector μ receives a normal prior. The full prior specification can then be formulated as follows:

$$\begin{aligned}
\beta_c &\sim \text{MultiNormal}(\mu, \Sigma) \text{ for } c = 1, 2, ..., C \\
\mu_k &\sim \text{Normal}(0, 1) \text{ for } k = 1, 2, ..., K \\
\Sigma &= \text{diag}(\tau)\Omega\text{diag}(\tau) \\
\tau_k &\sim \text{Exponential}(1) \text{ for } k = 1, 2, ...K \\
\Omega &\sim \text{LKJ}(3)
\end{aligned}$$

In the specification of hyperpriors and the implementation of prior structure more generally we follow recommendations for weakly informative priors in a hierarchical logistic model setting and utilize a non-centered parametrization (Stan Development Team, 2020). M1, which varies coefficients only over the three groups of physical goods, object-related services, and person-related services, omits the hierarchical structure as there is a lot of data in each group and the small number of groups would make it hard to correctly identify the scale and correlation parameters. The estimates presented here were obtained using the Stan probabilistic programming language and its variant of HMC sampling (Carpenter et al., 2017), which was run for 8 chains at 1,500 iterations each. Both models showed no divergent transitions during sampling and had reasonably high effective sample size (ESS) and $\hat{R}$-statistics close to 1 for all parameters.

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2

Time Banks as Transient Civic Organizations? Exploring the Dynamics of Decline

Abstract. Time banks have become a popular type of civic organization constructed to facilitate egalitarian economic exchange through a community-bounded currency. Especially after the recent economic crises in Europe, the rise in the number of time banks has been accompanied by relative transience and sometimes short lifespans. We adopt a relational perspective to explore the dynamics of decline in the civic engagement of a time bank in southern Germany. Using methods of longitudinal social network analysis, we analyze the relational processes and individual trajectories of members within the emerging transaction network over a period of eight years. Rather than explaining why, we have found how relational trajectories of members through a structure of core and periphery have led to creeping decline in activity and membership. Given the repeated observation that time banks and other types of alternative economic practices are often characterized by considerable volatility and potential collapse, relational thinking and network analysis are especially suited to unpacking the underlying relational mechanisms that shape these outcomes of volatility and demise.

Introduction

After the outbreak of the financial and economic crisis in the US and many European countries in 2007, alternative economic practices have become celebrated responses to cope with unemployment, precarity, and austerity policies. Yet although the economic recession triggered this new call for an "alternative," diverse (Gibson-Graham, 2008) or community (Gibson-Graham, 2014) practices are neither new nor are exclusively a response to phases of economic downturns. The relative nature of the denominator "alternative" has let its utilizers to conflate a vast variety of attitudes and approaches, ranging from claims to oppose (anti-capitalist), transform (neo-capitalist) or overcome (post-capitalist) the conventional market economy (Sánchez-Hernández, 2017). Despite these strong normative claims, empirical knowledge about the many forms of alternative practices and their ways of working is still limited, especially because a new multiplicity of practices has only started to emerge. Therefore, social and geographical research on new civic forms of organizing is a timely and valuable contribution to explore the contemporary flourishing of alternative economic practices.

The contemporary surge in these practices also marks a period of social and organizational innovation. The trend of building new forms of organizing co-production, local trade, and economic solidarity reinforces the notion of the organizational society. Contemporary societies are increasingly configured around (often multiple) memberships of individuals in organizations, such as corporations, associations, clubs, parties, corporations, charities, and other civil society organizations (Perrow, 1991). Hence, individual agency hardly occurs without touching upon organizational concerns, such as vested interests, normative positions, and the corresponding interdependencies (Lazega, 2018; Lazega et al., 2016). Time banks are one organizational expression of the wide variety of alternative economic practices. Although their number has grown globally (Cahn & Gray, 2015), and especially strongly in Spain in recent years (Valor & Papaoikonomou, 2016), the broader phenomenon of community currencies was already widely discussed before the 2007 economic crisis, e.g. in the UK (Batchelor, 2003; Boyle, 2003; Callison, 2003; Gregory, 2009; Seyfang, 2003a, 2003b; Thrift, 2002), the USA (Collom et al., 2012), and in other countries such as New Zealand (Diprose, 2016), Germany (Meier, 2000), Italy (del Moral-Espin, 2017), or Japan (Hayashi, 2012).

Researchers have often focused on time banks' normative dimension and design principles to strengthen democracy (Thrift, 2002), or to enhance cocreation and reciprocity (Clement et al., 2017). Despite growing empirical research, there is still a lack of understanding of the processes, mechanisms, and dynamics through which time banks evolve and operate. One empirical puzzle researchers have observed is the question why time banks have often been vulnerable and short-lived organizations. Some suggest that community currencies tend to fall short of their ambitious economic goals (Dittmer, 2013; Williams et al., 2001) and struggle with psychological barriers towards participation (Ozanne, 2010). Others find that time banks fail to achieve and retain the critical mass of people to show continuous commitment and long-term engagement (Seyfang & Longhurst, 2013). After the beginning of the economic crisis in 2007, time banks have blossomed in many Spanish and other European cities and regions (Sánchez-Hernández & Glückler, 2019), yet frequently, they began to wither after a few years. How, then, do time banks really work and what are the processes through which they grow and decline?

To answer this question, it is necessary to look behind the normative surface of these organizations and study the empirical practices that define local exchange: its (alternative) economic transactions. It is here that methods of social network analysis are especially helpful (see Chap. 8 by Diani, Ernstson, and Jasny and Chap. 9 by Glückler and Suarsana). They facilitate observing not only individual relations or transactions, but also enable one to map and analyze the overall network structure as well as to trace this structure through time. We argue that the question of how this activity is structured through time is essential for understanding the dynamics of emergence, reproduction, and demise. In this chapter, we offer a brief introduction into relational thinking and the characteristics of social network research, especially in human geography. To illustrate the potential of social network analysis for the study of alternative practices, we present parts of a more comprehensive case study of a time bank in Germany (Hoffmann & Glückler, n.d.). Specifically, we illustrate how formal network analysis may help one to understand the dynamics of organizational life through the lens of the structure and trajectory of individual alternative economic practices in a time bank.

Relational thinking and social networks

The analysis of social networks is inspired by a relational view of the social world. Relational thinking departs from the notion that social actors are not isolated beings who carry out atomistic behavioral scripts. Instead, they are embedded in a social context that constitutes meaning through interaction and institutions: "Relational thinking has become an overarching perspective in social theory that shifts the analytical focus from attributes and categories to context, process, and emergence" (Bathelt & Glückler, 2011, p. 240). In geography, for example, a relational view is opposed to traditional approaches, whose proponents use spatial structures or spatial variables as a starting point for analyses. Instead, adopters of relational geography focus on the actors most relevant to the problem or question under investigation. Researchers thus need to study the positioning of actors and agency within broader contexts of social and institutional relations. Social action is assumed both to be constrained by networks of social relations and at the same time to transform these structures in dynamic ways (Bathelt & Glückler, 2018). The concept of the network denotes a set of nodes that are connected by a certain number of ties. Social science researchers focus on social networks, in other words, the way in which individuals or organizations are related to one another (Wasserman & Faust, 1994). Beyond this formal definition, social network researchers proceed from the assumption that the structure of relationships as a whole conditions the opportunities and constraints for individual action in the network (Mitchell, 1969, p. 2). In other words, although individuals are embedded into a structure of social relations, the network structure itself also has an effect on individual action.

Researchers use the concept of the network on different analytical levels: as theory, as method, and as empirical object (Glückler, 2013). The starting point of a theory of social networks is the axiom of the anti-categorical imperative mentioned earlier. With it, one postulates that explanations of social phenomenasuch as power, cooperation, development, or innovationshould not only include the actors' categorical characteristics but also their embedding in manifold social relations. This relational perspective benefits from both interpretative theories, e.g. actor-network theory, and formal network theories, whose proponents focus on explaining the specific characteristics and effects of networks. Both approaches are necessary because network effects depend on the specific meaning of the relationships in a social context. Network structures thus do not have universal, but contingent, social meanings and consequences (Pachucki & Breiger, 2010). Depending on the research interest, three classes of theories can be distinguished (Borgatti & Halgin, 2011).

First, network theories explain the social consequences of structural network properties. The theories of weak ties (Granovetter, 1973), structural holes (Burt, 1992), structural equivalence (Burt, 1988), or the theory of small worlds (Uzzi & Spiro, 2005) are well-known approaches used, for example, to link individual advantages such as access to information, negotiation potential, or career opportunities with the increasing centrality of actors. However, specific network structures have differential rather than universal advantages. For example, proponents of the theory of structural folds (Vedres & Stark, 2010) postulate that it is precisely actors' cohesion that promotes successful innovation cooperation, which stands in opposition to those theorists focusing on networked resource-access such as structural hole theory. Second, and in contrast to relational theories, adopters of theories of networks are devoted to explaining structural properties of networks from categorical initial conditions. They show that relationships arise, for example, as a function of spatial proximity, similar social status, or common organizational affiliation. Third, proponents of network theories of networks attempt to explain network consequences from structural network properties. Those adopting dynamic approaches to network evolution, for instance, aim to identify geographically and historically specific development paths, in which the formation and dissolution of relationships is dependent on earlier relationships and in which the change of a development path can thus be explained endogenously from the knowledge of earlier structures (Glückler, 2007). Due to the low availability of longitudinal network data on social or corporate relationships, however, network analytical research on the geographical evolution of networks is still in its infancy (Ter Wal & Boschma, 2009).

Researchers can conduct their analysis of social networks with a wide variety of methods, ranging from formal network analysis (Borgatti et al., 2013; Wasserman & Faust, 1994) or qualitative to mixed methods of network analysis (Domínguez & Hollstein, 2014). In any case, the unit of observation is relational data, that is, information about the existence and quality of relationships between actors. In practice, researchers often use already existing (so-called secondary) data, such as official statistics of patent applications or research cooperation. They offer the advantage of relative completeness of information, depending on the quality of the source. On the other hand, primary data collection such as interviews or surveys enables researchers to observe otherwise inaccessible relationships such as the exchange of information, advice-seeking and recommendations, or mutual support and solidarity between persons. With good planning, they also achieve high response rates. The procedures of social network analysis start at different levels. They enable the description and analysis of positions of individual actors at the micro level (e.g., centrality), of subgroups of actors at the meso level (e.g., coherent clusters or functional roles), and of structural characteristics at the macro level of the whole network (e.g., centralization, fragmentation, role structures). Building on relational data and the three scales of analysis (actor, substructure, entire network), there is a continuous advance in methodologies and a growing interest in geography to use these methods (Glückler & Panitz, 2016; Glückler et al., 2017). Three recent examples of interest for geographers are methods for positional (Glückler & Doreian, 2016; Glückler & Panitz, 2016; Prota, 2016), evolutionary (Nomaler & Verspagen, 2016), and multi-level (Brailly, 2016; Lazega et al., 2016) network analysis. In the context of this chapter, we would like to portray a case study of the exchange network of a time bank that is geographically situated in a city in Southern Germany.

A network perspective on time banks

The inception of time banking in its current form is most often attributed to Edgar Cahn, an American law professor, who conceptualized time banks as a community-based measure against poverty in the 1980s (Cahn & Gray, 2015; Cahn & Jonathan, 1992). Time banks respond to a desire for egalitarian economic exchange, which is facilitated by providing a locally limited and community-specific currency. The value of a community currency is equivalent to the time spent on the provision of a service. Participants can valorize their own time through provision of services to other members, and, in turn, spend their income on services provided by others. Of course, the notion of organizing local exchange through a community currency has much older historical roots. Early concepts of community-based economic practices are found in the works of John Bellers (1654 to 1725), Robert Owen (1771 to 1858), or Silvio Gesell (1862 to 1930) (Polanyi, 1944).

In the relatively sparse academic literature, time banks have been associated with community development, social inclusion, and active citizenship (Gregory, 2009; Seyfang, 2004). As such, they have become a tool for local policymaking, aimed especially at the support of disadvantaged neighbourhoods. Despite a rising number of empirical studies on time banks, relatively little is known about the structure and dynamics of exchanges in time banks. Taking a relational view of this type of organization, we conceive a time bank as an evolving network of social exchange (Whitham & Clarke, 2016). As time banks increasingly use digital accounting systems (Cahn & Gray, 2015), transaction records enable us to track each individual transaction and to reconstruct the entire network's process of formation and change.

Although some empirical researchers have partially used transaction data (Carnero et al., 2015; Lasker et al., 2011; Seyfang, 2001), they have rarely exploited it for the analysis of the entire network structure. As an exception, Collom et al. (2008; 2012) collected egocentric data on the relational patterns of focal individual members (so-called ego networks). To take the potential of network analysis a step further, we aim to overcome the limitations of dyadic atomism (Granovetter, 1992) by using the connectivity of the entire network in a dynamic framework. Such an approach offers a unique opportunity to study the process of emergence and demise as well as aspects of systemic stability, which have been identified as a research frontier in previous studies (Valor & Papaoikonomou, 2016).

An urban time bank in southern Germany

We focus our research on a time bank (TB) located in Southern Germany (SG), called TBSG hereafter to comply with our agreement not to disclose its true name. Founded in the late 1990s as a loose coalition of citizens in southern Germany, TBSG was established as a mature legal entity of a charitable association by 2008. The main goal of the time bank is to develop a sustainable network for facilitating neighbourly help. TBSG facilitates the exchange of all goods and services unless prohibited by law or contrary to ethical principles. Offerings are broad and depend on the skills and abilities of the individual members. Services, such as massages, hair cutting, advice, repairs, gardening or teaching, are mainly exchanged directly among members, although the trade of goods, most often self-grown or self-made food, is also common at monthly meetings or celebrations. Members may exchange within the whole region, and some members live in the surrounding towns and villages.

The community currency (so-called ‘talents’) enables members to trade without cash and within a closed economic cycle. One ‘talent’ corresponds to 15 minutes of work; the time value of each trade can be negotiated among the trading partners. Every member registers an account at the beginning of their membership. New members must first earn an initial amount of talents through service or goods before being allowed to use their account. By statute, the account balance is constrained to a lower limit of -20, and to an upper limit of 200 talents (50 hours) to avoid both opportunism and accumulation. Furthermore, a monthly membership fee is collected to cover administrative costs, including a semi-annual magazine, which members use to advertise offerings and requests.

Today, TBSG counts about 100 registered members, not all of whom are necessarily active. The members' demographic composition has changed remarkably over the last 20 years. Although the average age was 43 years, with only 28% of the members being older than 50 years, in 2000, by 2018, a vast majority of 72% of the members were aged 50 or older, resulting in an average age of 56 years. In other words, the member base generation seems not to have changed very much over the observed period. 79% of the members are women. Despite the apparent endurance of TBSG since its foundation, the time bank has failed to rejuvenate its member base. The base's ageing points to the organization's creeping decline, and it reinforces calls for research on the transience of time banks, in particular, and organized forms of alternative economic practices, more generally.

A longitudinal network analysis

We use original relational data on over 6,000 transactions over a period of nine years between 2009 and 2017 to examine the structural characteristics and dynamic changes underlying and shaping the community-building process of TBSG. As members provide a considerable number of services to the time bank itself as organizational assistance, these services would distort the picture of social interaction among members and we have therefore discarded them from the analysis presented here. This leaves 4,477 transactions among a total of 192 participants over a period of more than eight years. We grouped these transactions year by year to construct eight directed networks, which vary in size (number of nodes) as people enter and leave the time bank through the years. As only incomplete data was available for the years 2009 and 2018 and a comparison with the other years is accordingly not possible, we have discarded these years from the dynamic analyses. Although

Table 2.1: Type, number, and connectivity of traded services and goods

	N	Transact./ Ties	Suppl.	Cons.	Density	InCentr.	OutCentr.
Arts and Crafts Production	97	186/158	65	75	.017	.11	.10
Beauty and Spa	107	299/222	78	86	.020	.14	.16
Cleaning, Light Tasks and Errands	116	338/261	82	103	.020	.12	.10
Computer and Technology	121	373/271	79	100	.019	.12	.10
Construction, Installation, Maintenance and Repair	119	312/241	92	92	.017	.12	.08
Entertainment and Social Contact	96	210/162	65	73	.018	.12	.21
Events and Program Support	52	57/54	33	34	.020	.16	.16
Foods	145	881/506	98	128	.024	.28	.12
Health and Wellness	138	601/383	100	119	.020	.09	.06
Office and Administrative Support	70	89/78	45	49	.016	.10	.10
Sales and Rentals of Items	89	143/124	54	67	.016	.08	.06
Transportation and Moving	129	499/358	95	115	.022	.19	.14
Tutoring, Consultation and Personal Services	79	130/106	49	60	.017	.16	.06
Miscellaneous	125	359/239	86	106	.015	.11	.07

people can of course have more than one transaction in a given time period, we have coded a tie from A to B as being present (1) if there is at least one account of A receiving a service from B and as absent (0) otherwise. Note the encoding of tie directions, which here follows the flow of currency: the tie A to B indicates that A paid an amount of talents to B in return for a service provided by B to A.

In accordance with previous classifications (Collom et al., 2012), we distinguish 13 classes of goods and services that are traded through the time bank, plus a 'miscellaneous' category for non-classifiable transactions. In Table 2.1, we present the distribution of participants and transactions as well as a few network statistics across the 14 types of goods and services. In Figure 2.1, we display the corresponding visual graphs for each category of traded services. From a network perspective, the sum of these different category networks represents a multiplex network with fourteen layers as they represent different types of ties. Considering raw counts of transactions and participating members, we observe considerable variation across the different service categories. Among the most frequent are exchange of food and other item trades and health services, followed by computer-related services. Less prominent are event support, office and administrative support, and transportation.

Network density is used to calculate the proportion of the total number of possible ties that is actually realized in a network. It is thus a measure of overall network connectivity and varies somewhat across the different category networks, with food being the most dense and office support and item sales being the least dense. More interestingly, degree centralization is used to assess to what extent a network's transactions are concentrated on a single actor. Centralization varies between 0 and 1, with 1 representing a star-configuration, where all ties are focused on a single actor. We distinguish here between centralization of indegree and outdegree as proxies for assessing the concentration of supply (indegree centralization) and demand (outdegree centralization), respectively. Here again, trade in food peaks with high indegree centralization, indicating a relatively small number of highly active members who supply food to a larger group of members. Other product categories, such as health and wellness, have much lower centralization in both indegree and outdegree, a sign of a more equally spread exchange structure. Tutoring and personal services are also characterized by a discrepancy in supply and demand concentration. Although the number of suppliers is generally lower than the number of consumers across all goods and services, differences are moderate and no trade category is fully monopolized in that only one or very few people supplied a service exclusively.

Evolution and demise of the TBSG network

In the following, we focus on a descriptive analysis of the evolution of TBSG's network structure. Displaying simple aggregate statistics on a year-by-year basis reveals that the number of members, ties, and transactions had initially risen to then revert to a decline of overall activity by 2012/2013. This demise is also

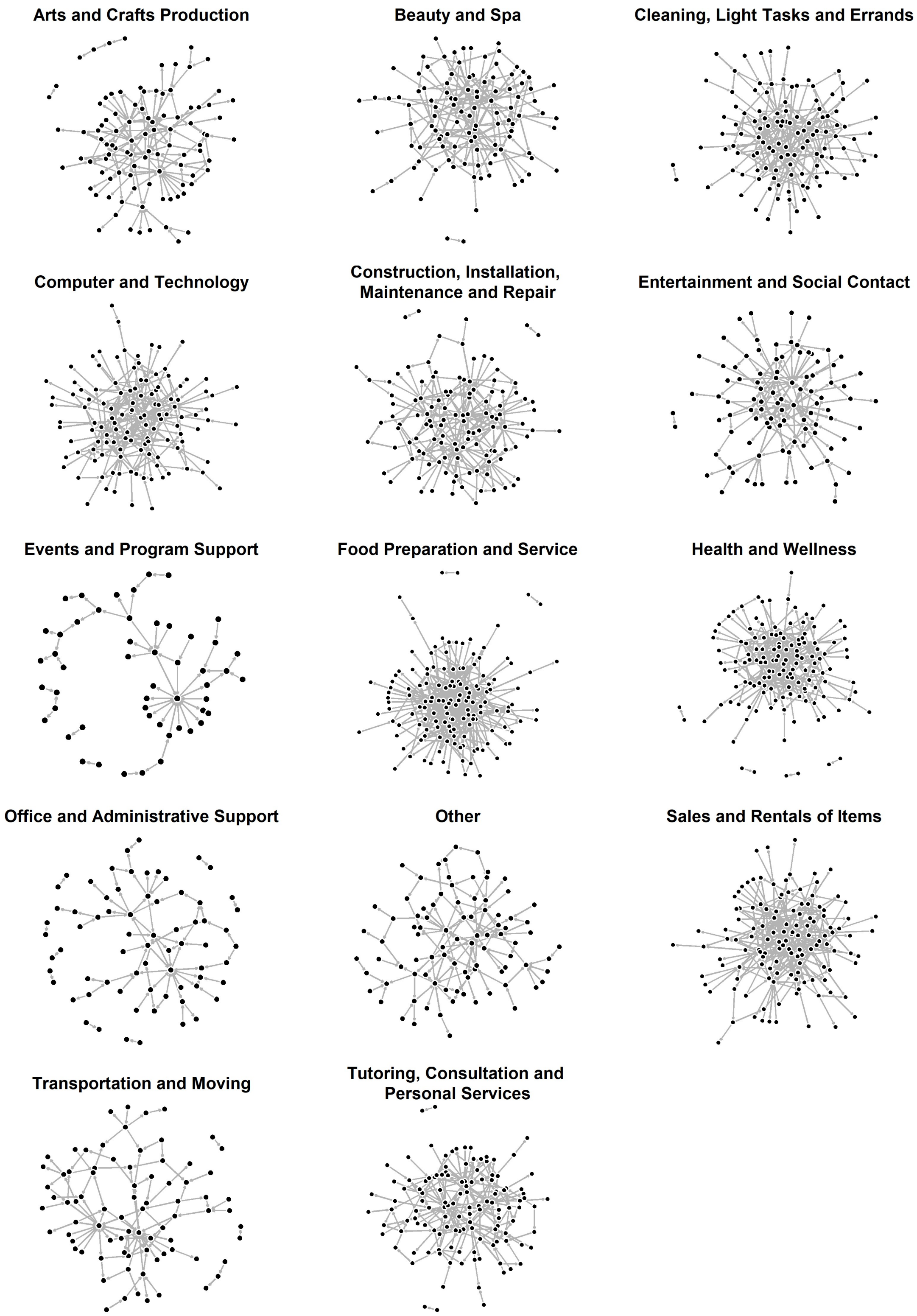

Figure 2.1: Network graphs of fourteen types of goods and services exchanged in TBSG.

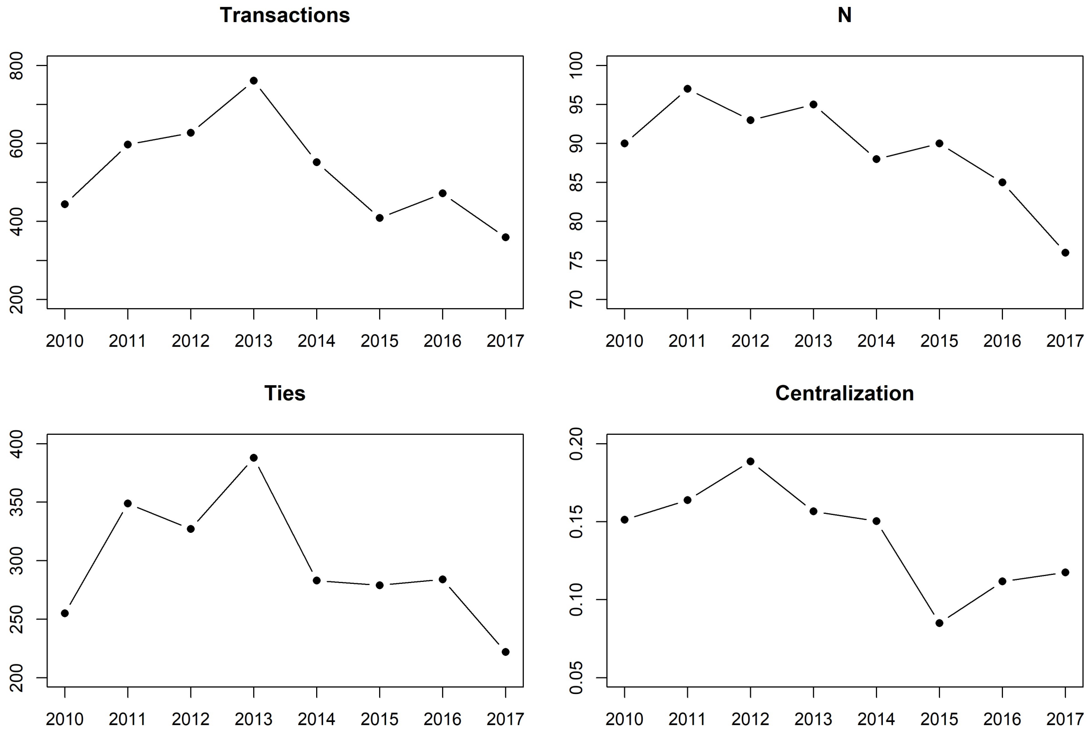

Figure 2.2: Changes in transactional activity in TBSG, 2010-2017.

reflected in the degree centralization, which started declining equally in 2012 (Fig. 2.2). Gross network indicators such as the number of actors and the number and structure of transactions thus suggest an evolution from initial rise to creeping decline of overall activity, which corresponds with an inverted U-shaped development curve. This trend also corresponds Seyfang and Longhurst's finding (2013) that time banks often lack durability. An analysis of the network dynamics allows us to take a deeper look into the structural changes to explore potential mechanisms and processes that help us to understand such demise.

To further examine the pattern of centralization and decentralization of transactions, we identify different trajectories of individual participation in overall exchange. The goal of such an approach is to provide a micro-level analysis of the relational process through which activities decline. Therefore, we consider the activity by network position and time rather than by type of transaction. For this line of analysis, we draw on methods of positional network analysis as well as methods from sequence analysis (Gabadinho et al., 2011). Positional approaches cluster actors into groups if they are located in equivalent positions within the network (Doreian et al., 2005; Faust, 1988; Glückler & Panitz, 2016). In contrast to conventional clustering approaches, such groups are defined by similarity in relations rather than in characteristics, in other words, by similarity in the way actors are connected to the rest of the network. Among the most discussed positional structures are core-periphery models (Glückler & Doreian, 2016; Prota, 2016). Such structures are composed of a densely connected core and a periphery, which is loosely connected internally as well as with the core. We here employ stochastic blockmodels (Lazega et al., 2011; Zhang et al., 2015) to cluster actors into core and periphery positions for each of the eight annual networks. Each of the 192 individuals—due to new entries and exits, the number of members exceeds the current number of members in TBSG—can now be assigned to one of three positions for any given point in time: core, periphery, and inactive. As we have eight years of analysis, we have 192 sequences of length eight, using each to summarize a member's positional trajectory of participation in the time bank between 2010 and 2017. We use a hierarchical clustering algorithm and an optimal matching distance measure (Gabadinho et al., 2011) to cluster these sequences into five types of characteristic trajectories (Fig. 2.3).

With each cluster of sequences, we present a distinctive trajectory of involvement in transactions: First, the *stable core* consists of 13 actors who occupy core positions over most of the observation period. Second, in the *fading core*, many members occupy core positions in the beginning of the observed period, yet as time goes on, many members reduce their activity and drift to peripheral positions. Third, the *stable periphery* includes 26 loyal but sporadic members who hold peripheral positions for long periods of time. Together, these three clusters of trajectories make up for the long-term backbone of the time bank but are also a source of declining activity, as can be seen by the fading part of the core. Fourth, *long-term* exits as well as, fifth, *short-term exits* largely consist of drop-outs. Whereas those of the former had maintained longstanding membership before finally becoming inactive, the latter includes people who had entered the time bank

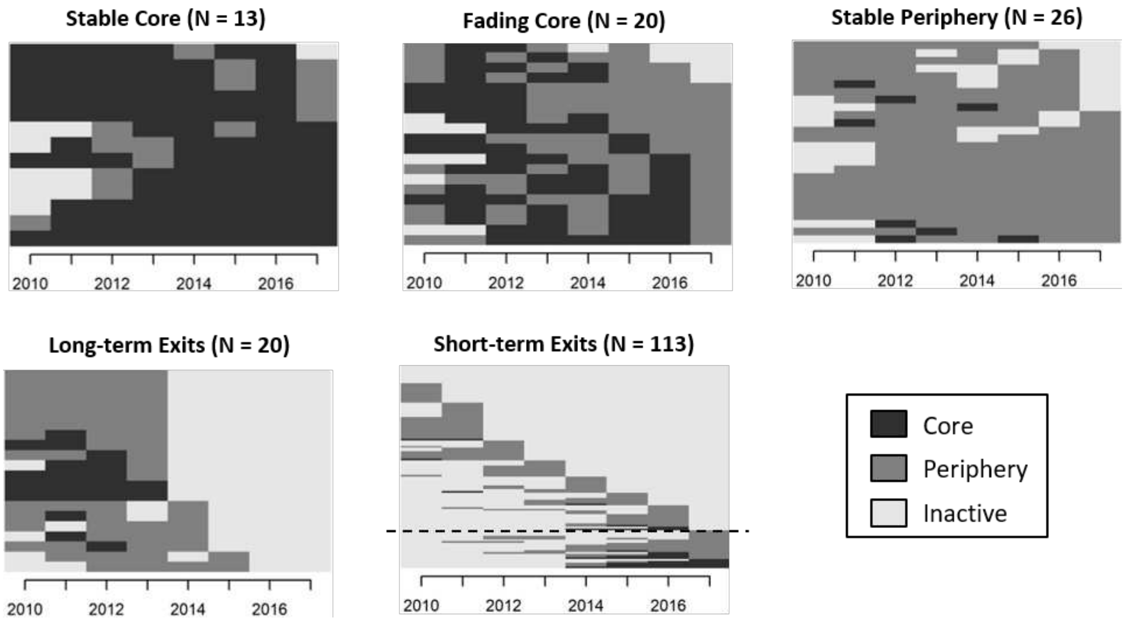

Figure 2.3: Types of member trajectories through core-periphery positions at TBSG.

and left shortly thereafter. The sheer size of the fifth cluster and the corresponding scale of relational turnover (Lazega et al., 2017) reflects the remarkable volatility around the smaller core of long-term members. The cluster of short-term drop-outs also holds some newcomers (indicated by the dashed line in Fig. 2.3), which are not enough to fully compensate for the rate of exits, as can be seen by the declining number of participants. The decomposition of differential histories of involvement presented here reveals several interesting insights into the exchange dynamics of TBSG. First, most exchanges revolve around a relatively small number of core actors who constitute the robust center of the time bank. Second, this core has not been durable throughout the observation period, as can be seen by many members moving to peripheral positions or becoming dropouts. Third, the densely connected core is surrounded by a relatively stable but smaller periphery of casual members as well as by a large and volatile group of short-term and perhaps experimental members. Finally, as researchers have often reported for time banks (Collom, 2005), recruiting new members is hard, as can be seen by the relatively low number of newcomers. As a consequence, the time bank struggles to replenish itself and risks fading out with its long-standing core members.

Conclusion

We have proposed a relational perspective to study time banks as a new type of civic organization to enact alternative economic practices. In seeking to understand the mechanisms of such a civic organization's rise and demise, we applied methods of dynamic social network analysis to analyze the relational processes within a Southern German time bank over a period of eight years. From dynamic social network analysis, one can gain original insight into the ways in which a time bank evolves. Given the repeated observation that time banks and other types of alternative economic practices are often characterized by considerable volatility and potential collapse, relational thinking and network analysis are especially suited for unpacking the underlying relational mechanisms that shape these outcomes of volatility and demise.

We have illustrated the benefits of formal methods of network analysis, but are by no means suggesting that researchers should disregard other ways of studying alternative economic practices. We acknowledge that a relational analysis of an emergent phenomenon, which may be easily misread from a dominant way of "capitalocentric" thinking, will benefit from thick description and interpretative methods to capture new logics of action (Gibson-Graham, 2014). In concluding this, however, we should not sacrifice the value of a detailed micro-relational analysis of the social process and the structural dynamics that these practices create. At their best, researchers conducting studies on civic organization and their practices should consider mixed-method designs that combine the best of both worlds (Glückler et al., 2020; Small, 2011). In any case, it is worthwhile and necessary to explore the empirical nature and dynamics of social practices in civic organizations more deeply, rather than limiting the debate to normative accounts of their potential virtues and liabilities. Relational thinking, quickly advancing methods of social network analysis, and an ever-increasing amount of available relational data are a promising offering to complement the diversity of empirical research approaches to civic life.

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3

From Scout to Scout: The Social Network of Corporate Opportunity Search

Abstract. Many corporations have created formal scouting positions to enhance their absorptive capacity for innovativeness. However, especially the role of non-assigned informal scouting and the interdependence between formal and informal scouts is virtually unexplored. Based on a primary network survey in a multinational chemical company, we capture a total of 431 scouts, two thirds of which are informal, and the social network of opportunity search between them. Our network analysis supports three findings: (1) Formal scouts spend more time searching for a larger number of projects for more radical innovations in more central positions of the network than informal scouts. (2) Rather than one depending on the other, formal and informal scouts are interdependently linked as they mutually source and share opportunities through the knowledge network. (3) Whereas informal and formal scouts are equally effective in mobilizing innovation opportunities across business units (organizational boundary spanning), formal scouts are more effective in discovering and mobilizing knowledge across locations (geographic boundary spanning).

Introduction

In pursuit of sustained innovativeness, business organizations no longer rely on internal research and development, but strive for enhanced absorptive capacity by screening their external environment for new opportunities. And because incorporating external knowledge wards against lock-ins and increases the potential for recombinant innovation (Hargadon & Sutton, 1997; Kaplan & Vakili, 2015; Kogut & Zander, 1992), many large corporations utilize innovation scouting as a strategy to stay informed about current developments in technologies and markets (Nicholas et al., 2013). The need for innovation foresight has also not gone unnoticed by policy makers, with, bodies such as the European Framework Program supporting the development of forecasting and innovation scouting solutions in industrial contexts (Radicic, 2020). Recent research shows how scouting units or 'listening posts' enhance the uptake of external knowledge in the firm and thus support innovation capabilities (Monteiro & Birkinshaw, 2017). Yet, the current state of knowledge also suggests that formal scouts are often unable to successfully mediate between a firm's external environment and the operations within the organization. Decreton et al. (2021) suggest that formal scouts can fail to serve as effective brokers when they are disconnected from a firm's core in the entrepreneurial ecosystem. The larger and more international a corporation, the more likely it is to convey redundant practices, i.e., 'reinvent the wheel', or to miss opportunities in some parts of the firm even though they are already developed and used in others. The recent focus of academic discourse has been especially on dedicated scouting units and formalized scouting practices as channels between a firm and its environment, which, while being a natural point of departure, risks missing more organic and informal practices that employees engage in as part of their work to mobilize innovation opportunities across the firm. In this paper, we adopt a comprehensive view of scouting beyond formal role assignments to include practices of informal scouting as well as the network of opportunity search that both formal and informal scouts establish through their information sharing channels. This way, we aim to capture not only the boundary spanning of innovation scouting between a firm and its environment but especially boundary spanning between the different units and sites within the organization (Klueter & Monteiro, 2017; Schotter et al., 2017). Such a comprehensive approach responds to the fact that formal and informal practices are often interrelated in organizations, many practices are not part of formal job descriptions, and not every formal rule turns into organizational practice. Instead, informal actions are embedded in formal organizational structures, and both are often mutually intertwined – a feature of knowledge management which is typical of large MNCs but has so far received comparatively little attention (Foss et al., 2010). Our analysis proceeds in the following way. In section 2 we appraise the state of research on innovation scouting in business organizations and identify two major research gaps to be explored: the role of informal and often invisible scouts in addition to formal scouts, as well as the mobilization of internal opportunities in addition to the sourcing of external knowledge only. Building on the corresponding research questions, we report our empirical research design, data and methods in section 3. Section 4 reports and discusses the findings of statistical and network analysis of a corporate scouting community. Results compare the scale, scope and connectivity of scouting practices between formal and informal scouts, and assess the ability of the types of scouts to mobilize opportunities across organizational and geographical divides. Section 5 draws conclusions and discusses potential implications for innovation management.

Innovation scouting beyond formalized external knowledge sourcing

A key capability in fast-moving, globalized, and highly competitive innovation landscapes is a firm's ability to source knowledge from the external environment and integrate it into internal processes, reflecting an organizational capability that has been defined as absorptive capacity (Cohen & Levinthal, 1990). Innovation scouting represents a mechanism by which organizations can enhance this capability. We purposively use the term 'innovation scouting' rather than the more commonly used term 'technology scouting' to include the search for knowledge beyond a narrow focus on technology, such as knowledge on new business models, new business partners, or investment opportunities. Scouts actively screen the environment for new information, concepts, and solutions that have the potential either to create new practices and markets (*radical innovation scouting*) or to improve on existing practices (*core innovation scouting*).

The degree to which innovation scouts foster the acquisition of radical or incremental innovations depends on the availability of resources (Parida et al., 2012): Especially in small and medium-sized firms, innovation scouts focus on incremental innovation given the lack of resources needed to comprehensively screen all technological developments. Beyond targeted search and screening endeavors, scouts furthermore might serendipitously stumble across knowledge they did not actively pursue but which nevertheless proves to be of value to the firm. As such, they can function, e.g., as maintainers of university-industry collaborations, which play an important role in external knowledge sourcing (Bierly III et al., 2009).

Extant research has concentrated on the role of scouting in the globalization of R&D, where a common strategy is the establishment of scouting units or 'listening posts' in key places such as in remote high-tech clusters (Birkinshaw & Hood, 2000; Gassmann & Gaso, 2004; Gassmann & Von Zedtwitz, 1999; Patel & Vega, 1999). These foreign units are useful to source localized knowledge and benefit from spillovers (Almeida, 1996; Bathelt & Cohendet, 2014; Maskell, 2014). More recently, scholars have explored the role of scouting at the firm level, with a focus on the processes of knowledge sourcing, distribution, and implementation. These studies evidence how boundary-spanning varies between 'harsh' and 'slack' times (Klueter & Monteiro, 2017), how it adds value beyond 'channeling' external information (Monteiro & Birkinshaw, 2017), and which types of scouted opportunities are (or are not) acted on (Monteiro, 2015).

From formal to informal innovation scouting

While these studies provide important insights into the processes by which scouts contribute to firm knowledge creation, they also often come with a relatively narrow definition of what constitutes scouting: Klueter & Monteiro (2017, p. 484), for example, propose that "technology scouts are unique in that they are not involved in other day-to-day operations – that is, spanning organizational and national boundaries to seek out external knowledge and spanning internal boundaries to make knowledge available within the organization 'is the only thing they do'". Such a definition tends to overlook many scouting activities practiced continuously as part of or in addition to the day-to-day work by individuals for whom it is not 'the only thing they do' and who are not formally scouts.

In contrast to dedicated, centralized, and technology-oriented scouts (Monteiro and Birkinshaw, 2017), the regional manager of an offshore subsidiary, for instance, may also perform scouting if she uses a broad network of local suppliers and customers to screen trends and opportunities (Meyer et al., 2020). While the formal position is that of a manager, this informal scouting can provide invaluable knowledge on business models, access strategies, or local technology trends to the firm. Similarly, a corporate research officer who actively participates in her academic field is likely to source external knowledge through personal contacts to former academic colleagues or by attending conferences (Bathelt et al., 2014; Lampel & Meyer, 2008). Accordingly, scouting not only comprises formally assigned roles of exclusive scouting but also appears as a 'natural' part of the informal practices embedded in every-day work (Lee et al., 2018; Park & Kim, 2014; Wolff, 1992). Integrating informal scouts into a corporate scouting strategy opens up new possibilities for the exploration of external search fields: when it is uncertain where to channel opportunities, it is helpful "for the organization to expose a fairly broad range of prospective 'receptors' to the environment" (Cohen & Levinthal, 1990, p. 132). Furthermore, as informal scouts have access to different information channels than more focused, formal scouts, informal scouting can increase the potential for serendipitous discovery. Informal scouts likely also have scouting interests more immediately related to the concerns of their 'actual' job, resulting in scouting orientations that differ from the (stereo)typical focus of technology scouts on radical, breakthrough innovation. Beyond such differences in profile, the integration of decentralized, informal scouting raises organizational challenges, e.g. with respect to visibility and reachability or with respect to issues of legitimacy and professional identities (Lifshitz-Assaf, 2018). Informal, decentralized scouts are also more susceptible to the challenges of 'multiple embeddedness', i.e., embeddedness in both organizational and local contexts (Meyer et al., 2011). The potential complementary benefits but also challenges of informal scouting in comparison to formal scouting motivate the first research question:

RQ1: How do informal scouts differ from formal scouts in the scale and scope of their opportunity search?

From external to internal innovation scouting

Innovation outposts often fail to redirect innovations and new ideas due to their missing connectivity within their organizations (Decreton et al., 2021) or 'not-invented-here' syndrome (Amann et al., 2022). In line with the finding that managers often consider internal transactions more difficult than external ones (Eccles, 1983), internal search for and redirection of opportunities is neither automatic nor necessarily easier than external sourcing. In a recent study, Grigoriou and Rothaermel (Grigoriou & Rothaermel, 2017) found that the efficiency of external sourcing for knowledge production is negatively related to the capacity for recombination and the costs of internal knowledge coordination. As a consequence, external sourcing and internal redirection of opportunities are two inter-related tasks that are necessary to advance opportunities to the right destination and to avoid reinventing the wheel. Dahlander et al. (2016), for example, found that both 'cosmopolitan', outward-oriented, as well as 'local', inward-looking, search strategies can be successful, with the latter even outperforming the former in many cases. While firms often allocate considerable resources to formalized knowledge management systems to establish systematic knowledge exchange, one of the most consistent findings is that these systems often fall short of their goals compared to informal interpersonal networks (Krackhardt & Hanson, 1993). In fact, most communication and knowledge exchange in organizations does not follow formal channels of command (Glückler & Sánchez-Hernández, 2014), allowing, e.g. controversial and peripheral innovation to succeed in the face of majority resistance (Glückler, 2014; McGrath & Krackhardt, 2003). Because the uncodified and uncertain nature of knowledge often impedes formalized communication, scouting practice is no exception to this rule.

In multi-business and multi-national corporations, formal and informal scouts are likely to be affiliated with different units ranging from basic research to business units, to be scattered across international locations, and to take different organizational roles and hierarchical positions. Pedersen et al. (2019), for example, found that individuals with global mandates, high levels of expertise, and a tertius-iungens (Obstfeld, 2005) orientation were more likely to span geographical, hierarchical, and functional boundaries than their peers. With respect to structural features, Caimo and Lomi (2015) suggested that ties spanning divisional boundaries were more likely to occur in reciprocal dyads, and Tasselli and Caimo (2019) observed that, depending on status differences, boundary spanning ties exhibit either cyclical (weak hierarchy) or transitive (strong hierarchy) patterns. To address the bottleneck of disconnection within the units of a multinational corporation our study is motivated by the general interest in how the network of formal and informal scouts mobilizes opportunities for innovation. More specifically, our second research question addresses how formal and informal scouts differ in the way they are distributed across the organization and its geography and how they differ in their tendency to bridge the boundaries imposed by this distribution:

RQ2: How do informal scouts differ from formal scouts in spanning organizational and geographical boundaries?

Methodology

Case study and data

To answer the two research questions on the differential nature of formal and informal scouting as well as on the differential mobilization of opportunities by way of boundary spanning, we study innovation scouts and the internal network of opportunity search at CHEMCO (anonymized), a multinational chemical corporation, that employs over 100,000 people at 241 sites in approximately 90 countries all over the world. It is organized in six business segments and comprises eleven divisions that cover a broad array of businesses in different sectors, such as agriculture, coatings, or nutrition. Rather than running a single scouting unit, CHEMCO had assigned formal scouts to a broad range of units in business (BDs) as well as research and support divisions (RSDs). Because of the emergent nature and dispersion of scouts, CHEMCO had no precise knowledge of either the degree to which the scouting community involved informal scouting or of the structure of the network of opportunity search, and so agreed to carry out a comprehensive empirical study of their scouting community.

Due to the nature of informal scouting and the inherent ambiguity of what constitutes a scout, the population of scouts in CHEMCO was unknown a priori. Therefore, we employed a snowball sampling strategy to run several waves of surveying both formal and informal scouting activities. The strategy was to start with the full list of identified formal scouts as well as potential informal scouts in a first wave of electronic questionnaires. The initial group of respondents was asked to identify other colleagues whom they believed were active in scouting, either formally or informally. We then ran a second wave of questionnaires to these nominated candidates, along with a reminder to previous non-respondents. This was repeated for a total of five times, after which we had reached a point where the yield of further identified scouts was deemed low enough to stop the sampling process (Figure 3.1). In total, the survey was sent out to 1,577 people and yielded 596 responses. This number was confirmed to be consistent with the expectations by scouting managers about the real population of scouts at CHEMCO. Considering this as well as the low number of additional candidates after the five waves, we were confident to have exploited almost the entire population of scouts at the firm.

Types of scouts. To distinguish between formal and informal scouts, we invited management representatives to jointly elaborate on a succinct definition of scouting: "a scout is someone who explores (external) content within a search field and makes it available to the firm as an option for action". Drawing on this definition in the questionnaire, respondents were asked to indicate whether scouting is part of their

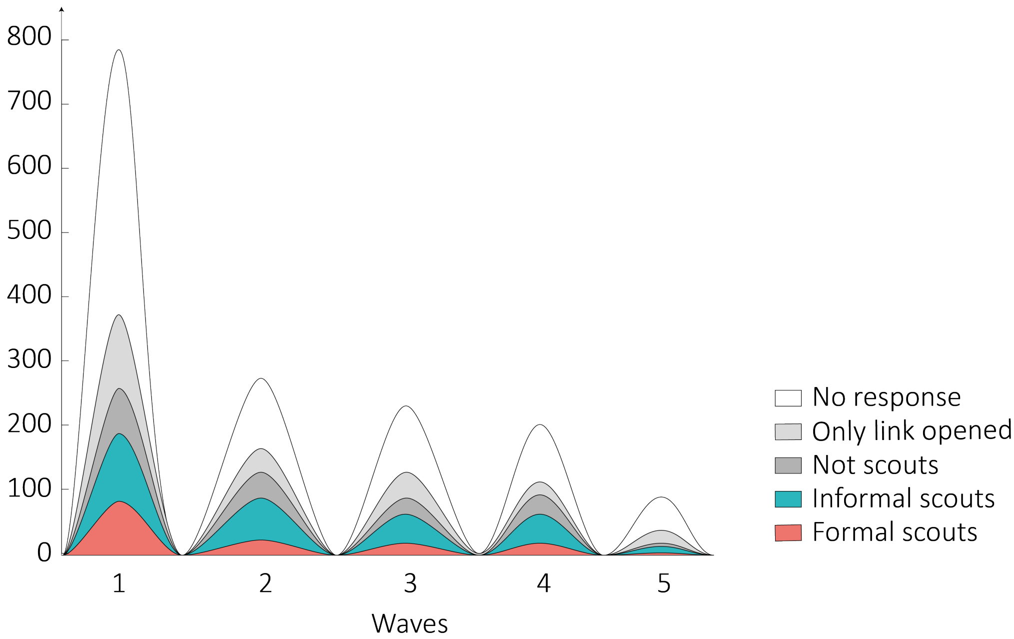

Figure 3.1: Survey strategy: Snowball sampling, survey waves, and responses.

job description (formal scout), whether they frequently engage in scouting although it is not part of their job description (informal scout), or whether they never or only rarely engage in scouting activities (no scout). Of the total sample of 431 scouts, 126 reported to be formal and another 295 to be informal scouts.

Network of opportunity search. The type of relationship that was used to construct the scout-to-scout network of opportunity search was defined by the following name generator: "Who of your colleagues have helped you to carry out your scouting activities successfully over the past two years?" Because the focus of this study is on the network among scouts inside the corporation, the network included the 431 scouts identified in the survey, excluding both those respondents who claimed not be involved in scouting activities as well as non-respondents. A total of 258 scout respondents suggested at least one other person to be a scout during the five survey waves. On average, scouts named 2.4 scout contacts, with a maximum degree of 25 contacts, whereas 81 scouts did neither name other scouts nor were they named by any other scout, thus being isolates in the network.

Measures

The following variables were used to explore and assess the differences between formal and informal scouts regarding the scale and scope of their scouting activities as well as their connectivity in the scout network.

Scale of scouting. The scale and intensity of scouting was measured by several variables: (i) the amount of time (hours) spent on scouting per week; (ii) whether a scout served as a key contact to external partners; and (iii) the number of internal projects to which a scout provided input. While it is tempting to consider project contributions as a performance measure, this may be misleading for several reasons: projects vary in size, novelty (technology readiness) and impact; and individual involvement depends in part on the organizational role of a scout, where more senior and transfer-oriented scouts are more likely to be involved in many projects.

Scope of scouting. Opportunity search also varies in terms of the novelty of knowledge: On the one hand, scouts can focus on extending and improving core markets and technologies or on pushing into existing markets and technologies (core scouting). On the other hand, scouting often aims to capture potential breakthrough technologies or emerging markets that are not yet established in either the firm or the field (radical scouting). The former is targeted at establishing short-to-medium-term competitiveness in the core business while the latter is targeted at not missing the 'next big thing'. As such, the two forms can be argued to be complementary to a certain degree as they target different needs but likely also have different requirements for their successful execution. To capture this spectrum of scouting forms, respondents were asked to indicate, based on their past scouting work, their scouting orientation in terms of the Ansoff matrix displayed in Figure 3.2, which is a common management tool at the firm and thus is well understood by respondents (multiple assignments were possible).

Utilizing their entries in the Ansoff matrix, we perform hierarchical clustering (simple matching distance and Ward's linkage) to identify two groups of scouts with relatively homogeneous scouting profiles: core vs radical scouting.

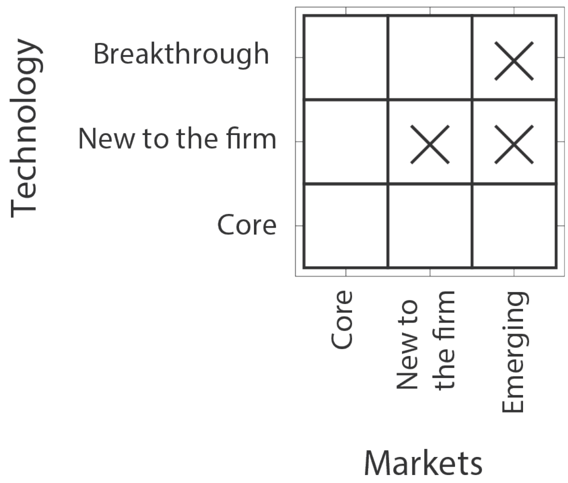

Figure 3.2: Ansoff matrix as adapted by CHEMCO and used here as a survey instrument to capture scouting orientation (exemplary illustration).

Network activity. We use simple measures of out- and indegree centrality. Degree indicates the number of contacts that a scout has to other colleagues in the network. More complex centrality measures capturing structure beyond a node's first-order neighborhood, such as betweenness centrality (r = .86) or eigenvector centrality (r = .78), were strongly correlated with degree and yielded no substantive advantage in the interpretation of findings.

Boundary spanning. Relations in the network are considered as boundary spanning if they reach contacts either across locations (geographical) or departments (organizational) Accordingly, we record the number of contacts located in other units (or sites, respectively) among the total number of contacts of a scout.

Control variables: Finally, we include scouting time (except when itself treated as outcome), seniority (i.e. the time in years a scout has been with the firm) and unit affiliation as control variables as these could be expected to mediate differences between formal and informal scouts across the discussed measures of comparison.

Models

We assess differences between formal and informal scouts with respect to scouting scale and scope, network activity and boundary spanning with a set of varying-effects regression models which allow intercepts and formality coefficients to vary by unit. We furthermore include control variables for time spent on scouting and seniority (i.e. time spent with the firm), both centered and scaled, respectively, yielding the following illustrative model representation for indegree:

$$\text{indegree}_i \sim \text{NegativeBinomial}(\mu_i, \phi)$$
$$\mu_i = \exp(\alpha_{U[i]} + \beta_{U[i]}\text{informal}_i + \text{time}_i + \text{seniority}_i)$$

Here, $U[i]$ indicates the unit affiliation index for the scout i so the models contain intercepts and formality coefficients differentiated by a total of 34 units across which scouts were distributed. To allow for easier and more meaningful comparisons, results are aggregated at the higher-level divisions instead of the lower-level units in the results section. For the example of indegree shown above, a negative binomial distribution is chosen as an appropriate model for count data. For other outcome variables, distributions and link functions are similarly chosen as appropriate for their data type, e.g., Bernoulli with a logit link for whether a scout serves as key contact and binomial distributions and logit links for the number of boundary-spanning contacts among a scout's total number of contacts.

For the estimation of models, we use Bayesian methods, which are increasingly encouraged also in the organizational and management sciences (Krackhardt et al., 2019; Kruschke et al., 2012) and which are well suited for exploratory research strategies such as the one utilized here (Gelman, 2004). We fit models with the Stan ecosystem for probabilistic programming (Carpenter et al., 2017), computed network statistics with the statnet suite of R packages (Goodreau et al., 2008) and utilized the tidyverse ecosystem for data handling and visualization (Wickham et al., 2019).

Findings

The scale, scope and network of scouting

The scouting network spans across a broad range of organizational units and over eight divisions. The divisions are further grouped in either business divisions

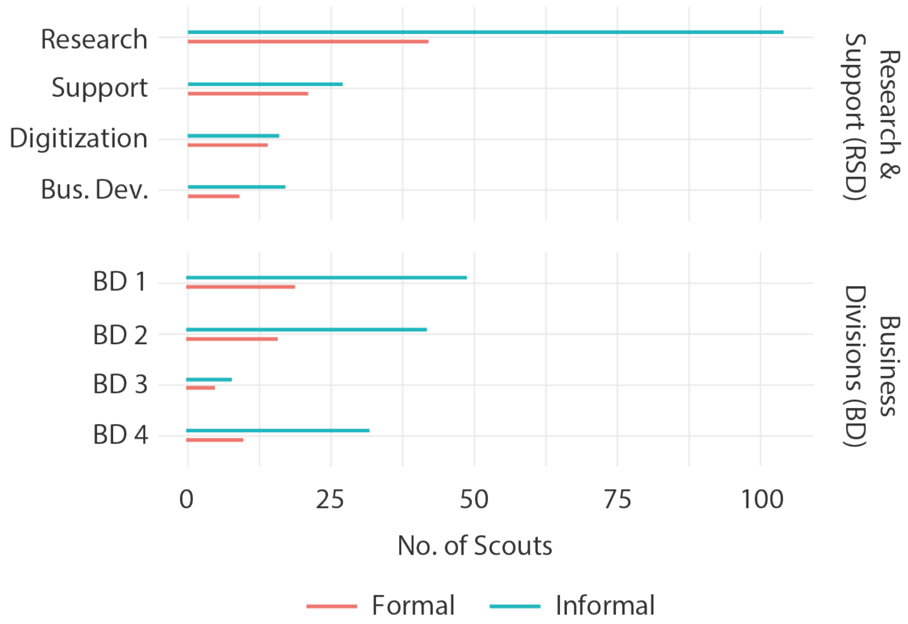

Figure 3.3: Distribution of formal and informal scouts across the organizations divisions.

(BDs), which include the production of chemical products and related services, or research & support divisions (RSDs), which combine R&D and several other support activities. Of the total of 431 scouts, a majority of 250 were located in RSDs, with a concentration in research units (33,9% of all scouts), whereas the remaining 181 scouts were affiliated with BDs (Figure 3.3). With an overall share of 31.5% in the scout population, formal scouts were slightly more concentrated in the RSDs (34.4%) than in the BDs (27.6%). This overall concentration of scouting on research units does not come as a surprise because it illustrates the close connection between R&D activities and innovation scouting. Regarding the geographical distribution, the vast majority of scouts was located in Germany (54%), and the United States (20%), whereas the remainder was found scattered across sites in Europe, Asia, South America and Africa (Figure 3.4).

Over the two years preceding the study, the 431 scouts had provided input to a total of 1,056 projects and spent a total of 336,000 hours (466 person months) on scouting new ideas and solutions in 15 major technological fields, 38 industry sectors, and across 26 countries. Scouts reported to be key contacts to more than 500 organizations and work groups, facilitating access to external sources

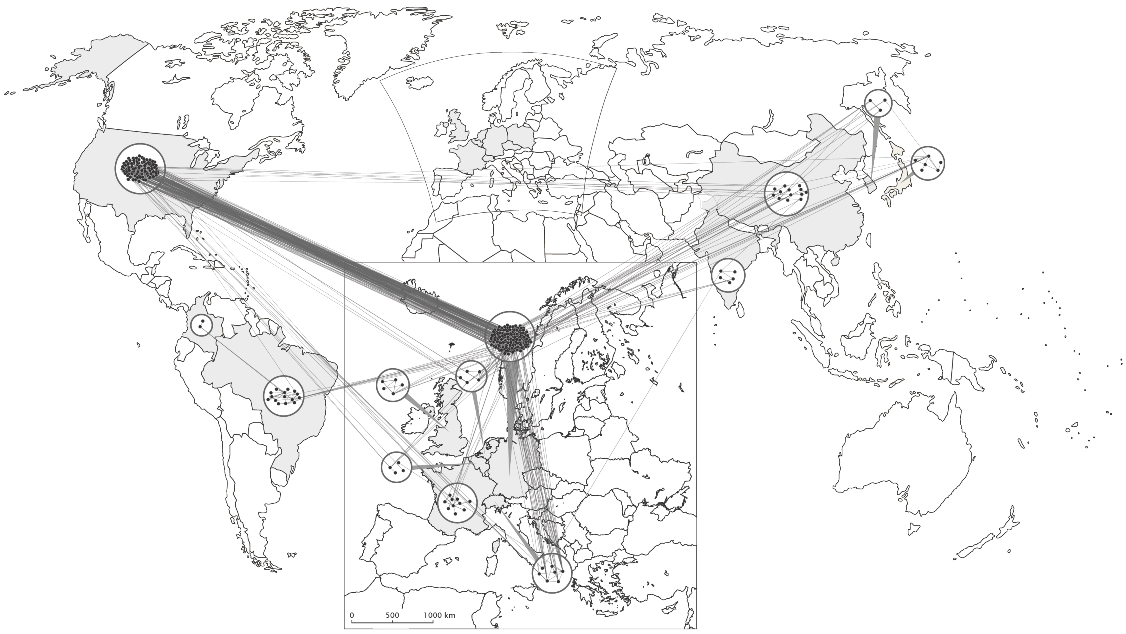

Figure 3.4: Scouting network across firm sites.

of knowledge around the world. Formal and informal scouts were found to differ both in terms of scale and scope of their activities.

Regarding the *scale of scouting*, formal scouts spent around three times as much time on scouting than informal scouts (13.4 h/week vs. 4.8 h/week, respectively), contributed to 1.8 times more internal projects (4.4 vs. 2.5) and were about 1.5 times as likely to serve as a key contact to an external party of interest. Regarding the *scope of scouting*, scouts were classified by their tendency to seize either 'core' or 'radical' opportunities, a profile that we assessed by way of hierarchical clustering of their responses to an item on the novelty of search and as represented by the Ansoff matrix (Figure 3.5a). While 151 scouts tended towards radical search, 280 reported to pursue core search. Whereas radical scouts indicated a stronger focus on the top right quadrant, i.e. breakthrough technologies and emerging markets, core scouts emphasized a pursuit of either extending core markets or tapping into new markets with technologies that are new to the firm.

The two kinds of scouting scope were distributed unevenly across the organization (Figure 3.5b): The share of scouts with a radical scouting orientation was largest among formal RSD scouts, at 50%. At the other end of the spectrum, only around a quarter of informal scouts in BDs reported radical scouting, with formal scouts in BDs and informal scouts in RSDs in-between at around a third, respectively. Radical and core scouts not only varied by their location in the organization but also by the degree to which they were connected in the scout network: Radical formal scouts had significantly more contacts (mean=11.6, n=60) than their formal core (mean=4.7, n=71) counterparts. For informal scouts, on the other hand, number of network contacts varied much less with scouting scope (means=3.3, n=186 and mean=4.2, n=91 for core and radical, respectively). Regarding network activity more generally, the 431 scouts reported 1,033 relationships among each other, which corresponds to a density of 0.56 % and an average degree of 4.8 contacts. This tie distribution resonates with similar findings in comparable organizational contexts (Panitz & Glückler, 2020). While 81 scouts who were isolated, 326 scouts (94% of non-isolates) were members of one coherent main component indicating that the scouting community was mutually reachable across both spatial and organizational units. In the scout network, formal scouts were named by approximately 4.0 and informal scouts by 1.7 other scouts as a source of knowledge (i.e. their indegree or network prominence). Conversely, formal scouts named 3.7 and informal scouts 1.8 other scouts as sources of knowledge (i.e. their outdegree or search activity).

Table 3.1 reports coefficients for regression models predicting differences in the abovementioned variables with respect to formality status. Next to formality, the models account for time spent on scouting, seniority (i.e. the number of years with the firm) and organizational unit affiliation, as these are likely to influence observed differences between formal and informal scouts. The models show that in most cases differences between formal and informal scouts cannot only be accounted for by differences in time, seniority, or unit-based resource endowments. Controlling for these factors, formal scouts still tended to provide more input to projects[1], were

[1]The negative binomial models utilize a log link function, so exponentiating a coefficient yields a multiplicative factor: e.g., the model expects informal scouts to be involved in around $\exp(-.4) * 100 = 67\%$ the number of projects of a formal scout, given the same seniority, scouting time and unit affiliation. For the Bernoulli model, exponentiating yields the odds ratio, i.e., $P(\text{key contact})/(1 - P(\text{key contact}))$.

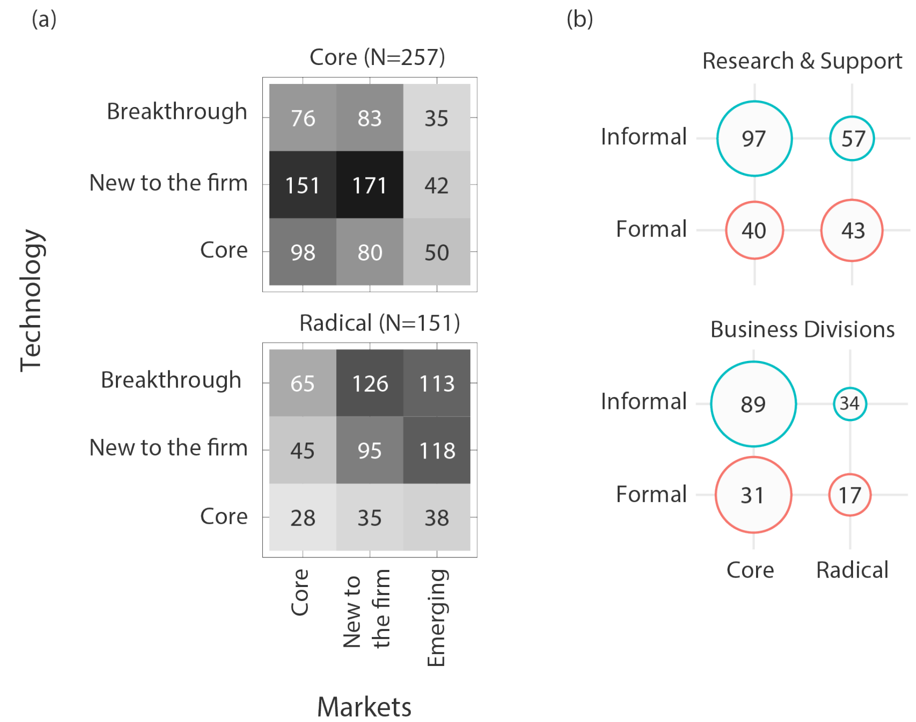

Figure 3.5: (a) Ansoff profiles of core and radical scouts (number of responses, multiple answers possible). (b) Organizational distribution of scouting orientations by formal and informal scouts.

more likely to serve as key contacts and had higher activity and prominence in the scout network than informal scouts. However, there is strong divisional variation to these patterns (Figure 3.6): Most strikingly, formal scouts in the research division stand out with an average of around 14 contacts (indegree and outdegree combined), almost three times the number of their informal research division counterparts, but also almost double the number of formal scouts in any other division. While these scouts make up for less than 10% of the full sample, they account for 30% of all ties, respectively, and would cause a 53% drop in the total number of connections in the scout community if removed from the network. Higher counts of contacts for formal than for informal scouts can also be observed in other RSDs and BUs, albeit to a lesser degree and with high statistical uncertainty.

Finally, the model results indicate that while an increase in time spent on scouting (ceteris paribus) is not associated with an increase in projects or in the likelihood to serve as a key contact, it is strongly positively associated with network

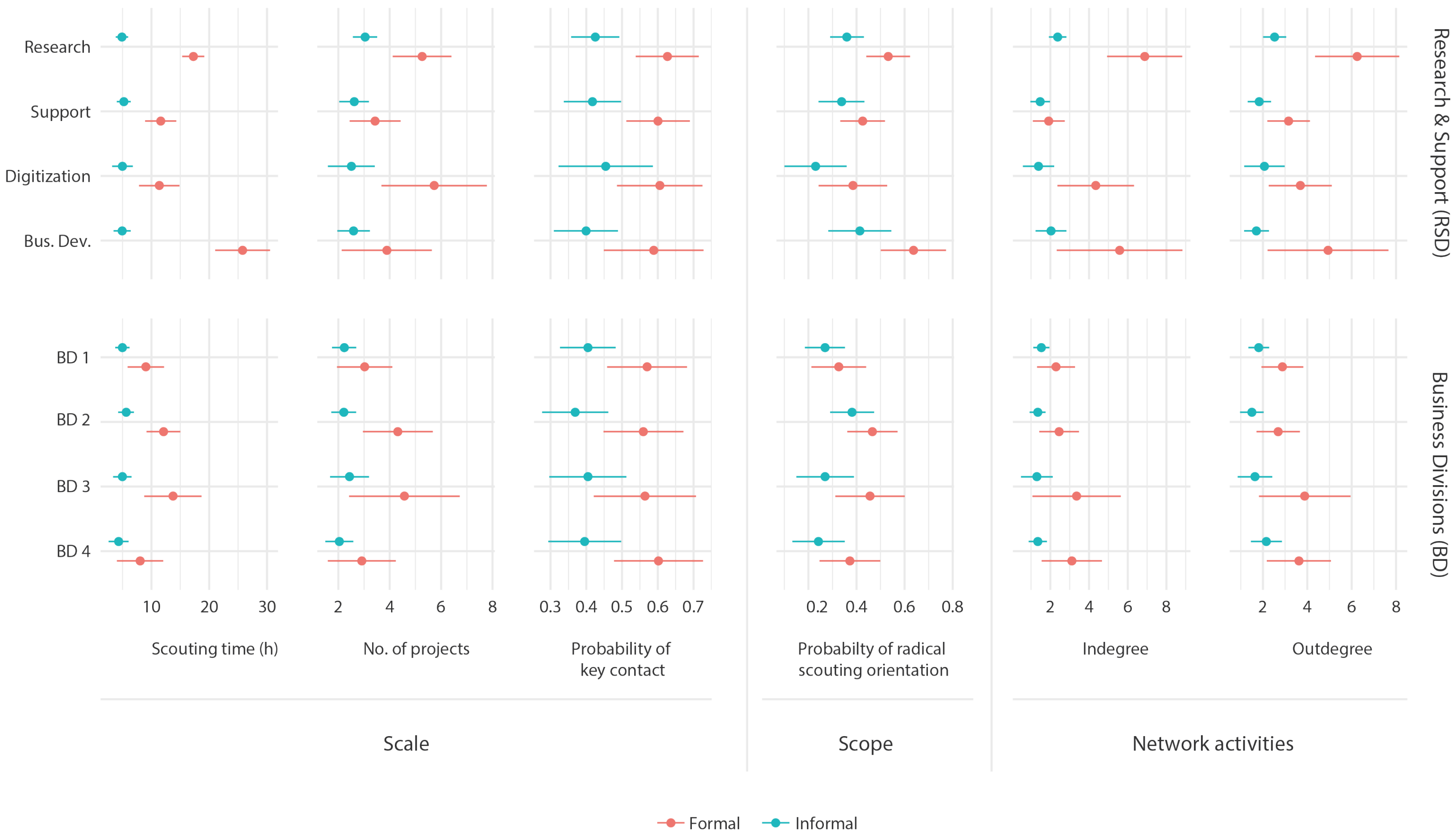

Figure 3.6: Estimated means for scouting and network outcomes differentiated by division and scouting status. Error bars represent 90% uncertainty intervals.

activity (outdegree) and prominence (indegree) and varies itself strongly with respect to scout formality and divisional affiliation. Overall, formal and informal scouts differed considerably in the scale and scope of their search, especially within the research division. Formal scouts were found more concentrated in formal research and support divisions of the corporation (RSD), spent more time on opportunity search for a larger number of projects for more radical knowledge and in more prominent positions of the network than informal scouts. However, by ignoring informal scouts the corporation would miss the potential of two thirds of people that regularly seize new opportunities for innovation, and it would miss about half the time actually dedicated to scouting across the organization: Informal scouting accounted for more than 1,400 hours spent on scouting activities per week, with formal scouts accumulating a total of 1,800 hours per week. Informal scouts provided input to more than 740 and formal scouts to more than 600 research projects. Finally, informal scouts are key contacts to 118 and formal scouts to 83 external organizations. Hence, informal scouts, though being less invested and less prominent in opportunity search, made a marked contribution to the mobilization of knowledge.

Spanning organizational and geographical boundaries

Going beyond comparisons of scale and scope of activities conducted by formal and informal scouts, the second research question focuses on how both types of scouts contribute to mobilizing innovation opportunities across internal boundaries of divisions and locations. To answer this question, we analyzed the scout-to-scout network including organizational and geographical affiliations of the individual scouts. Regarding the general relation between formal and informal scouts we found evidence to refute the assumption that formal scouts would serve as the principle sources of new opportunities to be diffused to local informal scouts for utilization. Although formal scouts were more active and central in the network, there is no evidence of hierarchical structure or division of labor between suppliers and receivers. Instead, opportunities travelled both ways with formal scouts and

Table 3.1: Regression models for scouting scale, scope, and network activity

	Scouting scale			**Scouting scope**	**Network activity**	
	Time	Projects	Key contact	Ansoff	Indegree	Outdegree
	Gaussian	Neg. Binom.	Bernoulli	Bernoulli	Neg. Binom.	Neg. Binom.
	N=378	N=329	N=375	N=378	N=378	N=378
Intercept	12.99	1.27	.36	-.48	.77	.98
	(1.77)	(.15)	(.23)	(.22)	(.20)	(.15)
Informal	-7.92	-.40	-.74	-.25	-.39	-.35
	(1.90)	(.16)	(.28)	(.28)	(.22)	(.17)
Scouting time		.08	.06	.38	.32	.32
		(.06)	(.13)	(.14)	(.07)	(.08)
Seniority	-.28	.14	.10	-.19	.30	.09
	(.45)	(.06)	(.12)	(.13)	(.07)	(.08)
Unit intercept (sd)	8.59	.50	.40	.51	.70	.41
Unit informal (sd)	8.86	.45	.41	.48	.73	.25

Note: Standard errors are in brackets. Scouting time and seniority variables are centered and scaled. All models control for unit affiliation through varying intercept and scout effects, for which the standard deviation is reported.

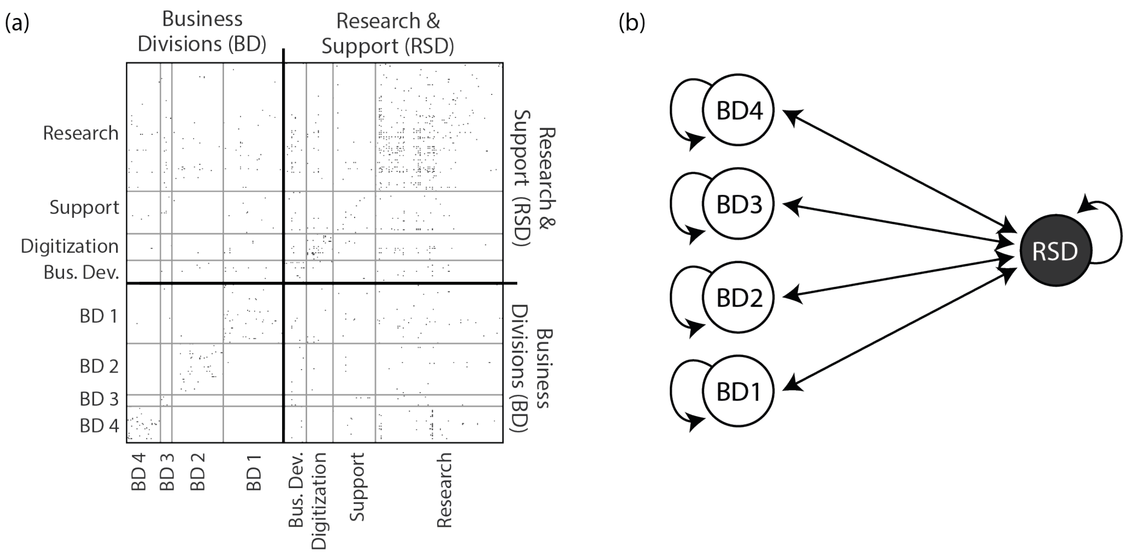

Figure 3.7: (a) Adjacency matrix of the scout network permuted by divisions. (b) Hypergraph representation of scout networks divisional structure.

informal scouts mutually transmitting knowledge at about the same frequency among and between each other: There were 211 ties from formal to informal scouts and 248 ties from informal scouts to formal scouts. This structure suggests that informal scouts can represent an integral part of corporate innovation scouting, serving both as sources and destinations of scouted opportunities.

In a next step we assess if and how the scout network is structured by the formal organizational structure of the firm. The blockmodel displayed in Figure 3.7a visualizes the adjacency matrix of the network as permuted by membership in divisions and confirms that the divisional affiliation of scouts affects the structure of the network. As the diagonal blocks of the matrix are most densely populated, scouts are more likely to share opportunities with scouts inside their divisions for both business and research and support divisions. At the same time, there is a considerable lack of direct interaction between the four business divisions as documented by the empty off-diagonal blocks in the bottom left quadrant. Compared to 131 ties established within the BDs, there are only 5 ties connecting the BDs across the whole network. Furthermore, the scouts in the business divisions are loosely linked to scouts in research and support divisions in addition to being connected internally.

The more general pattern underlying this structure is represented by the hypergraph in Figure 3.7b, where RSD scouts serve as a structural bridge for the business divisions which are otherwise disconnected from each other. Such disconnection impedes the mobilization of new opportunities between the business areas of a corporation and increases the risk for redundant scouting efforts. In terms of geography, most ties are established within the regions of Europe (EU), North America (NA), Asia-Pacific (AP), and South America (SA). There is however also a strong connection between European sites (especially headquarters) and the United States, which host various important research centers of the firm. The general trend of organizational and geographic impacts on the structure of the scout network is more heterogeneous when looking at the smaller-scale regional and organizational structure: around 56% of all ties connect different sites and around 59% of ties are established between scouts in different units, compared to only 25% and 45% for the larger-scale corporate greater regions and divisions, respectively.

Apart from the general organizational and geographical pattern, our analysis further shows that exchanges between formal and informal scouts are distributed unevenly across the organizational and geographical structure of the firm. Figure 3.8a displays tie counts across the four blocks induced by the combination of BDs and RSDs. Whereas ties among formal scouts are the most frequent in the RSDs, the number of linkages among informal scouts are more than threefold compared to ties among formal scouts within the BDs. Accordingly, the most frequent mode of interaction in the research and support divisions is among formal scouts, whereas interactions among informal scouts stand out in the business divisions. Similarly, Figure 3.8b reports the distribution of network linkages for formal and informal scouts within and between the two regions of Europe and North America (other regions were negligible in terms of interconnection). On the one hand, in North America ties among formal scouts are more frequent (40% of all ties) than those involving informal scouts, compared to Europe (21% of all ties). On the other hand, formal scouts are more likely than informal scouts to send and receive ties across the two regions.

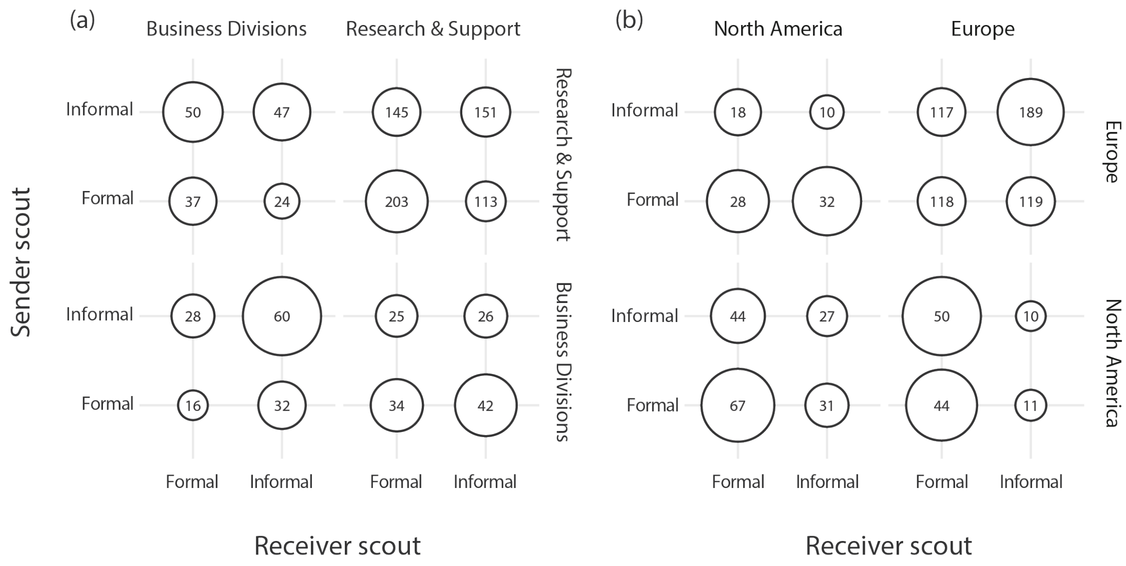

Figure 3.8: Tie counts across BDs and RSDs (a) and the North America and Europe) greater regions (b), distinguished further by sender and receiver formality status. Size is scaled by block share.

The regression models reported in Table 3.2 provide further statistical support to the observation that whereas formal scouts tend to be more actively involved in boundary spanning ties than informal scouts for cross-site ties, this is much less so for cross-unit ties, as indicated by the large and significantly negative coefficient for informal scout status in the first model and the much smaller and more uncertain coefficient in the second. Again, we observe some organizational variation for this tendency. The higher likelihood of formal scouts establishing boundary-spanning ties compared to informal scouts is especially visible for the Research, Digitalization and Support divisions, yet for other divisions this difference disappears.

There is also strong variation in terms of the base rate of boundary spanning ties across the divisions, which is likely explained at least in part by divisional size differences, as some units house only a handful of scouts and thus provide little opportunity for local ties. For others, such as regional support units, a generally high tendency to cross unit boundaries comes as a natural part of their work. And finally, such differences might be indicating different levels of integration or 'self-sufficiency' in terms of scouting knowledge within the corporate scout community. Beyond differences with respect to formality, there is also a significant association

Table 3.2: Regression models for boundary spanning

	Cross-site boundary spanning	**Cross-unit boundary spanning**
	Binomial	*Binomial*
	N=378	N=378
Intercept	.96	1.37
	(.24)	(.24)
Informal	-.65	-.14
	(.20)	(.25)
Scouting time	.02	.05
	(.06)	(.05)
Seniority	-.33	.21
	(.06)	(.06)
Unit intercept (s.d.)	1.10	.87
Unit informal (s.d.)	.67	.57

Note: Standard errors are in brackets. Scouting time and seniority variables are centered and scaled. All models control for unit affiliation through varying intercept and scout effects, for which the standard deviation is reported.

between boundary spanning and seniority (conditional on formality): While higher seniority coincides with a higher share of unit-spanning ties (i.e. organizational boundary spanning), this pattern is reversed for site-spanning ties (i.e. geographical boundary spanning). In sum, the results reported in this section show that the uneven distribution of scouts and their differential capabilities and motivations to bridge boundaries produce specific patterns of knowledge circulation within and across the organizational divisions and geographic locations of the firm.

Conclusions

While informal scouts have been rather neglected in academic discourse, our study is amongst the first studies that offers a comprehensive view of an entire corporate scouting community including not only formal scouts, but also informal scouts and the informal relations of opportunity search among and between them. Our analysis suggests a few conclusions:

First, due to the formal assignment of tasks and resources it was not surprising to find that, on average, formal scouts spent more time on scouting, contributed to a greater number of projects, were more likely to serve as gatekeepers to other organizations, pursued more radical innovation leads and were more actively involved in the scouting network than informal scouts. Despite these differences in the scale and scope between formal and informal scouting, however, informal scouting as a whole vastly expanded the corporate search for innovation opportunities. Informal scouts significantly increased the total scouting time, project contributions and knowledge exchange, which suggests that corporations should include informal scouting in more comprehensive innovation strategies. Second, formal and informal scouts were found interdependent. Rather than either one depending on the other or both conducting their search on unrelated channels, we found that opportunities travelled both ways and that formal and informal scouts built an interrelated network of scout-to-scout communication. This bidirectionality of information flow and the interrelatedness of the network has immediate implications for corporate innovativeness. (i) The scout-to-scout network enables the effective redirection of opportunities that arise either outside or inside the corporation to those units where it conveys innovative or productive potential. It particularly includes the discovery and mobilization of untapped knowledge pools that exist inside the organization, providing support for peripheral innovation (Glückler, 2014). (ii) This mobilization reduces redundant search effort and facilitates the potential for recombination of existing knowledge. While we have shed light on the extent and structure of exchange among formal and informal scouts, it remains a topic for further inquiry to unravel the mechanisms by which these effects are realized and how they can be included in strategic management of scouting.

Third, the analysis has shown how the organizational structure of a firm shapes the flow of opportunities across a scouting community. Whereas in the firm's business divisions (BD), relationships among informal scouts were more frequent than among formal scouts, this was reversed in the research and support divisions (RSD). In addition, informal business division scouts focused mostly on core scouting, whereas formal RSD scouts tended to concentrate more often on scouting radical innovation opportunities. Given these differences, we found that the RSDs served as structural bridges to rewire opportunities between the different BDs (Martin & Eisenhardt, 2010; Panitz & Glückler, 2017), which would otherwise be disconnected from each other. RSD scouts, themselves strongly focused on radical innovation, thus brought together different pools of 'core' knowledge distributed across the BDs, creating an ecology of structural complementarity in the scouting community. Despite this overall positional bridging between BDs, formal and informal scouts were individually equally involved in efforts to bridge organizational boundaries. Across geographic boundaries, however, formal scouts were disproportionally more likely to establish bridging ties. Local, intra-site, exchange among scouts was likely facilitated by existing acquaintances or 'next-door' neighborhood effects, which apply equally to formal and informal scouts but do not exist for cross-site exchanges. Across regions, on the other hand, formal scouts likely enjoyed higher visibility and perhaps functional legitimacy due to their formal status to mobilize and rewire innovation opportunities across the global geography and divisions of the corporation.

Consequently, there are two challenges for firms when trying to adopt a comprehensive approach to innovation management: to identify and integrate informal scouting with formal scouting practices. Our case study suggests that informal scouting is an almost natural part of knowledge-intensive work. Given the freedom and possibility, a scouting community involving informal scouts that are invisible to management may be able to evolve some self-governance to a certain extent. Yet it is unclear if such a self-organized system is effective if it remains hidden underneath the surface of actively managed innovation strategies. Recognizing and rewarding informal scouts might have advantages, not the least of which is the promotion of high-profile informal scouts to a formal scouting position. In terms of the integration of informal scouting into existing practices, formal scouts should be incentivized to not only source external knowledge but also tap into easily overlooked internal sources of innovation through the establishment of ties to informal scouts. Due to the nature of their work, informal scouts are more closely involved with the core business and can contribute to the 'grounding' of innovation opportunities. On a final note, the more informal aspects of scouting discussed here are difficult to assess with conventional evaluation criteria. Managers need to be careful in pondering a scout's role in internal knowledge exchange against classical scouting tasks. The lack of a unanimous performance measure is also one of the main limitations in this study and an open problem in studies on innovation scouting, more generally. Due to the interconnected nature of scouting revealed in this study, we suggest that the effectiveness and efficiency of corporate scouting should be evaluated at the community rather than at the individual level.

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4

Interrelated Technology Evolution in the Field of Plastic Recycling: A Main Path Analysis

Abstract. Plastic materials have become ubiquitous in consumer and industrial applications, but so has plastic waste, which poses a serious danger to environment and health. Driven by the increasing severity and publicity of the plastic waste crisis, there have been increased efforts in the development of recycling technologies aimed at the reduction of plastic waste. However, plastic recycling is a heterogeneous technological field which involves different application contexts, process stages, and technological approaches. In this paper, we study the structure of interrelated technological development of different recycling technologies. Utilizing patent citation data on more than 100,000 patents and focusing on textile applications, separation techniques, and biological recycling as examples, we use patent-based main path analysis to delineate the co-evolution of technological trajectories in this heterogeneous technological field.

Introduction

The plastic waste crisis has taken the center stage in many arenas of politics and policy: In March 2022, representatives of 175 states signed a resolution to end plastic pollution in the context of the United Nations Environment Assembly (United Nations, 2022). And since July 2021, many single use plastics are banned from distribution in the European single market (European Commission, 2021). And indeed, the need for action is dire: Geyer et al. (Geyer et al., 2017) estimate that of more than 8,000 Mt of plastics produced since the 1950s, about 60% accumulate in landfills and the environment while less than 10% of plastic waste has been recycled, a rate which is even lower for specific market segments, such as fiber plastics. However, below the surface of high-level political endorsements and policies, both policy makers as well as industry leaders face difficult decisions in terms of the technologies to promote or prohibit and adopt or avoid, respectively. Comprehensive information on technology alternatives and their respective qualities is usually hard to come by, making any choice inherently uncertain. Consequently, most technological innovations are initially controversial in nature (Delacour & Leca, 2017; Glückler & Eckhardt, 2022; Glückler & Sánchez-Hernández, 2014; Krackhardt, 1997), i.e. their potential benefits and drawbacks compared to the status quo are not unanimously known or agreed upon. Difficulties in strategic decision making in such a regime are further amplified by at least three issues: First, technological developments are often interrelated in that the usefulness or feasibility of one new technology hinges on the state of another, or on the compatibility with the technological status quo. Consequently, it is rarely enough to monitor individual technology alternatives, but instead decision makers need to evaluate networks of interdependent technologies. Second, technological progress is path dependent (David, 1985; Dosi & Nelson, 2010): Innovation and technology adoption do not take place in a vacuum but are embedded into firm histories and existing knowledge bases and their success accordingly often depends on their compatibility with the status quo (Breschi et al., 2003; Makri et al., 2010). And third, individual decisions are embedded into a collective action problem, as an industry-wide shift to a new technology regime carries implications for the individual firm through network effects, standardization, or increasing returns (Arthur, 1989; Farrell & Saloner, 1985; Majumdar & Venkataraman, 1998). As a consequence, individual adoption decisions are potentially interdependent. A broad understanding of interrelatedness at both technological and economic levels is critical for assessing likely or unlikely future pathways, making it an invaluable resource for strategic decision making. From a historical perspective, technological interrelations are sources of interdependencies or path-dependencies, which shape the technological trajectory. Examining the dynamics of structural features of technological networks can help reveal the underlying processes through which interrelated technologies influence the evolution of a technological field. Although there are many studies that focus on single science and technology domains, such as fuel cells (Ho et al., 2014; Verspagen, 2007), coronary disease treatments (Fontana et al., 2009; Mina et al., 2007), or CRISPR sequencing (Magee et al., 2018), more holistic studies of the interplay of multiple technologies have been neglected. Therefore, this paper aims to assess the structural variation among and the structural interrelations between different technological building blocks in the development of a heterogeneous and emerging technology field: plastic recycling. The technologies of plastic recycling have to respond to a wide array of different requirements (e.g., textiles vs. packaging), a complex process chain with interrelated stages (e.g., sorting, separation, and depolymerization), and distinct technological approaches at varying levels of maturity (e.g., mechanical, chemical, or biological recycling). The analysis presented in this paper focuses on the interrelated technical evolution of three example technologies: textile recycling, separation techniques and use of enzymes for biological degradation of polymers. To do so, we utilize patent citation data and a variant of main path analysis to delineate the co-evolution of technological trajectories. While main path analysis is usually used to investigate the history of technology development within a single technology, we here use a more comparative and integrative approach that captures interdependencies between different technologies within a field, in line with the issues discussed above. The paper proceeds as follows: Section 2 gives a brief overview of the current state of plastic recycling technologies and its challenges. Section 3 discusses the literatures on technological change and technological trajectories. Section 4 then describes the data selection process and introduces the main path analysis method before section 5 presents the results of the empirical analysis. Section 6 discusses the findings and their implications for future research.

Plastic recycling: A brief overview

The technological field of plastics recycling broadly includes all processes that enable further utilization of discarded or residual plastic materials. The literature distinguishes four types of recycling: primary, secondary, tertiary and quaternary recycling (Hopewell et al., 2009; Lee & Liew, 2021). Primary recycling refers to closed-loop recycling, i.e., the recovery of an equivalent output. This is most common for post-industrial waste, i.e., scrap material which accrues as a byproduct of industrial processes and has a high degree of purity. Closed-loop recycling is also a target for some post-consumer wastes, especially when deposit schemes are in place to guarantee selectivity. However, even the 'poster child' of plastic recycling, PET bottles, is far from full closed-loop recycling: Despite the comparatively high recycling rate of about 50%, only an estimated 17% of PET bottles on the European market find their way into another plastic bottle after recycling, with downcycling (e.g., to polyester fibers) instead being the norm (eunomia, 2022).

Primary recycling relies on mechanical reprocessing, usually through a process called extrusion, which involves the use of heat and pressure to achieve plasticization and reshaping of a polymer material (Schyns & Shaver, 2021). While mechanical recycling routes are in principle available for the most common polymers, such as polyethylene terephthalate (PET, commonly found in dimensionally stable food containers such as bottles), high-density polyethylene (HDPE), low-density polyethylene (LDPE, usually found in films or plastic bags), or polypropylene (PP), the materials differ in their susceptibility to degradation during the extrusion process and thus must ideally be treated separately (Schyns & Shaver, 2021). Beyond the established mechanical recycling routes of standard packaging polymers, recent studies investigate recycling of more exotic polymers, such as polylactic acid, a biopolymer (Beltrán et al., 2019).

Secondary recycling refers to mechanical recycling processes that result in a product of reduced quality, i.e., the downgrading of the original material. A typical example is the reprocessing of high quality PET, such as found in clear bottles, into polyester fibers (Park & Kim, 2014; Tshifularo & Patnaik, 2020). While secondary recycling can also rely on extrusion as a final processing step, it usually involves mechanical preprocessing of the material, such as separation, removal of contaminants, and shredding, to reach a sufficient degree of purity (Ignatyev et al., 2014; Singh et al., 2017). Post-consumer, household wastes usually contain a range of different polymers and are contaminated with other materials, such as paper, metal, or glass. Reducing the material degradation that commonly comes with recycling such household wastes is one of the major research challenges in the field (Antonopoulos et al., 2021; Eriksen et al., 2019; Larrain et al., 2021; Soto et al., 2018). Given this focus, many recent approaches target related issues such as combined recycling of composite materials (e.g., polycotton, Palme et al., 2017), solvent-based (Ügdüler et al., 2020; Walker et al., 2020) and biotechnological (Jönsson et al., 2021; Navone et al., 2020) separation and additive extraction processes, or on avoiding composite materials in the first place (Jabbari et al., 2016). Primary and secondary recycling rely on mechanical recycling, which keeps the basic polymeric structure of the recycled material intact, albeit with possibly degraded properties.

Tertiary recycling, on the other hand, implies the depolymerization of the original material, i.e., breaking up a polymer into its constituent monomer components (Hopewell et al., 2009). Lee and Liew (Lee & Liew, 2021) distinguish three kinds of approaches towards tertiary recycling: thermal degradation or pyrolysis, chemical degradation, and biological or enzymatic degradation. In contrast to chemical and biological approaches, pyrolysis can handle mixed waste streams but results in fuels as an output, which cannot be reused in plastic production. Chemical and biological recycling are generally more selective but result in components that can be reused for polymer synthesis, such as ethylene glycol or terephthalic acid. While pyrolysis and some forms of chemical recycling, such as glycolysis and methanolysis, are, at least to a certain extent, already established industrial processes (Lee & Liew, 2021), biological recycling is still in its infancy: Sparked by the discovery of plastic-degrading bacteria (Bornscheuer, 2016; Yoshida et al., 2016), current research focuses on identifying the most effective bacterial strains and enzymes (Tournier et al., 2020), with some promising industrial applications in sight (DeFrancesco, 2020).

Finally, quaternary recycling refers to energy recovery through incineration of waste. While plastics have high energy density in principle, waste incineration has higher CO2 emissions (Jeswani et al., 2021; Wollny et al., 2001) and lower energy recovery rates (Overcash et al., 2020) compared to other recycling approaches. It is generally only preferrable as an option when material recovery is not feasible (Al-Salem et al., 2009). This brief overview already illustrates the technological complexity of recycling plastic materials: There is no one-size-fits-all approach but instead the efficacy of each method depends greatly on characteristics of the input material, such as polymer structure, waste composition, degree of contamination as well as on application context and the desired outputs. There is also great potential for interdependencies across technical subdomains: The development of more effective separation techniques, for example, would increase the relative usefulness of material-specific recycling approaches and could spur development of recycling techniques for multi-component applications. In the context of this heterogeneous technological field, the aim of this paper is to explore differences and interdependencies in the development pathways of technology subdomains relating to specific application contexts, process stages, and approaches.

Example technologies for empirical analysis

In our patent-based empirical analysis of the interdependence between technological developments, we limit our attention to three technical domains in the larger field of plastic recycling: First, textile recycling as a large but specific use case: Textile recycling has increasingly received public attention over the rise of fast fashion but poses unique challenges compared to the more mainstream issue of recycling plastic packaging and so far only shows low recycling rates (Geyer et al., 2017). The textile industry not only covers large consumer markets, such as apparel and footwear, but also comprises a broad range of industrial and household applications, such as carpeting, the automotive sector, or geotextiles. As such, synthetic textiles by themselves encompass a variety of materials and properties that are utilized in different contexts, from polylactic acid nonwovens for hygiene products to nylon fabrics for apparel or polyester fibers for artificial turf. For some of the most common textile materials, such as polyester, nylon, or cotton, recycling routes exist in principle (Harmsen et al., 2021). Second, as in the case of packaging, a main challenge in recycling textiles is the use of composite materials such as polyester-cotton blends (Palme et al., 2017), which are pervasive across the industry. Accordingly, we investigate separation techniques as a process stage of cross-sectional relevance, which already has been briefly discussed in the previous section. Separation is a central concern across applications given the pervasiveness of composite materials, which are hard to process with common polymer-specific recycling routes. And third, we investigate biological or enzymatic recycling techniques, also discussed previously, as a promising new avenue which has only recently emerged but caters to many demands for sustainable new technologies. Because the approach taken by enzymatic recycling differs from other recycling technologies in terms of the underlying knowledge base and necessary technological preconditions, one goal of this paper is to explore to what degree such technological disconnect is identifiable through the structure of evolving patent citation networks.

Data and methods

Patent data and selection strategy

Patent data have been utilized as a technology or innovation indicator for many years due to their unparalleled ability to provide both detailed insights into specific technologies and high coverage with respect to technological fields, historical development, and geography (Bekkers & Martinelli, 2012; Hall et al., 2005; Jaffe et al., 1993). However, patent-based indicators are also not without issues, especially when the ultimate goal is to evaluate economic performance: While many patents are of little impact or worth, some protect immensely lucrative business models, and telling which one is which is not trivial (Griliches, 1990). This shortcoming is often argued to be less of an issue when the focus is not on the value of individual patents but on the larger structure and development of a technology field (Verspagen, 2007), an approach which is also chosen here.

The first step in any patent analysis is the selection of an appropriate subset of patents to study. In the wake of the application process, patents are classified by expert examiners according to standardized technology classification systems, such as the Cooperative Patent Classification (CPC) collaboratively implemented by the European Patent Office (EPO) and the United States Patent and Trademark Office (USPTO). Such classification systems often provide a good starting point for topical patent searches. For tracing technologies in plastic recycling, we here select patents classified in either the maingroups B29B17 (titled 'Recovery of plastics or other constituents of waste material containing plastics'), C08J11 (titled 'Recovery or working-up of waste materials'; this maingroup contains subgroups on recovery of waste solvents and polymers), and the subgroup Y02W30/62 (titled 'plastics recycling; rubber recycling'). We then download all patent applications classified with at least one of the above labels from the open data platform Lens (Lens.org, 2021) as of October 2022, for a total of 116,021 applications. As protection for a single invention is often sought in multiple jurisdictions, there can be multiple applications per invention, which form what is called a patent family. In our dataset, applications are grouped into a total of 61,321 families, for an average family size of 1.9. In the following, the terms 'patent' and 'family' will be used interchangeably.

Patent citation networks

A key feature of patent data is the inclusion of citations to related prior patents (and non-patent literature) during the examination of an application's novelty. This enables the compilation of patent citation networks and the tracing of technological development 'chains'. Because in some jurisdictions (such as the EPO) citations to related technologies are collected by the examiner and not by the applicant (as is the case in the US), a citation does not necessarily allow for the interpretation that the cited patent was a direct reference to the invention covered by the citing patent. Nevertheless, a citation implies that the earlier technology is in some way relevant for or related to the later technology, which enables the tracing of path dependent technological development. We here extract the (reverse) citation network at the family level by creating an edge from family f_1 to family f_2 if at least one application from the latter cites an application from the former and if the earliest filing date of f_2 is after that of f_1. This second step is to prevent citations 'into the future', which can occur as a consequence of the time lag between applications in a family and the resulting potential for bidirectional overlap between families. Such citations would create cycles in the citation network and thus destroy its property as a directed acyclic graph (DAG), which is required for methods such as main path analysis. Applied to our selection of families, the procedure then yields a citation network with a total of 57,956 family-to-family edges. Beyond citations among the selected patents, there is also the possibility of citations to patents outside of the selection. Among the 200,548 total citations issued by the applications in the set, 84,228, or around 42%, are to other applications included in the selection, i.e., those applications having one of the specified classification labels. We here restrict our attention to the network of citations among patents within the field of plastic recycling.

Main path analysis

To empirically explore structural features in the technological co-evolution of plastic recycling technologies, we here employ a variant of main path analysis, a bibliometric method first proposed by Hummon and Doreian (1989) in a study on the development of DNA theory. The principal idea behind the method is, as the name implies, the extraction of the most important citation path(s) from a given citation network. As such, we regard main path analysis first and foremost as a tool for complexity reduction as it provides a filtered view into a potentially large and complex network. While there are many variants of the method (for a recent overview, see Liu et al., 2019), most variants involve two steps: First, the computation of some kind of traversal weight for either nodes or edges, and second, the traversal of the network along the highest weight paths given one or more starting positions, yielding the actual main path(s). For traversal weights, we here employ the Search Path Count (SPC) method, for which an efficient algorithm was given by Batagelj (2003), which we implemented in an open source software package for the Julia programming language (MainPaths.jl). SPC implements a concept of 'flow' through the citation network, where edges (or nodes) that lie on many of the paths connecting source nodes (i.e., nodes without any cited predecessors) to sink nodes (i.e. nodes without any citing successors) will receive high traversal weights.

To capture main paths for specific topics in plastic recycling, we select starting patents for the main path traversal based on the following three steps: First, we select a CPC subgroup label representing a target technology as a classification requirement for a starting patent. To identify patents within the technological domains of textile recycling, separation, and enzymatic recycling selected for analysis, we filter the subset of recycling patents by CPC section label 'D', class label 'B03', and subgroup label 'C08J11/10', respectively. Second, we specify a time window from which a starting patent may be selected. We here choose the period from 1995 to 2020 and thus exclude both patents with primarily 'historical' relevance as well as very recent developments whose impact cannot yet be discriminated by e.g., observing forward citations. And third, we pick the k=20 patents from the selection yielded by step 1 and 2 which score highest in terms of year-normalized forward citations. Year-normalization is performed to counteract recency-biases induced by the fact that older patents had more time to accrue citations. And k is chosen to yield main path networks with manageable complexity. Given the set of starting patents with the specified requirements, a forward and backward traversal of the citation networks is performed, where the neighbor chosen in each traversal step is the one with the highest traversal weights.

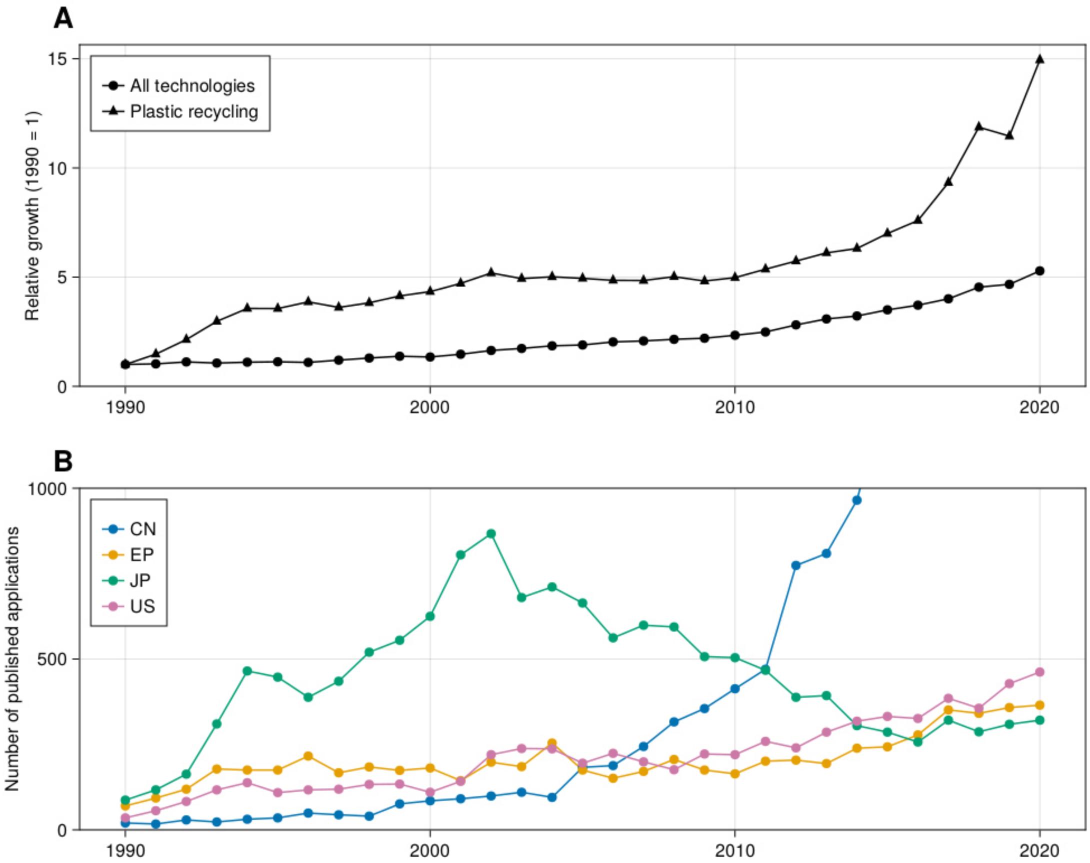

Figure 4.1: Patenting trends in plastic recycling, 1990-2020. Note: The y axis in Panel B is truncated for readability; The plot for China extends to more than 4,000 published patents by 2020.

Results

Patenting boom in plastics recycling

Looking at the overall trend of newly published patent applications over the last 30 years, two growth periods stand out: the first in the 1990s and early 2000s, and the second starting around 2010 and accelerating recently, with a 10-year period of stagnating growth in between (Figure 4.1 A). Differentiating between the jurisdictions in which an application was filed (Figure 4.2 B), we can see that the first growth period was especially driven by Japanese patent applications, while the second growth period is due to an explosion of applications in China.

The latter trend is generally observable across many technology areas and is at least partly explainable by a government-driven push to create an internationally competitive Chinese patenting system, which drove up domestic application numbers but also came with a drop in patent quality (Prud'homme, 2015; Sun et al., 2021). The strong growth of recycling patent applications in Japan during the 1990s and early 2000s coincides with a policy push in the form of a waste management reform, as implemented in the Containers and Packaging Recycling Act enacted in 1995 or the Home Appliances Recycling Act enacted in 1998 (Japanese Ministry of the Environment, 2014). In comparison, patenting in the US and Europe for the field of recycling appears to be on a trajectory of slow growth, with some slight acceleration over the last 10 years. Comparing recycling to patenting trends in all technologies, it seems that recycling has received disproportionate attention: The number of published applications in recycling has increased by a factor of 14.9 from 1990 to 2020, compared to a factor of 5.3 across all technologies. Overall growth is still larger for recycling compared to all technologies when taking Japan and China out of the equation, albeit at a much lower multiplier of about 6.4.

Structural heterogeneity across technical domains

We next investigate the three example topics of textile recycling, separation technologies and enzymatic recycling. For each of these, we select the top k=20 families in terms of year-normalized forward citations as starting points for forward-backward main path traversal. Traversal is not limited to patents within the topic, however; the main path is allowed to move to any family in the full sample (see Figure 4.2 for a visual representation of the three main paths). Accordingly, each topic has three associated sets of patents: (1) all families within the topic (i.e., with the respective CPC classes), (2) the 20 start points, and (3) the families on the main path. Based on these, we compare aggregate statistics on organizational and geographic composition and network structure among the topics and against the full sample of recycling patents (Table 4.1).

First, the topics vary strongly in terms of size and maturity: While close to 1,500 families feature CPC classes associated with separation techniques, only

234 families concern enzymatic recycling techniques, with textiles somewhere in the middle. Furthermore, patents on enzymatic recycling are very recent, with a median earliest publication date of 2018. This reflects the fact that major breakthroughs enabling the technique have only recently occurred, such as the discovery of the PET-degrading bacteria strain Ideonella sakaiensis found at a Japanese recycling plant (Yoshida et al., 2016). Separation technologies, on the other hand, had a peak in the 1990s, followed by a long period of stagnation, and have only recently experienced another push.

Second, the three topics vary strongly in their degree of organizational concentration: Table 4.2 gives values for the Herfindal-Hirschman Index (HHI) indicating the degree of concentration in the distribution of patent families across applicants (and jurisdictions). A value of 1 would indicate that a single organization holds all patents (the lower bound depends on the number of organizations). Again, enzymatic recycling stands out, with a comparatively large degree of organizational concentration across the three sets of total topical patents, main path patents and start patents. This is mainly due to the French late-stage startup Carbios, a technology leader in the field, having built a comprehensive patent portfolio: half of the 20 high-impact start patents were filed by Carbios, which is thus identified as a key player in shaping the enzymatic recycling trajectory. While jurisdictional concentration is overall more homogeneous across topics than organizational concentration, it interestingly is higher for the full sample of recycling patents. This is likely a consequence of Chinese patents, the largest group within the full sample, being less dominant in the more selective topical subsets.

Third, the three topics vary with respect to main path structure. While the separation and textiles networks are separated into multiple disconnected components, the components apart from the main component are small and topically not clearly separated. For the enzymes main path separation into disconnected components is however also reflected in the patented technologies within the two components: The larger one contains chiefly the recent patents in the Carbios portfolio, which is primarily concerned with PET / polyester recycling and the

Table 4.1: Summary statistics for selected recycling topics

Statistic	Total	Textiles	Separation	Enzymes
Families	61,321	807	1,491	234
Publication date (median)				
Total	2016	2013	1999	2018
Main path	2007	2001	1999	2004
Start patents	2018.5	2015	2000.5	2015.5
Applicant concentration (HHI)				
Total	0.00016	0.00306	0.00141	0.01549
Main path	0.00947	0.00761	0.01092	0.03702
Start patents	0.055	0.085	0.055	0.195
Jurisdiction concentration (HHI)				
Total	0.15124	0.07807	0.07341	0.10601
Main path	0.08432	0.09232	0.07631	0.09167
Start patents	0.09991	0.16078	0.05615	0.10348
Main path structure				
Components	5	3	3	2
Diameter (main component)	52	45	30	19
Mean geodesic distance (start pat.)	19.71	18.79	12.51	8.1
Mean forward citations	25.6	26.57	32.44	19.98
Topic homogeneity (% topical)	-	21.8	37	42.7

Note: Topic homogeneity refers to the percentage of patents in the main path network that share the CPC classes used to identify the respective start patents.

means by which to achieve it, such as the development of new esterase enzymes and polypeptides with degrading capabilities. The second component, on the other hand, is primarily concerned with the devulcanization of rubber and prominently features the Goodyear tire company.

As measures of the overall degree of connectivity within each topic, we use the network diameter (i.e., the longest path among any two nodes in a network, representing visual 'branchiness') and the mean of the pairwise geodesic distances among the start patents in the main path. If the patents on the main path (or only the start patents in the case of the latter statistic) are highly clustered, this will reflect in low scores on these metrics. Especially textile recycling stands out with a large diameter of 45 and higher mean geodesic distance compared to the other two topics. Looking at Figure 4.2, we can see that indeed many of the start patents sit on branches representing different kinds of textiles or related processes, such as continuous filaments, artificial turf, carbon fibers, or non-wovens for sanitary use, which only connect relatively far back through a 'shared history'. Overall, the two measures then capture the degree of internal heterogeneity for this case. Interestingly, textile recycling also scores less in terms of topic homogeneity, i.e., the share of patents on the main path with the respective topic CPC labels, than the other topics. This is likely related to the fact that many of the starting patents bring their 'own history' of non-textile historical antecedents, as indicated by the large diameter.

To summarize, comparison of the three examples reveals heterogeneity with respect to organizational composition as well as main path structure. On one end of the spectrum, enzymatic recycling, a very recent approach focused on depolymerization via biological processes, is topically homogeneous, dominated by a single patent portfolio, and it exhibits a strongly clustered main path structure. At the other end, the application field of textiles is topically more heterogeneous than the other subdomains due to the inclusion of different fiber-based materials. This heterogeneity is represented by a more 'long-armed' structure of the patent trajectory (i.e., high diameter and start-to-start geodesic distances).

Interrelated technology evolution in the combined main path network

So far, we have treated the three topics separately. However, they are not: As argued in the introduction, technological development is often linked across related domains. To capture this kind of interdependence, we create an integrated or combined main path network by initializing the main path traversal at the union

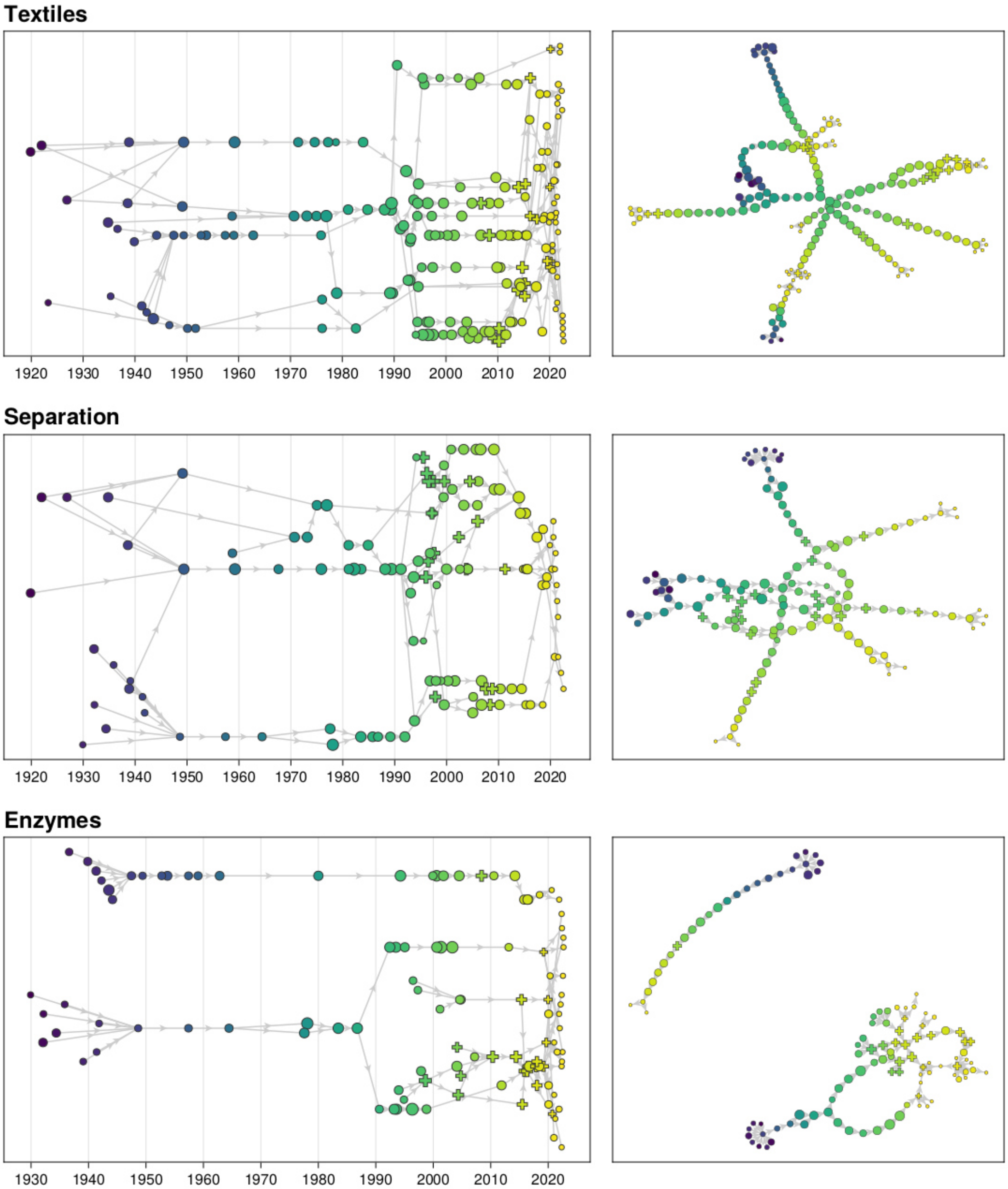

Figure 4.2: Main path network for selected recycling technologies. Sugiyama (left) and Kamada-Kawai (right) layouts to highlight different structural aspects. Plus markers indicate starting patents for main path traversal. Only main component shown for textiles and separation technologies.

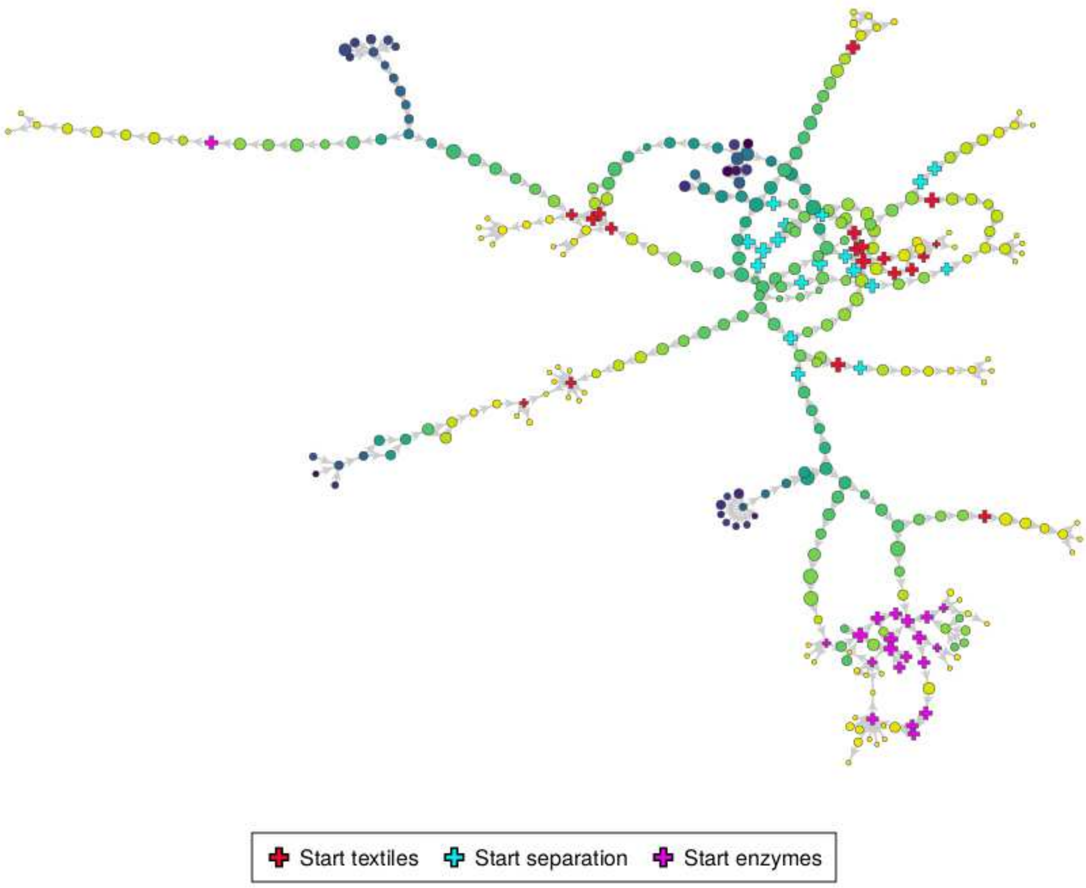

Figure 4.3: Combined main path network (only the largest component is shown). Base color represents publication date, as in figure 2.

of the start patents from the three topics. This way, patents from one topic can be encountered on forward or backward paths from/to patents in another topic.

Looking at Figure 4.3, the degree to which enzymatic recycling is disconnected form the other topics becomes quite clear: the only connection is through a 'common ancestor' while none of the enzymatic recycling start patents are on a direct path to or from the start patents in the other fields (Table 4.1B). The separation between the topics is also evident from the high mean (undirected) geodesic distances between the start patents in enzymatic recycling and the start patents in the two other topics (Table 4.1A), which is more than double compared to the score between the textiles and separation domains. This structural disconnect is plausible from a technological standpoint: While most of the predominant recycling technologies are

Table 4.2: Pairwise main path connectivity for topics

	Geodesic distance (A)			Backwards reachability (B)		
	T	S	E	T	S	E
Textiles	13.5	11.5	26.1	-	0.65	0.00
Separation	-	7.7	24.2	0.05	-	0.00
Enzymes	-	-	7.5	0.00	0.00	-

Note: Panel (A) shows mean undirected geodesic distances between the start patents in each topic. Panel (B) shows the share of the k=20 start patents in a topic (column) that are reachable from a start patent in another topic (row).

rooted in mechanical engineering and classical polymer science, enzymatic recycling is rooted in biotechnology and thus builds on a different knowledge stock. Textile recycling and separation technologies, on the other hand, are much more integrated. Many separation patents (13 out of 20, or 65%) are located on backwards paths for the textile recycling patents, indicating a flow of knowledge from the former to the latter. This is however not the case the other way around, with only a single textile patent being backwards reachable from a separation patent.

Accordingly, developments in separation techniques seem to serve as a precondition for many textile recycling technologies. Indeed, upon closer inspection some of the separation patents address issues such as reclaiming of carpet components, indicating co-development of specific applications and process stages, such as textile recycling and separation techniques. Here again, the structural importance of single patent portfolios becomes apparent, with e.g., Mohawk Industries, a world leader in flooring and carpets, taking a leading role in both the separation and textiles fields. Overall, the metrics considered here reveal a variegated structure of interrelation between the three technological subdomains of recycling, with enzymatic recycling being largely independent of the other domains and a unidirectional historical dependency of more recent developments in textile recycling on earlier advancements in separation techniques.

Discussion and conclusions

In this paper, we have studied the structure of technological co-evolution in the field of plastic recycling, using textile applications, separation techniques, and enzymatic recycling approaches as example subdomains. We use an original research design based on patent-based main path analysis to explore (a) structural differences and (b) structural interdependencies (or the lack thereof) between these technology domains. First, the three domains differ with respect to main path connectivity, topical homogeneity and the organizational concentration of innovation activity: Enzymatic recycling, a comparatively young technology domain, is characterized by a high degree of organizational concentration, topical homogeneity and strong connectivity between major patents (induced by high portfolio concentration), characteristics which might more generally be indicative of early-stage technologies. Textile recycling, at the other end of the spectrum, is characterized by topical heterogeneity, a lower degree of organizational concentration and low connectivity between high-impact patents, which indicate a more diversified domain combining different specialized fiber application contexts. Second, the analysis indicates patterns of technological (in)dependence in the evolution of the three domains. In an integrated main path representation, enzymatic recycling, an approach based in biotechnology, is largely disconnected from the other two domains, which in turn are characterized by a unidirectional historical dependence of textile recycling applications on separation techniques. While only representing a small excerpt of all technological approaches in plastic recycling, these results provide insights into a technological field which is characterized by both long-term historical interdependencies as well as recent approaches with disruptive potential, which however have not yet reached full maturity and do not yet interface with some of the core issues in the field.

Developing a better understanding of these patterns is helpful for at least two reasons: First, in-depth understanding of the structure of interrelated technology domains and their interdependencies can aid in the identification of bottleneck technologies or bridging technologies (and the respective dominant actors). These in turn can be important targets for policy to spur development of a larger field or for corporate innovation strategy to enable early adoption and the occupation of key 'technology niches'. Second, it can aid in the identification of the technological contexts (and the key actors) from which new and potentially disruptive approaches emerge. If such new approaches are largely incompatible with existing knowledge bases, as is the case for enzymatic recycling techniques, incumbents in the field need to reevaluate their own position and knowledge stock and balance the risk of being 'left behind' against the risk of a premature lock-in (Frenken et al., 2004). In such a situation, having monitoring systems in place that shed light on how and where a new technology interfaces with existing ones is crucial, as is demonstrated by the wide-spread existence of IP screening systems for corporate innovation strategy.

On a more methodological note, our study shows how main path analysis initialized to capture multiple technologies of interest can be combined with simple and well-known network analytical procedures, such as reachability analysis and geodesic distances, to gain insights into the interdependent development of related technologies. We believe that this approach is a promising research avenue for the future, which might ameliorate some of the problems with main path analysis: past applications of the method usually have taken the resulting main path and its constituent patents as an accurate representation of the major developments in the underlying technological field to be studied qualitatively (Fontana et al., 2009; Mina et al., 2007; Verspagen, 2007). However, this has been shown to not always be the case (Filippin, 2021). By shifting the focus from in-depth, qualitative analysis of singular main paths as a faithful representation of technological trajectories to more structural analysis of heterogeneous main path networks as 'filtered' representations of the underlying citation network, some of the interpretive challenges with the former approach might be avoided.

Future research related to the approach presented here could be fruitful in at least three areas of interest: First, methodological research on the robustness of the approach in the context of different parametrizations would be valuable:

E.g., the quantity and selection criteria for the start patents used to initialize the main path traversal usually follow ad-hoc heuristics and it would be important to know more about how sensitive different structural aspects of the resulting main path network are to differences in input. Second, while the fundamental idea of path-dependent and interrelated technological change is well theorized in the evolutionary economics of Dosi et al. (2010), theoretical substantiation of specific structural features and the conditions under which they occur remains largely an open problem. Future applications could also theorize different structural patterns than the ones studied here, such as technological junctures or patterns of convergence and divergence. Third, patents as a data source encode different kinds of information: a patent might protect a new application based on existing technical principles, a new material with improved properties, or a more efficient process, all of which could indicate different kinds of interdependencies: A more efficient process in one area might enable the development of a new material in another, which might again enable new applications in yet another domain. Extracting more fine-grained information from the available data sources could help in generating richer pictures of technological interdependencies, which in turn would prove more useful as information bases for decision making.

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5

Technological Cohesion and Convergence: A Main Path Analysis of the Bioeconomy, 1900 - 2020

Abstract. The bioeconomy comprises a range of industries that are related through their reliance on biomass and their use of biotechnology, such as agriculture, food processing, and parts of the life sciences. While the bioeconomy has received increasing attention in the context of innovation policy, the internal structure of its underlying technological field remains opaque, and little is known about the long-term processes through which its subdomains have co-evolved. It is precisely the structure (cohesion) of this field and its evolution (convergence) over the course of more than a century of technological development that this article seeks to disentangle. For this purpose, we draw on a dataset of more than 1.5 million patent families and use bibliometric methods and main path analysis to assess the internal and external cohesion of the field and trace its long-term technological development. Our analysis supports two main findings: First, instead of becoming more closed as a field, the cohesion of technologies within the bioeconomy with external technologies has increased over time. Second, the bioeconomy technological field shows clear signs of structural convergence over the second half of the 20th century, with the biochemical domain absorbing most of the trajectories of technological knowledge originating in the traditional application areas. As such, the study illustrates the long-term processes of technological cross-fertilization through which the bioeconomy, as an example of a heterogeneous technological field, developed its backbone of technological knowledge.

Introduction

Both national governments as well as international organizations increasingly rely on economic strategies and policies targeted not at individual technologies, but instead at large-scale technological fields spanning multiple sectors and industries (see e.g., the EU's target investment areas (European Commission, 2023), currently comprising 'deep and digital technologies', 'clean technologies', and 'bio technologies'). Such strategies offer at least three advantages compared with more specific alternatives: First, they avoid having to predict the next big breakthrough and thus hedge against betting on the 'wrong' technology. Second, they have lower requirements regarding the technical evaluation of specific alternatives in the context of funding decisions. Third, they can exploit synergies and second-order effects in technological fields, which are understood to be internally coupled in some capacity, and thus lead to positive externalities.

However, technological fields are often only vaguely defined, and both their external boundaries, as well as their internal structures, are often contentious, which hampers precise policy support and risks inefficient allocation of resources. Furthermore, technological fields evolve along unstable trajectories as their member technologies evolve through recombination (Dosi & Nelson, 2010; Hargadon & Sutton, 1997; Mazzucato & Dosi, 2006; Strumsky & Lobo, 2015). The bioeconomy technological field is a prime example of these issues: Demarcations of the bioeconomy often comprise both traditional industries, such as agriculture or forestry, as well as more recent, high-tech sectors, such as the life sciences or biosynthetic materials (McCormick & Kautto, 2013; Staffas et al., 2013). Similar breadth is also inherent to the technological and scientific knowledge bases underlying these sectors, which span the biological, chemical, and engineering sciences, and which have evolved as field-integrating technologies from different points of origin (Buchholz & Collins, 2013). Despite or maybe because of this heterogeneity, the bioeconomy has become a nexus for different visions of a more sustainable future, often combining novel resources, novel technologies, and novel business models (D'Adamo et al., 2022).

In this paper, we are interested in the historical emergence of the technological field underlying the modern bioeconomy. More specifically, we use patent data and bibliometric methods to study the structural evolution of the bioeconomy technological field and the underlying emergent patterns of technological cohesion across its subdomains over a period of more than 100 years. In doing so, we especially focus on (a) the degree of cohesion in the field, (b) the positions that different subdomains take in the overall structure of the field, and (c) the historical trajectory along which the current manifestation of the field has developed. The paper is structured as follows: Section 2 discusses the literature on technological trajectories and fields and the processes through which they evolve. It also introduces the bioeconomy technological field. Section 3 presents the patent database used for empirical analysis and the bibliometric methods used to investigate structural evolution. Section 4 presents the results of the analysis and Section 5 discusses the findings and conclusions of the paper.

Evolution of heterogeneous technological fields

From technological trajectories to technological fields

In the dominant stream of research, technological evolution has been theorized as following technological trajectories that are embedded into overarching technological paradigms (Dosi, 1982; Dosi & Nelson, 2010): technologies receive incremental improvements in the context of a given paradigm, as exemplified by the increasing miniaturization of computer chips (Epicoco, 2013), while the fundamental approach towards the problem at hand remains the same. This process of incremental improvement produces relatively stable technological trajectories, which Dosi (1982, p. 152) defines as "the pattern of 'normal' problem-solving activity (i.e., of 'progress') on the ground of a technological paradigm". Trajectories can, in turn, be disrupted through paradigm shifts, i.e., changes to the fundamental solution approach (Martinelli, 2012). While this conceptualization is a powerful representation of technological development, it invites (but by no means necessitates) investigations of individual technological trajectories and paradigms (e.g. Aaldering & Song, 2019; Huenteler et al., 2016; Martinelli, 2012; Verspagen, 2007). We take the broader perspective of the technological field as our starting point, which we define as the set of all technologies that are connected by either (a) common outputs, (b) common inputs, or (c) common processes. This purposefully broad conceptualization accommodates a variety of definitions of technological fields found in both scientific studies as well as policy roadmaps: It allows for technological fields that are characterized by a common overall purpose of its member technologies (i.e., by a common output). An example is the field of life sciences (Powell et al., 2005), in which all member technologies have the overall goal of improving human health. It also allows for fields where technologies do not share a common purpose but instead make use of a common resource (or class of resources), or a common set of techniques. This is also the case for the bioeconomy technological field, which cannot easily be characterized by its output as it produces a variety of them, ranging from foods over pharmaceuticals to biobased materials, but which is instead usually defined through its use of biomass inputs (Bioeconomy Council, 2023) or its use and development of biological and biotechnological techniques (El-Chichakli et al., 2016; OECD, 2009). Given the fact that this definition can encompass a heterogeneous set of technologies, the ways in which individual technological trajectories and paradigms interact to shape the overall trajectory of the field become of central interest.

Processes of technological field evolution

Processes of technological evolution that involve the flow of knowledge across industries and scientific domains have become increasingly prevalent, with many studies highlighting how the recombination of existing technologies at different degrees of similarity can provide a competitive advantage for firms (Hargadon & Sutton, 1997; Kaplan & Vakili, 2015) and shape technological trajectories and transitions (Frenken et al., 2012). Even 30 years ago, Kodama (1992) sketched out the disruptive potential of technological convergence that was taking place in Japan's optical, electronic, and communication technology industries—hitherto largely separate sectors—which gave rise to fiber-optical communication technologies and liquid crystal displays. Since then, the study of technological convergence has proliferated: Research in the area has distinguished convergence at different levels, from basic science to whole industries (Curran et al., 2010; Sick et al., 2019), has investigated the breadth of convergence processes across industries (Jeong et al., 2015), and studied its relationship to standardization processes (Gauch & Blind, 2015; Han & Sohn, 2016) and firm-level absorptive capacity (Bröring & Leker, 2007). Research has also established empirical measurement procedures to trace convergence, often based on patent data (Caviggioli, 2016; Curran & Leker, 2011). Based on such conceptual and methodological approaches, case studies have focused on convergence in a broad range of industries such as electronics (Gambardella & Torrisi, 1998) and ICT (Duysters & Hagedoorn, 1998; Han & Sohn, 2016; Jung et al., 2021), (nano)biotechnology (Curran & Leker, 2011; No & Park, 2010), electric vehicles (Feng et al., 2020), robotics (Kose & Sakata, 2019), and printed electronics (Kim et al., 2014). This paper investigates technological convergence across the subdomains of the bioeconomy technological field. It explicitly foregoes both the study of convergence at the market or industry level (Sick et al., 2019) and an analysis of the larger societal processes that are at play when considering the bioeconomy as the playground for a socio-technical transition (Sanz-Hernández et al., 2019), as these likely follow different processes and mechanisms. Instead, the paper takes a long-term perspective to identify processes of convergence in the main trajectories of technological knowledge within and across the subdomains of the field and to assess its cohesion with technologies outside the field.

The bioeconomy technological field and its subdomains

While there is no agreed-upon list of industrial sectors or technological domains that constitute the bioeconomy, most definitions include reliance on biomass as an industrial input and the use of biological, biochemical, or biotechnological processes as defining features (McCormick & Kautto, 2013; OECD, 2009; Staffas et al., 2013). Additionally, the bioeconomy is often associated with notions of circularity (Giampietro, 2019; Kakadellis & Rosetto, 2021; Muscat et al., 2021) and a more sustainable economy (Lewandowski, 2018). In the following, without any claim on completeness, we give a brief overview of some of the most frequently encountered bioeconomy subdomains. Closest to the biomass source are agriculture and forestry-related industries: For the former, a major promise of modern biotechnology is in the engineering of crops to improve yield (Bahaji et al., 2014; Bailey-Serres et al., 2019) and create more resistant crops (Sharma et al., 2002), but also, e.g., in the use of biorefineries to produce improved fertilizers (Jiao et al., 2019; Santamaría-Fernández et al., 2018). Wood-processing industries, on the other hand, are expected to play an important role as providers of cellulose, which is increasingly relevant not only in the paper industry but also for other fiber-based applications such as the textile industry (Kallio, 2021; Morland & Schier, 2020), and as a feedstock for fuels and chemicals (Rajesh Banu et al., 2021), e.g. for the production of bioplastics (Esposti et al., 2021; Rosenboom et al., 2022). While probably the original application field of biotechnological processes, the food industry is also one of the core domains of a modern bioeconomy, touching on topics from fermentation, yeasts, and dairy cultures, to improvements of food quality or modifications of taste or nutritional value (Barbosa & Teixeira, 2022; Shetty, 2006). However, the food industry is linked with other bioeconomy domains not only through its reliance on biotechnology but also through questions of competing land and water use (Hertel et al., 2013; Lewandowski, 2015; Rosegrant et al., 2013). This is especially the case for the energy sector, for which the production of biofuels from agricultural feedstocks is seen as enabling a transition towards a biobased alternative to fossil fuels (Golembiewski et al., 2015; Zilberman et al., 2013). Finally, as the source of modern biotechnology (Buchholz & Collins, 2013), the life sciences constitute one of the core domains of the bioeconomy and represent the origin of many of today's bioeconomy policy efforts. While early medical applications focused especially on the production of antibiotics, the 'new biotechnology' of the 1970s saw major breakthroughs in recombinant DNA technology, leading, among others, to the approval and production of insulin (Buchholz & Collins, 2013). These breakthroughs facilitated further downstream progress, e.g., in enzyme technologies, which in turn percolated into other application fields, such as detergents (Gupta et al., 2002; Paul et al., 2014), and triggered large-scale shifts in industry structure and the dominant innovation model (Mazzucato & Dosi, 2006). Today, biotechnology is in widespread use across a range of medical domains such as pharmaceutical discovery (Muttenthaler et al., 2021) and pharmacogenomics (Evans & Relling, 2004), and emergent approaches such as gene therapy (Dunbar et al., 2018).

Based on the practical and theoretical considerations outlined above, the goal of the paper is to assess structural patterns of cohesion and convergence in the bioeconomy technological field. In pursuit of this goal, it addresses the following research questions: First, does the bioeconomy constitute a cohesive technological field and what structural positions do its subdomains occupy? Second, to what degree is the bioeconomy connected with outside technologies and does the field close over time? Third, are there patterns of convergence within and across the bioeconomy subdomains and how do these unfold over time? In the next section, we present an empirical delineation of the bioeconomy and its subdomains based on patent data and discuss methods for assessing structural cohesion and its evolution across the bioeconomy technological field.

Data and methods

Mapping the bioeconomy with patent data

We draw on patent data for empirical analysis, following common practices in research on technological trajectories and technological convergence (Caviggioli, 2016; Curran & Leker, 2011; Kim et al., 2014; Verspagen, 2007). Patent data are a uniquely suited database for this purpose due to their combination of breadth and depth: In terms of breadth, patents are available in standardized form for most industries (although industries differ with respect to patenting intensity), are available on a global scale (although heavily biased towards the core markets of the US, the EU, Japan, and more recently China), and go back more than a century. As such they allow for global and historical tracing of innovation activity across industries. In terms of depth, high-resolution hierarchical classification schemes (such as the Cooperative Patent Classification, CPC) allow for detailed delineations of technological domains, while citations of related state of the art (i.e., related previous patents) can be used as a measure of the flow of technological knowledge over time and across domains. To delineate the bioeconomy technological field and its subdomains, we depart from the list of CPC technology classes contained in the narrow definition of the bioeconomy presented in Wackerbauer et al. (2019) and reproduced in Table 5.1.

Table 5.1: CPC labels used for selecting bioeconomy patents.

IPC Technology Class	**Description**
Agriculture, foods	
A01H	New plants
A01P	Chemical agents for the regulation of plant growth
A21D	Conservation of flour and dough for baking
A23 (excluding A23N, A23P)	Foods
A24B	Tobacco
A43B,C	Shoewear
C05F	Organic fertilizer
C13	Sugar industry
F23G7/02,10	Burning of organic matter
Life sciences	
A61K38	Drugs containing peptides
A61K39	Drugs containing antigens or antibodies
A61K48	Drugs containing genetic material
G01N33/44-98	Analyzing biological materials

Continued on next page

Table 5.1: CPC labels used for selecting bioeconomy patents. (Continued)

Wood, paper, textiles	
B27K	Treatment of wood
B27N	Manufacturing articles from wood chips or fibers
D21B,C,D	Cellulose for papermaking
C14	Hides, skins, leather
D01B,C,D	Treatment of natural fibers and filaments
D01F02,04	Filaments from natural materials
Chemistry	
C02F3; C02F11/02,04	Biological treatment of water and sludge
C07G11-15	Antibiotics, vitamins, and hormones
C07K	Peptides
C08C	Treatment of rubbers
C08H	Derivatives of natural macromolecular compounds
C08B	Polysaccharides
C08L 01,03,05,07,13,15, 17,19,21,87,89,91,93,97,99	Compounds based on natural macromolecular compounds
C09D 11/04,06,08	Inks based on natural substances
C09D 103,105,107,113,115,117, 119,121,189,191,193,197,199	Coating agents based on natural substances
C09F	Natural resins
C09H01	Natural substances for the production of glue
C09J 101,103,105,107,113,115, 117,119,121,189,191,193,197,199	Natural dyes
C11B,C,D	Natural fats, waxes, cleaning agents
C12	Biochemistry
G01N 33/2-14,44,46	Analyzing natural substances

Note: Translated adaptation of Table 3 in Wackerbauer et al. (2019).

Using this list, we obtain a total of 4,096,554 patent applications containing at least one of the listed CPC labels from the PATSTAT database (autumn 2022

Table 5.2: Bioeconomy subdomains

Domain	CPC Class (3-Digit)	N Maingroups	N Families
1 Biochemistry	C12, C07, C08	263	686,837
2 Life sciences	A61, G01	4	128,782
3 Detergents and dyes	C11, C09	53	116,851
4 Foods and tobacco	A23, A21, A24, C13	98	482,997
5 Textiles, paper and wood	A43, D01, D21, B27, C14	83	208,176
6 Agriculture and fertilizers	A01, C05, C02, F23	31	109,347

Note: The selection of bioeconomy patents is based on table 1, which in many cases relies on CPC labels under the class 3-digit and accordingly not all patents belonging to the classes listed here are included in the final selection of patents.

edition). These applications reduce to 1,525,980 patent families after accounting for multiple applications referring to the same technology, e.g., in the context of applications in multiple jurisdictions. In terms of splitting the bioeconomy technological field into subdomains, we deviate slightly from the four groups presented in Wackerbauer et al. (2019): First, we separate agriculture and fertilizers from foods (and, much less frequently, tobacco), as the latter constitutes a large domain in itself and is conceptually distinct from the former in terms of the contained technologies. Second, we split the very broad chemistry category into a more focused biochemistry/biotechnology category and a more application-specific category containing especially technologies related to the production of detergents and natural dyes, resins, and fats. Notably, the energy sector is missing from the reference list. This could be a consequence of biofuels receiving decreasing policy attention due to a shift towards electromobility and public attention towards issues of food security that arise with the use of crops for energy purposes (Lewandowski, 2015). Table 5.2 contains an overview of the CPC class labels used to distinguish the resulting six domains as well as their sizes in terms of technologies and associated patent families.

Co-classification and patent citations

Based on the selection of patents and the distinction of bioeconomy domains presented in the last section, the paper first relies on co-classification as a static measure of cohesion at the technology level, represented by 8-digit CPC maingroups. Two technologies (i.e., CPC maingroups) are connected through co-classification to the degree that they appear on the same patents. To give an example, patent EP3853359A1, applied for by the biotech firm Novozymes and claiming an animal feed product containing polypeptides with lysozyme activity, carries a total of 14 subgroups contained in maingroups C12N9 and C12Y (both classifying enzymes), A23K10 (animal feedstuffs), A23K20 (accessory factors for animal feedstuffs), and A23K50 (feedstuffs specially adapted for particular animals). In the co-classification matrix of all technologies at the maingroup level, the cells corresponding to the pairs of these five technologies would each be incremented by one through this patent. All five of these technologies are furthermore considered bioeconomy technologies because they are descendants of one of the CPC labels listed in table 1 . Overall, 8079 CPC maingroups appear as classifiers on the patents in the dataset, of which only 535 directly belong to the bioeconomy.

A second, more dynamic representation of cohesion can be obtained from patent citations. Patent citations arise during the process of examination and contain references to previous patents (and other representations of the ‘state of the art’, such as scientific publications) that are in some way related to the technology to be protected by the examined patent. As such, they are often taken to indicate knowledge flow (Jaffe et al., 1993; Verspagen, 2007). These citations can then be combined into citation networks that have an inherent temporal structure, where ‘backward citations’ imply that a patent builds on earlier technologies and ‘forward citations’ (i.e., citations received from subsequent patents) indicate influence on future technologies. We aggregate citations at the family level and eliminate all citations into the future, which can arise due to applications belonging to two families overlapping in time. Furthermore, the direction of citation edges is reversed to represent the forward flow of knowledge. The resulting network is then a directed acyclical graph, which is a necessary requirement for methods such as main path analysis. In total, this procedure results in a citation network of 1,525,980 nodes and 5,952,648 edges; however, 446,106 nodes are isolates, i.e., they do not cite and are not cited by any other patents in the dataset.

Measuring convergence based on main path networks

To measure convergence, we employ main path analysis (Hummon & Dereian, 1989; Liu et al., 2019), a bibliometric method, to extract the most relevant chains of citations, i.e., main paths, from a citation network. Main path analysis typically involves two steps: First, the computation of some flow measure that captures the importance of individual nodes or edges in the overall network. We use Search Path Count (SPC) edge weights [68], which count the total number of shortest paths from all source nodes to all sink nodes in the citation network that contain a given edge. The SPC method relies on topological sorting of the vertices, which is possible due to a citation network's nature as a directed acyclical graph (DAG). This in turn enables an efficient algorithm that is linear in the number of edges and allows for the analysis of very large networks (Batagelj, 2003). Second, after weights have been computed, a set of start nodes is selected; this selection can follow different heuristics and could, e.g., include all source nodes, nodes in a specified period or domain, or nodes with high flow weights. Departing from all start nodes, the citation graph is traversed forward, backwards, or both, following the highest-weight outgoing (or incoming) edge(s), based on the weights computed in step one. As such, the variant of main path analysis used here implements a greedy priority-first search algorithm (Hummon & Dereian, 1989). Depending on the selection of start nodes and the structure of the original citation network, the resulting main path networks can be simple or complex, both in terms of size as well as structure. We create main path networks for each domain by taking the top 5% vertices as measured by their SPC vertex weight as start positions and then perform forward and backward traversal to capture both trajectories leading to these high-impact technologies as well as the subsequent developments building on them. Due to the large sizes of the original domains, this still leads to relatively large (in the order of 10,000s of nodes) and structurally complex main path networks. Compared with, e.g., forward traversal initialized at early source nodes, an 'endogenous' selection of start nodes based on flow weights combined with bi-directional traversal has a series of advantages: First, it allows for more focus to be put on periods that spawned highly relevant innovations (as indicated by high SPC vertex weights). Second, it enables more structural variation, as backward traversal can produce branches in the final main path network that are unlikely to occur purely based on forward traversal. Third, it allows for backward paths to deviate from the source domain of its starting points and thus reveal the existence of origins in a different domain.

Based on such a representation of major technological pathways, we conceptualize convergence as a function of time: For a given period, structural convergence can be measured as the absolute or relative reduction in parallel paths that occurred during that period (Figure 5.1). In the example in Figure 5.1, a total of five paths enter the period at t_1, while only three paths remain at t_2 due to a series of merges (but also branches) that take place during the period, amounting to a total reduction of two or a convergence rate of 60%. The same approach could also indicate divergence, represented by an increase in parallel paths. To additionally account for whether convergence takes place within the same technology or domain, or whether a shift to a different domain is occurring, we record the domains of the patents from which the outgoing paths in a given period originate. In the above example, then, two out of three outgoing paths originating from a new domain (represented by filled nodes) would indicate a majority domain shift and thus indicate inter-domain convergence. In the following, we split the full observation period, starting in 1900 and ending in 2020, into 24 five-year periods and record the above network statistics for visualization and analysis. All data analysis has been performed using the Julia programming language and its package ecosystem.

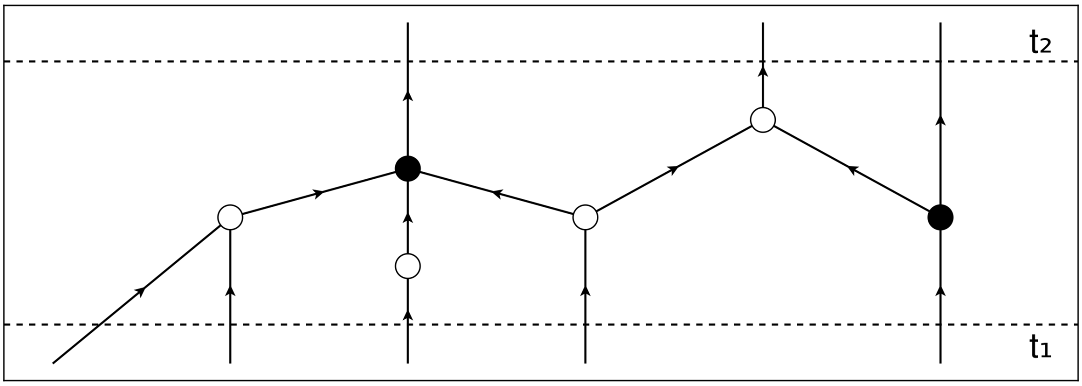

Figure 5.1: Structural convergence in main path networks. Filled and blank nodes represent patents belonging to different domains.

Results

Internal and external cohesion of the bioeconomy technological field

The bioeconomy is a heterogeneous technological field: it comprises both traditional sectors, such as agriculture, foods, or textiles, as well as more recent advances, e.g., in biotechnology or modern medicine. Inspecting yearly patent counts since the start of the 20th century, different levels of innovation activity and especially different growth trajectories become visible across these domains (Figure 5.2): Detergents and dyes, textiles, paper, and wood processing technologies, and food-related technologies exhibit already comparatively high patent counts at the outset and show consistent but comparatively slower growth throughout the observation period. In contrast, the life sciences bioeconomy domain produced negligible patent counts until the 1950s; however, this was followed by explosive growth throughout the second half of the century. While already at a non-negligible patenting rate at the start of the 1900s, the biochemistry domain has similarly experienced accelerated growth throughout the second half of the observation period, in line with the rise of biotechnology, of which it is one of the most important components.

In this context of technological heterogeneity and differently-paced growth, we

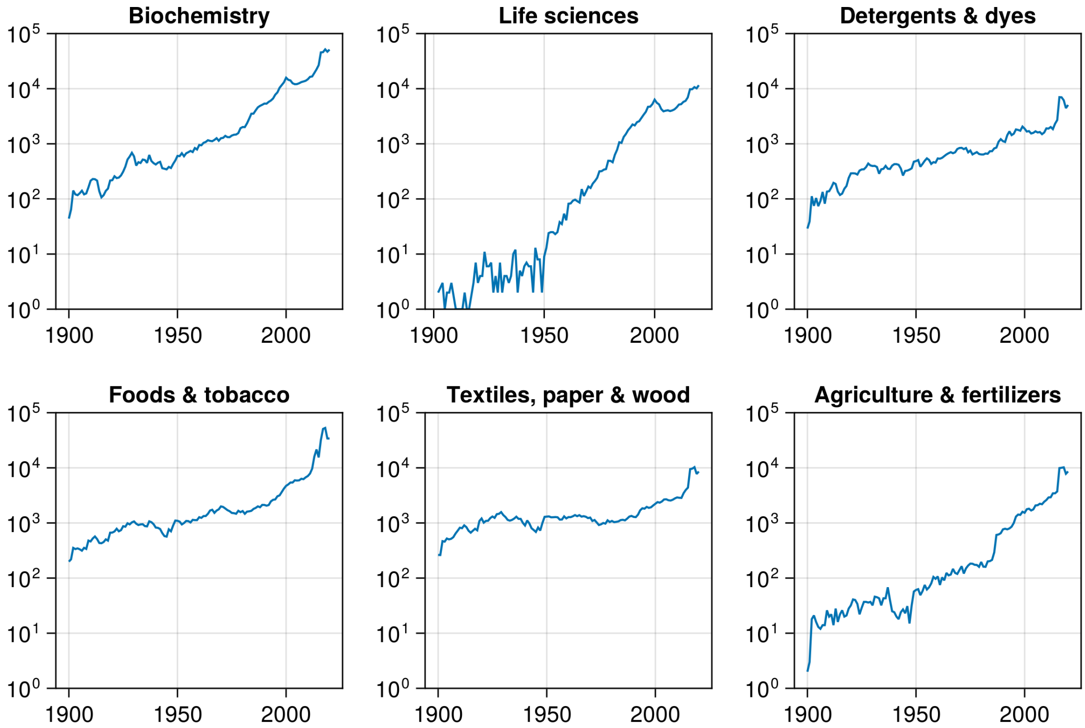

Figure 5.2: Development of patenting activity across bioeconomy subdomains.

examine technological cohesion based on co-classification. Figure 5.3 A,B display the main component of the aggregated co-classification network of all 8-digit (main-group) CPC classes featuring in one of the 1,525,980 initially selected patents, dichotomized at a minimum of 30 co-classified patents. This main component contains a total of 2030 technologies (i.e., CPC maingroups) and 27,388 linkages. Of these technologies, 535 are themselves bioeconomy technologies and form the network in Figure 5.3 B,C after removing all non-bioeconomy technologies. This juxtaposition hints at two structural features of the bioeconomy technological field: First, it is not closed with respect to other technologies but integrates strongly with technologies outside of the scope of the bioeconomy as delineated in Wackerbauer et al. (2019). Second, its internal cohesion is not homogeneous across its subdomains; whereas developments in (bio)chemistry and life sciences (but also food technologies, which form a separate but still closely related cluster) seem to be strongly interconnected, this is much less the case for wood, paper and textile technologies. They are instead strongly interlinked with non-bioeconomy

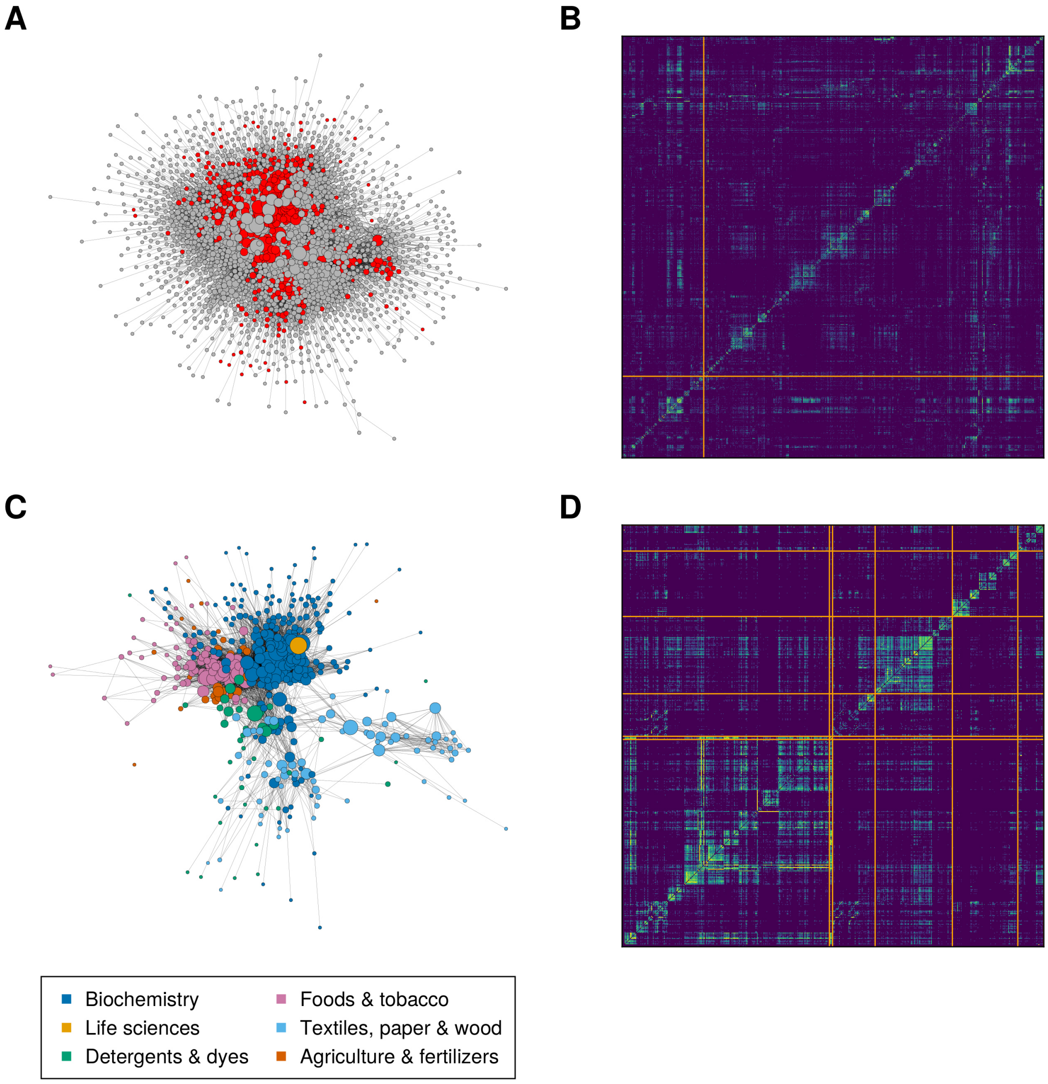

Figure 5.3: (A) Full co-classification network with bioeconomy technologies (CPC maingroups) marked red and non-bioeconomy technologies marked grey. (B) Co-classification matrix permuted by bioeconomy (left, bottom) and non-bioeconomy technologies. Brighter color indicates higher degree of coclassification. (C,D) Same as A and B but showing the bioeconomy induced subgraph with nodes color-coded and matrix permuted according to the six subdomains.

technologies but are much less connected to the other technologies within the field and even to other technologies in their own domain.

Figure 5.4 offers a reduced-form overview of the application domains' internal cohesion with the field-defining biochemistry domain as well as their external cohesion with technologies outside the field over the course of the observation period. Three major trends become apparent. First, there is a shift in the main applications of bio-chemical technologies: while in the first two periods, more co-classifications connect biochemistry to the food and the textiles, paper, and wood domains than the life sciences (which at this stage are still small), this pattern began to invert in the 1960s and the life sciences has since become the dominant domain connecting with biochemical knowledge. Second, notwithstanding this relative shift, the use of biochemical techniques in the traditional domains has also increased over time, with biochemistry co-classification rates at less than 1% in the first period for all application fields (except for life science technologies, which are always co-classified with biochemistry at close to 100%) but having increased to 7.4% (detergents and dyes), 7.0% (foods), 4.4% (textiles, paper, and wood), and 16.5% (agriculture and fertilizers) by the latest period. Third, instead of becoming more closed over time, the bioeconomy technological field has increasingly integrated with non-bioeconomy technologies, as indicated by the rising shares of non-bioeconomy CPC classes (with the exception of the agriculture domain, which also started at a much higher level than the other domains). This coincides with an increase in the average number of CPC classes received by a patent, which could indicate an overall increase in technological complexity and connectivity but which could also be an artifact of changed classification practices over the course of the observation period. In sum, these findings indicate an increase in both external and internal technological cohesion, with a shift towards the life sciences as the main driver of development in the integrative biochemistry domain.

Intra- and inter-domain convergence of main paths

As a next step, we use main path analysis to assess the degree of structural convergence of the major pathways of technological knowledge within and across the bioeconomy subdomains. We construct separate main path networks for each domain by initializing a forward–backward traversal departing at the top 5% of all nodes in terms of SPC vertex weight for each domain and extracting the main component. Figure 5.5 contains a visual representation of these main path networks (only forward trajectories are shown to facilitate readability) and indicates some

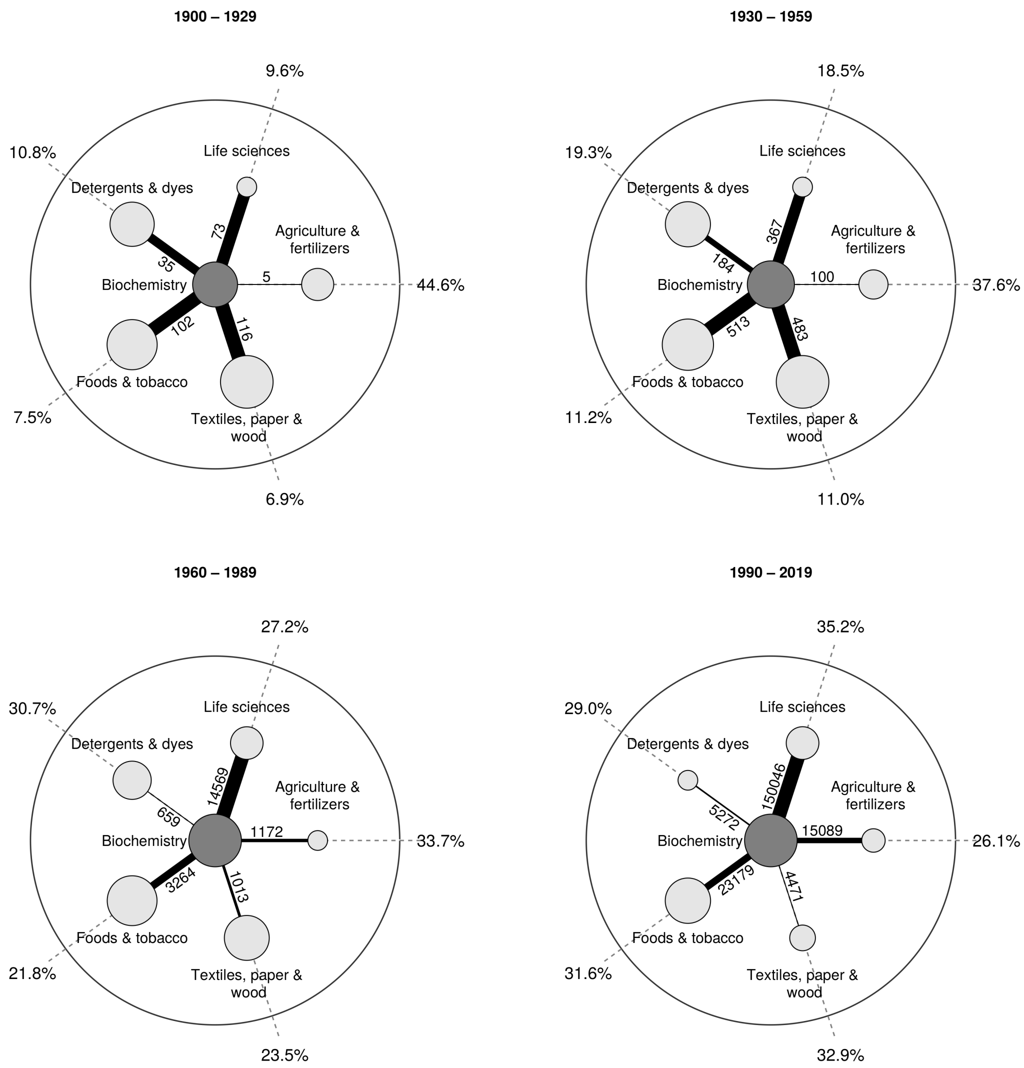

Figure 5.4: Internal and external cohesion in the bioeconomy. Edge weights indicate co-classification counts, node sizes are scaled according to patent counts, and percentages connected to dashed lines indicate the average share of field-external CPC maingroups for a patent of the given domain.

basic differences in the timing of high-impact innovations across the fields. In particular, the foods and textiles domains exhibit a larger amount of early high-impact start patents (leading to visually longer paths) than the other domains, whereas life sciences and biochemistry start patents are much more recent, on average. There are also some common trends: The ragged top indicates structural convergence of main paths, i.e., the merging of parallel chains of citations. The differences in horizontal position and the depth of these 'valleys' indicate differences

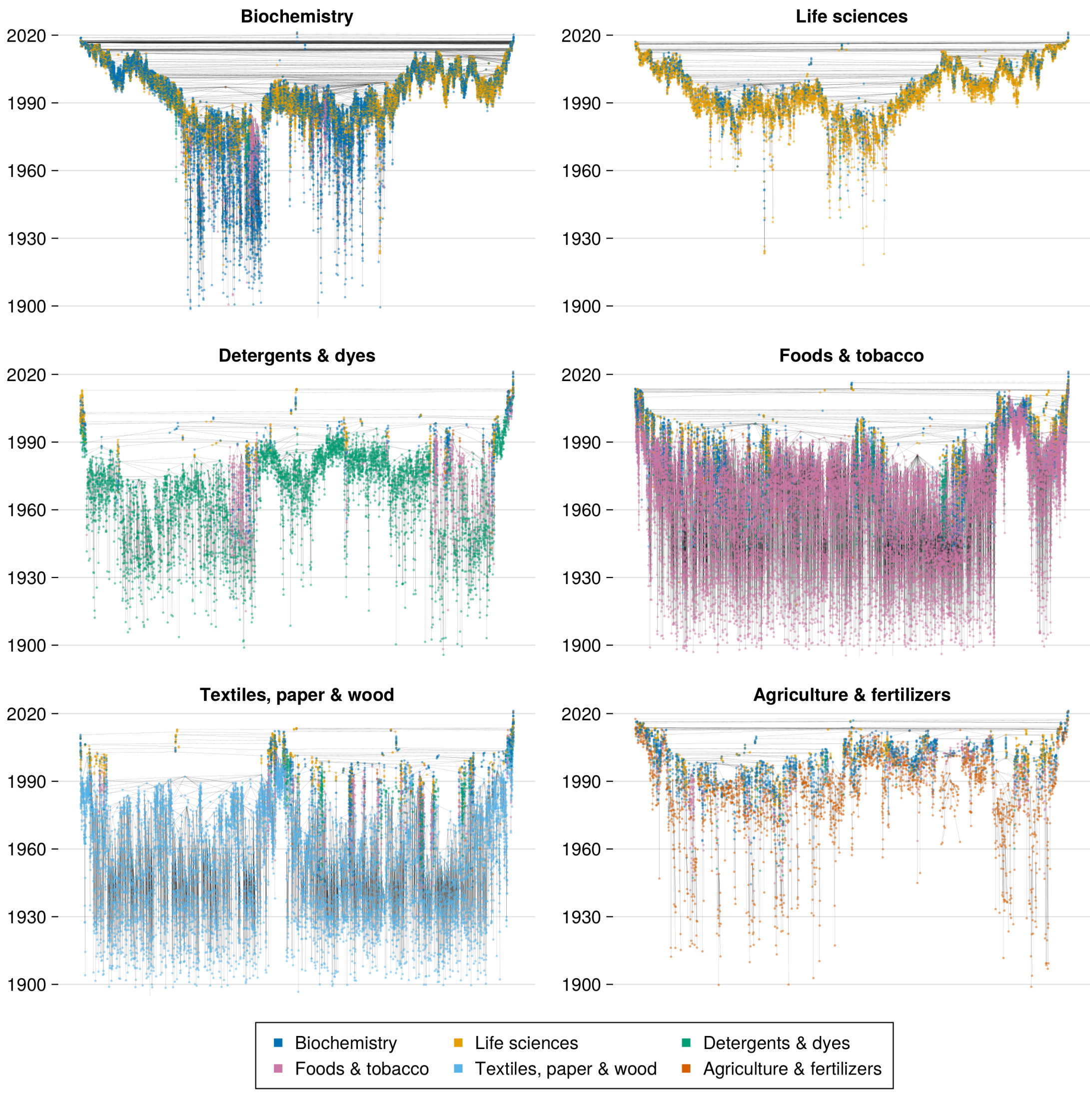

Figure 5.5: Main path networks for the six domains. Only forward paths originating from start nodes are shown to facilitate visualization. Main paths used for convergence analysis also contain backwards paths.

in the timing of convergence events. The fact that many of the main paths at some point culminate in dark blue (biochemistry) and yellow (life sciences) nodes further hints at inter-domain convergence, a trend which is visible, to some degree, for most domains.

Convergence patterns become more obvious when applying the procedure described in Section 3 to 5-year windows over the full observation period. Figure 5.6 displays the amount by which the number of parallel paths increases or decreases in a given period for all domain main paths (structural convergence, top panel).

Note that an increase in parallel paths can arise due to branching/divergence but also due to the first appearances of nodes that have no earlier citations in the dataset, which is especially the case in the earlier periods. It also shows, for each domain, the share of patents originating an outgoing path in a given period that belongs to that domain, which serves as a measure of inter-domain convergence. All domains show signs of structural convergence after an initial growth phase, indicated by subsequent reductions in parallel paths. They differ in terms of timing and intensity: Whereas the textiles, paper, and wood domain experienced a first period of convergence in the 1940s followed by a second period in the 1970s, the detergents and foods domains only started to converge in this second period. For the life sciences, biochemistry and agriculture domains, convergence occurred only throughout the 1990s and was generally much less pronounced for the latter than for the other application fields. Comparisons across the six domains reveal some more interesting patterns. First, especially for the textile domain and to a lesser extent for detergents and foods, early reduction in parallel paths was not accompanied by increased outward traversal into other domains, indicating an early phase of intra-domain convergence.

The second, stronger phase of structural convergence, however, is associated with a domain switch, indicated by the increased share of outward paths connected to biochemistry patents. Whereas convergence with the biochemistry trajectory occurred in all of the four application fields (excluding the life sciences), it varied in timing and started earlier for agriculture than for the others. Finally, looking at the life sciences and biochemistry trajectories, their intricate co-evolution becomes apparent: both of them show considerable shares of patents in the respective other domain (with a high degree of co-classification) and both of them share a common origin in food technologies, as indicated by high shares of food patents among the outgoing paths in the first half of the observation period. The timing of the increasing co-evolution of biochemistry and the life sciences is in line with major medical breakthroughs in the 1970s, such as recombinant DNA technology, which

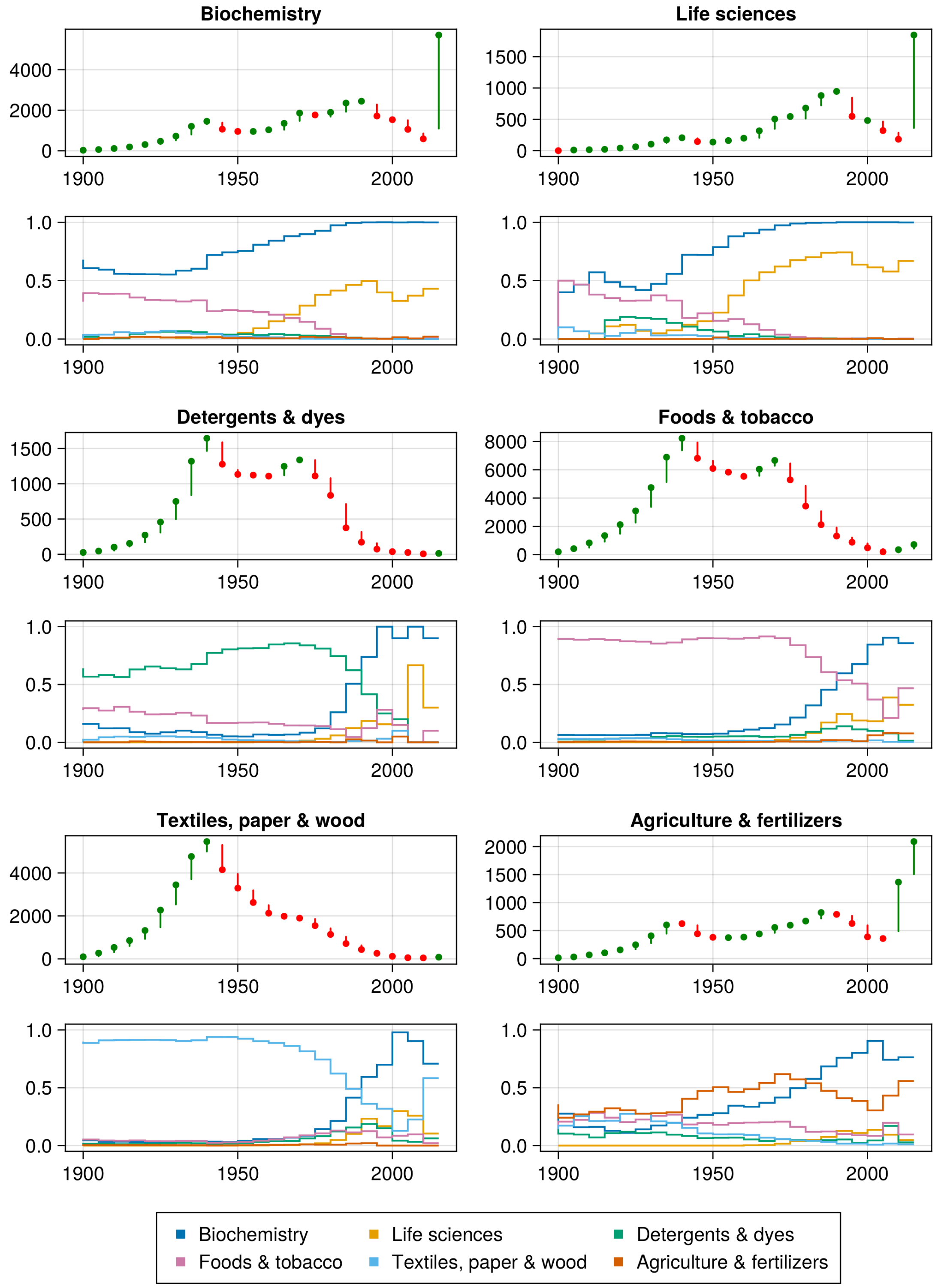

Figure 5.6: Intra- and inter-domain convergence. Top panels show the number of incoming and outgoing paths for each period (green indicates a positive change, red a negative change). Bottom panels show the shares of patents originating outgoing paths that are associated with each of the six domains. Because patents can belong to multiple domains, shares do not necessarily add to 1.

enabled the industrial production of insulin and thus the treatment of diabetes (Govender & Naicker, 2023).

To summarize, the technical evolution of the bioeconomy technological field has been characterized by clear signs of structural convergence of its major technological trajectories over the second half of the 20th century, with biochemical and biotechnological trajectories absorbing most of the trajectories originating in the traditional application fields. However, the biochemistry trajectory, which forms the backbone of the field and was itself strongly coupled to advances in the life sciences later on, at least partly originated from advances in food technologies in the early 20th century.

Discussion and conclusions

In this paper, we have investigated technological cohesion and the structural convergence of major technological trajectories across the subdomains of the bioeconomy technological field. Using patent co-classification as a measure of technological cohesion, our analysis first shows that, over time, the bioeconomy technological field has become more interrelated with technologies external to the field, instead of becoming more closed.

This might go against expectations regarding field evolution at first sight, when considered from the perspective of a field that increasingly revolves around a common technological backbone and thus might become increasingly 'self-sufficient'. However, there are multiple plausible explanations for increasing external connectivity instead of closure: First, it could reflect the increasing relevance of bioeconomy technologies beyond the confines of the field as delineated here, or, vice versa, the increased relevance of technologies outside the field for advancements of bioeconomy technologies, both of which are plausible. Second, increased connectivity across field boundaries can also be an effect of an overall increase in technological complexity induced by more and more innovations relying on recombination beyond local technological neighborhoods (Kaplan & Vakili, 2015;

Strumsky & Lobo, 2015). Third, increased cohesion as measured by patent co-classification might to a certain extent be an artifact of increasing complexity in the classification itself or of changed practices in the examination process, which ultimately gives rise to classification data. Discerning these explanations fully might be difficult, but studies focusing on, e.g., comparisons of field closure across multiple fields, more sophisticated indicators of field closure that take global trends into account, and historical analyses of the evolution of patenting systems would prove valuable for the validation of classification indicators as a stable data source.

Consistent with historical accounts (Buchholz & Collins, 2013), a simple measure of convergence based on main path analysis shows how the development of modern biochemistry (as the core of biotechnology) absorbed earlier technological trajectories, especially in food technologies, and became the technological backbone of the overall field trajectory. This increasing dominance of the biochemistry trajectory is closely linked to the rise of biotechnological life sciences in the 1970s, which witnessed a series of technological breakthroughs that stimulated the development of a range of downstream applications (Buchholz & Collins, 2013). This pattern of initial emergence from food technologies and the subsequent co-evolution of biochemistry and the life sciences indicates a pattern of demand-driven innovation (Freeman, 1994)—both industrialized foods and life sciences represent high-impact 'carrier applications' that provided a vehicle for the development of integrative, cross-sectional technologies in biochemistry in the historical contexts where they had major societal impacts.

The approach outlined here also has some limitations. So far, the use of main path analysis has been largely descriptive, and while this analysis has aimed to provide some more systematic investigation of the structural features exhibited by main paths, it is no different in that regard. Theoretical models that specify, e.g., under which conditions or by which stimulants general-purpose technologies can branch from their origin applications and attach to new applications are currently underdeveloped. They would, however, make for a valuable contribution in that they could provide a much-needed foundation for future applications of main path methods. More generally, both empirical and theoretical contributions that directly relate convergence of technological fields, or other evolutionary patterns, for that matter, to changes in industrial organization (Mazzucato & Dosi, 2006) would make for a good basis not only for future research but also for policy that seeks to assess and diversify risk arising from fast-paced technological change. Furthermore, despite the many advantages of patents as a data source for assessing technological development, it is not always clear to what degree variation in patenting activity reflects variation in the underlying innovation rates or in the proclivity to file patents for those innovations. Because main path analysis focuses on structural aspects instead of application rates and 'filters' a corpus of patents by selecting only chains of high-impact patents, it is presumably somewhat more robust against differences in patenting activity over time or industries (Verspagen, 2007). However, the precise relationships between structural aspects of main paths, patenting rates, and innovation rates are still speculative, a fact that would need to be remedied to unlock the full potential of main path analysis as a tool for historical analysis.

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Vollständige bibliographische Referenz/*Complete bibliographic reference:*

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