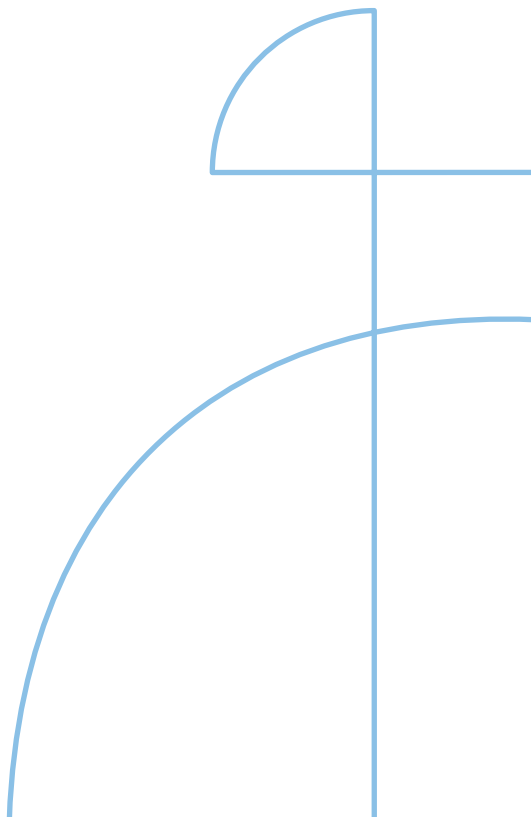
Doctoral Thesis in Business Studies

Networks of Innovation and Finance

Resource Mobilization in Swedish Life Science Ecosystems

JOAKIM FICHTEL

KTH ROYAL INSTITUTE OF TECHNOLOGY



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Abstract

The biotechnology industry is known for being highly networked and knowledge-intensive, as well as highly internationalized. Young firms within this sector are reliant on long term support from financiers, research collaborators and access to highly skilled human capital. Further, contributing to the unique circumstances for entrepreneurship in this industry, it is not uncommon for firms to have no product or service, nor revenues, many years or even decades after its founding. Creating and maintaining relationships with their external environment therefore becomes essential for survival and development.

This thesis aims to study how interorganizational networks form and evolve over time and to contribute to the understanding of how activities of entrepreneurial actors draw on and shape the networks in which they are embedded. Empirically, the thesis studies 319 Swedish dedicated biotechnology firm longitudinally over a ten-year period (2004-2013). Data were collected on firms' activities and relationships with actors in their surrounding entrepreneurial ecosystem, resulting in a relational database of 7,745 interactions among 2,868 unique actors. The relational database is analyzed using social network analysis and panel data regression modelling.

The findings show that the structure and implications of interorganizational networks differ significantly across network layers. First, entrepreneurial ecosystems are shown to be supra-local phenomena, integrated in and through network activity transcending traditional geographical confines of ecosystems. Second, international network activity varies substantially across layers, with R&D and commercialization networks exhibiting higher internationalization than financing networks. Third, the thesis shows that firms' ability to build and mobilize a strong resource base is closely tied to their financing networks, including positive effects from international orientation and a curvilinear relationship with network size. Finally, the thesis demonstrates that brokerage advantages are layer-specific and configuration dependent. Brokerage in the finance layer is directly associated with resource-based expansion while brokerage in R&D and commercialization contributes to asset growth primarily when held simultaneously across both layers.

Overall, the thesis conceptualizes the biotechnology industry as a network of networks in which firms' activities constitute distinct relational layers with different implications for firm development. The findings show that international reach and resource base expansion depend less on general network activity and more on layer-specific ties and structural positions, as well as the alignment of positions across layers. Taken together, the thesis advances a multilayer perspective on how knowledge-intensive firms mobilize capital, leverage knowledge and progress toward commercialization.

Keywords
Social network analysis, interorganizational networks, multi-layered networks, internationalization, entrepreneurship, entrepreneurial ecosystems

Sammanfattning

Den bioteknologiska industrin är kunskapsintensiv och till hög grad både sammanlänkad i nätverk och internationaliserad. Unga företag i denna bransch är beroende av långsiktigt stöd från finansiärer, partners inom forskningssamarbeten och tillgång till högkvalificerat humankapital. En ytterligare omständighet som bidrar till de unika förutsättningarna för entreprenörskap i denna miljö är att det kan dröja år, ibland årtionden, efter företagets grundande innan deras produkter och tjänster når marknaden, med total frånvaro av intäkter som följd. Att skapa och underhålla relationer med sin externa miljö blir därför avgörande för överlevnad.

Denna avhandling syftar till att studera hur interorganisationella nätverk bildas över tid och att bidra till förståelse för hur entreprenöriella aktörer utnyttjar och formar de nätverk de är inbäddade i. För att uppnå detta syfte studerades 319 svenska företag inom den svenska bioteknologiindustrin longitudinellt över en tioårsperiod (2004-2013). Data samlades in om deras aktivitet och relationer med aktörer i deras entreprenöriella ekosystem, vilket resulterade i en relationsdatabas med 7 745 interaktioner mellan 2 868 unika partners. Databasen analyseradess med hjälp av social nätverksanalys, och ytterligare statistisk analys genomfördes med linjär regressionsmodellering för paneldata.

Resultaten visar att struktur och konsekvenser av interorganisationella nätverk har signifiktanta skillnader mellan de olika nätverkslagren. För det första beskrivs entreprenöriella ekosystemen som supra-lokala fenomen som integreras i och genom nätverksaktivitet som överskrider traditonella geografiska begränsningar av ekosystem. Vidare visar resultaten att internationell nätverksaktivitet skiljer sig mellan lagren, där forskning och utveckling- och kommersialiseringsnätverken uppvisar en högre grad av internationalisering än de finansiella nätverken. För det tredje antyder resultaten att företagens förmåga att bygga och mobilisera en stark grund för finansiella resurser är nära kopplat till deras finansieringsnätverk, där positiva effekter uppvisas från en internationell orientering samt en kurvlinjär relation tillnätverksstorleken. Slutligen påvisar resultaten att fördelar från en position som *broker*, mellanhand, i nätverken är lager-specifika och beroende av hur nätverket är konfigurerat. I det finansiella nätverket är positionen direkt associerad med resurstillväxt, medan i forskning & utvecklings- och kommersialiseringsnätverken

påvisas de positiva effekterna primärt när positionen innehas i båda nätverken samtidigt.

Sammantaget konceptualiserar avhandlingen bioteknikindustrin som ett nätverk av nätverk, där olika typer av relationer utgör distinkta nätverkslager med olika effekt på företagens utveckling. Resultaten visar att internationell räckvidd och expansion av företagens resursbas i mindre grad beror på generell nätverksaktivitet och i högre grad på lager-specifika relationer och strukturella positioner, samt hur positioner samspelar och koordineras mellan lagren. Avhandlingen bidrar till att utveckla ett multilagerperspektiv på hur företag i en kunskapsintensiv bransch mobiliserar och sysselsätter kapital och kunskap i sin resa mot kommersialisering.

Nyckelord
social nätverksanalys, interorganisatoriska nätverk, multi-layered nätverk, internationalisering, entreprenörskap, entreprenöriella ekosystem

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Joakim Fichtel
Stockholm, October 2026

List of publications

Essay 1: Basu, E. M., Lindstrand, A., & Fichtel, J. (2025). Pushing the boundaries of entrepreneurial ecosystems: antecedents to international network activity of entrepreneurial firms. *Small Business Economics*, 65(3), 1363-1384.

Essay 2: **Basu, Eve-Michelle, Lindstrand, Angelika and Fichtel, Joakim. (20xx).** Local, international, or glocal? The network activity of entrepreneurial firms in multi-layered networks. *Will be submitted to Entrepreneurship and regional development*

Essay 3: **Basu, Eve-Michelle, Lindstrand, Angelika and Fichtel, Joakim. (20xx).** How financing network size and composition shape the resource base of entrepreneurial firms. *Submitted to Entrepreneurship and regional development*

Essay 4: **Lindstrand, Angelika, Fichtel, Joakim Basu, Eve-Michelle and Eriksson, Kent. (20xx).** The Differential Effect of Brokerage in Network Layers on Innovative Firms' Resource Base.

List of abbreviations

DBF	Dedicated Biotech Firm
EE	Entrepreneurial Ecosystem
SNA	Social Network Analysis
UN	United Nations

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1. Introduction

The COVID-19 pandemic highlighted the importance of bringing biotechnology innovations to market fast and making the results of collaborative research efforts available on a global scale. Supporting the development of treatments and vaccines for communicable and non-communicable diseases is included in the goals of United Nations' sustainable development agenda (UN, 2023) and this research project studies how financial, governmental, commercial and other actors play a part in shaping the ecosystems of businesses that can make this possible.

Successful development of high technology firms requires access to a diverse pool of resources. For firms founded on novel technologies or discoveries at universities or research institutes, the time between the first concept of a product and its launch on the market can span decades. During this time, these firms rely on relationships and support from their surrounding environment. Studies have identified that biotechnology innovations are made in networks of multitude organizations that collaborate (Powell et al, 1996), but subsequent research has had little focus on how biotechnology innovations are brought to market. Major factors are relationships to finance and regulatory actors (Lindstrand et al., 2011), but few studies have combined these and other actors in systematic quantitative network studies. Lindstrand et al. (2011) find that a key factor is the social capital in the relationships between the biotechnology firms, organizations providing financing and government agencies. The biotechnology industry is, in addition to being highly networked, also highly internationalized, and the development of international social capital is an essential

factor for commercial development of biotech innovations (Lindstrand & Hånell Melén, 2017).

As an industry and field develop, so do the networks of relationships and exchange between firms, regulators, investors and other organizations necessary for the development and commercialization of new technology. The structure that emerges on an inter-organizational level represents relationships and exchanges, formal or informal, which change, evolve or dissipate over time. Networks of individual firms become interconnected with the networks of others, and a pattern of interactions and exchange emerge. In these structures, relative position matters. Access to the best ideas, newest technologies, financing options and other necessary resources, can be limited by being positioned too isolated or distant from potential partners.
The structure of the network is the result of the behavior of actors, over time. Because the entrepreneurial process is dynamic and the resources required by firms changes over time, it follows that longitudinal studies of an inter-organizational network provides a useful empirical study setting, as it studies how the network evolves over multiple time periods.

The commercialization of biotechnology innovations refers to the process by which an invention is developed into a product that gets regulatory approval and can be sold on commercial markets, domestic or international. Given their long development cycles and substantial need for funding, biotech firms are particularly likely to develop network ties of various length and intensity with a multitude of commercial and financial actors. The project aims to contribute to research because there is currently little research which focuses on the roles of financiers and other network actors on the commercialization of biotech innovations both in general and over time. The real-world implications of this research is considerable, as is evidenced by the urgent need for the development of vaccines for COVID-19 in the recent past.

In this thesis, the study of the biotechnology industry will be an application of social network research. While it is common to use a simple network approach to study organizations within large networks, where only one type of relationship is taken into account, few have considered that different types of relationships exist at the same time (such as financial, commercial and R&D ties), here called layers. Studies of multi-layer networks are on the rise within informatics and computer science (Magnani &

Wasserman, 2017) where increasing computational power makes it possible to study ever larger networks and their dynamics over time. In these networks, the different types of interactions constitute separate layers, where a subset of actors are present and active. Conceptually, these layers can be viewed as stacked, and actors can be present in multiple layers at once, taking different roles and positions across the network. So far, multi-layer network studies are few, even though some studies have shown that inclusion of diverse ties is critical for understanding network evolution (Powell et al., 2005). In order to fulfill the purpose of this project, we will analyze the network relationships between biotech firms and the actors and stakeholders around them. We will use multi-layer network analysis to study the networks of biotech firms and various types of partners as separate, but interconnected layers.

2. Purpose of thesis

The purpose of this thesis is to study how the network relationships of entrepreneurial biotechnology firms and their ecosystem partners form and develop over time, and how the resulting interorganizational, multi-layered networks shape firms' international engagement and their ability to mobilize resources required for innovation and commercialization. Because biotechnology firms typically operate under long development cycles, high uncertainty and long pre-revenue periods, their development depends on access to external resources through relationships with financiers, research collaborators and commercialization partners. The thesis therefore examines both (i) how firms' network activity and ecosystem conditions influence local and international network activity over time, and (ii) how network configuration and network position within and across key network layers relate to the growth of firms' resource based, operationalizes as asset growth.

2.1 Research questions

To address this purpose, the thesis is guided by three overarching research questions:

(i) How does entrepreneurial firms' network activity shape the structure and geographic reach of entrepreneurial ecosystems over time, and to what extent do these ecosystems become supra-local through cross-border international ties?

(ii) How and why does international network activity differ across network layers (finance, R&D and commercialization) and how do structural properties of these layers enable or constrain firms' international engagement?

(iii) How do firms' financing network configurations and brokerage positions within and across network layers influence the expansion of firms' resource bases over time?

3. Theoretical and empirical background

This section provides an overview of the theoretical frameworks and empirical background relevant to understanding the dynamics of interorganizational networks.

3.1 Ecosystems and interorganizational networks.

The concept of entrepreneurial ecosystems (EEs) has garnered significant attention, focusing on localized sets of interdependent actors and factors that support or undermine entrepreneurial innovation and growth (Stam, 2015; Stam & Van de Ven, 2021). Within these ecosystems, interorganizational networks – constituted by connections between entrepreneurial firms and various stakeholders – are the key conduits for essential resources like knowledge, capital and legitimacy, influencing firms' innovative capabilities and growth trajectories (Sullivan & Ford, 2014; Provan et al., 2007). Contrary to the view that structure is destiny in EEs, recent literature emphasizes the agency of entrepreneurial actors. Firms are not merely passive recipients of ecosystem advantages; they actively shape and are shaped by their networks (Stam, 2015; Giddens, 1984). This dynamic interaction between structure and action suggests a fluid, evolving nature of interorganizational networks, with implications for how individual firms can operate and manage their network relationships to gain reach and influence.

The role of interorganizational networks in transcending geographical boundaries has been a key focus, especially in fields like biotechnology. These networks are not limited to local regional or national actors but often extend internationally, facilitating global resource mobilization and market expansions (Knight & Cavusgil, 2004; Lindstrand & Melén Hånell, 2017). Such networks serve as bridges, connecting EEs that are geographically dispersed, enabling the flow of information and resources across borders which contributes significantly to the internationalization of entrepreneurial activity (Amin & Cohendet, 2004; Boschma, 2005).

3.2 International network activity

Innovativeness and growth orientation varies between entrepreneurial firms and prior work suggests that innovative and high-growth firms in entrepreneurial ecosystems behave differently than the average entrepreneur (Stam, 2015). This includes their international orientation, or the intensity of international connectedness, which is commonly viewed as a factor that enhances firm growth and innovativeness (Audretsch, 2012). In particular, for engaged in advanced research in biotechnology and drug discovery, it is also a way to find and establish their presence in markets large enough to motivate the high costs of development. Empirical evidence suggests that internationalization through foreign market entry is a growth strategy entrepreneurial firms need to employ in order to benefit from innovation more generally (Kafouros et al., 2008; Kyläheiko et al., 2011).

For firms pursuing opportunities in foreign markets, relationships to foreign partners have been shown to be key firm-level internationalization mechanisms (Johanson & Mattsson, 1988; Lindstrand et al., 2011; Lindstrand & Melén Hånell, 2017; Sharma & Blomstermo, 2003). It can therefore be expected that entrepreneurial firms with high growth ambitions will be more likely to explore international opportunities and to form relationships with foreign partners at a higher rate than less growth-oriented peers.

3.3 Network structure and position

The activity of entrepreneurial firms in international networks is not just dependent on their international orientation (Blankenburg Holm et al., 1999; Giddens, 1984). The ability to engage in building international relationships is also a function of the position

of a firm within the interorganizational network they are part of (Owen-Smith & Powell, 2004; Powell et al., 1996, 1999; Whittington et al., 2009). Social network theory suggests that occupying a position of high centrality, as opposed to a peripheral position, in the interorganizational network they are part of, is linked to cross-boundary activity (Burt, 2004; Kilduff & Brass, 2010; Obstfeld, 2005). Network centrality in this context refers to the positioning of a firm within the interorganizational network of relationships, that characterizes entrepreneurial ecosystems, and the degree of connectedness relative of each actor compared to the rest of the network. Centrality thus indicates the extent to which a firm is connected within the network, which can signify influence and access to diverse resources, as well as the entrepreneurial firms' ability to shape their individual network. Central firms are by definition well-connected, and can act as crucial nodes through which information and resources can flow, potentially giving them a position with considerable bargaining power. This gives firms in central positions a wider array of opportunities to evaluate and act upon.

However, a highly central position can be a constraint. Occupying a central position provides access to exclusive and non-redundant information from the surrounding network, but as centrality increases, there are also costs associated with coordination as well as the risk of becoming locked-in to your surroundings (Bell, 2005; Borgatti, 2005; Burt, 2004; Kilduff & Brass, 2010; Whittington et al., 2009). Having already established the firm as a centrality actor within the network might in itself reduce the perceived need to further extend the network and explore new and less visible opportunities at the periphery. The coordination and transaction costs required to maintain a large number of interorganizational relationships can also reduce the willingness to extend networks and increase the dependency on already established ties to existing partners (Gnyawali & Madhavan, 2001; Powell et al., 1996). To summarize, prior work seems to indicate that high centrality provides opportunities to bridge structural holes between disparate groups within the network and act on new information, but also highlight the costs associated with maintaining and coordinating these relationships. This also applies to international network activity, as centrality can increase a firm's opportunities to form international ties, but also result in greater reliance on existing network connections, potentially limiting the firm's inclination to seek new and distant international partnerships. Balancing leveraging existing

network ties and exploring new international connections therefore poses a critical strategic consideration for firms competing for network influence.

3.4 Finance networks and resource bases

In this thesis, the resource base refers to the stock of tangible and intangible resources a firm draws on to pursue opportunities and sustain development over time. For innovation-driven biotechnology firms where long development cycles, high uncertainty and extended pre-revenue periods are common (Pisano, 2006; Powell, 1996), growing and maintaining a firm's resource base is especially consequential and depends on the ability to mobilize long-term external financing. Funding of a biotechnology firm is therefore best thought of not as a single or even sequence of funding events, but an ongoing relational process in which firms interact repeatedly with a variety of financial actors and intermediaries. Recorded over time, this set of accumulated interactions create a firm's financing network through which firms access funding opportunities, develop their fundraising capabilities and build legitimacy in the broader marketplace for entrepreneurial finance (Shane & Cable, 2002; Slotte-Kock & Coviello, 2010; Stuart et al., 1999; Stuart & Sorenson, 2007; Vanacker et al., 2020). Consistent with this logic, Paper III and IV operationalize the expansion of the firms' resource base primarily through asset accumulation, capturing the build-up of resources that supports development in pre-revenue periods (Delmar et al., 2003).

3.5 Brokerage in multilayer networks

As described in 3.3, outcomes depend not only on connections and tie presence, but also on structural position. One key positional feature of a network node is the concept of brokerage. A node is said to have a brokerage position if it occupies a bridging position that connects otherwise weakly connected actors or groups of actors, enabling access to non-redundant information as well as potential influence over flows of information or resources (Burt, 1992, 2004; Obstfeld et al., 2014). When brokerage opportunities arise at such structural discontinuities between groups, brokers may seize the opportunity to gain unique advantages in accessing and mobilizing resources through shaping the terms and timing of exchange between actors (Burt & Soda, 2021; Halevy et al., 2019). Brokerage is commonly operationalized as betweenness centrality and measures the extent to which a network node lies on the shortest path between other nodes (Freeman, 1978; Newman, 2018).

Brokerage is typically theorized as a positional advantage in a single-layered network. In this thesis, the interorganizational networks are conceptualized as being multi-layered, where multiple interdependent, yet distinct, domains of relationships are recorded. Firms simultaneously engage in activities related to R&D, financing, commercialization, marketing and organizational changes and become embedded in a multi-layered interorganizational network. This is an important premise for Papers III and IV where we argue that each layer develops its own topology and therefore its own opportunities and constraints. In paper IV, the multi-layered perspective is developed further into the idea that brokerage should be layer-specific and that brokerage in one layer may create opportunities, but converting these opportunities into expansion of the resource base may require complementary positions in other layers that enable funding, commercialization or legitimacy. This is the motivation to analyze brokerage both within individual layers, as well as brokerage interactions across layers, to find the effects on asset growth.

4. Data, method and operationalization of variables

In the following section, the process of gathering data, data processing and formatting for social network analysis and panel regression modeling is described. The first part describes how data was collected and a relational database was created. In the second part, the networks are constructed from the relational database using social network analysis and descriptive statistics are presented. The final part describes the process of operationalizing network and firm variables suitable for panel data regression analysis.

4.1 Data collection

This thesis explores the interactions between biotechnology firms and the properties of the resulting network of ties that evolves over time. At the micro-level, this requires detailed accounts of the actions of individual firms in their pursuit of external resources, commercial and technological opportunities and new knowledge. Connections between firms create dyads which are constituents of triads, which then become embedded in a macro-level network of actors. Building a longitudinal macro-level network from micro-level networks requires firm-level data that provide sufficient detail on the events taking place, time and place of said events, other organizations involved in events as well as continuity in the reporting of events. The aim of the data collection was therefore to compile a database with a structure that facilitates the analysis of individual firms, as well as uniquely identifying relationships between actors.

4.1.1 Network boundaries

One of the first challenges that faces any user of social network analysis is defining the boundaries of the network being studied (Marin & Wellman, 2011; Heath et al., 2009) which will inevitably involve trade-offs between inclusivity and specificity. This challenge, in particular when studying dynamic industries like biotechnology, stems from the complex, multilayered and often transnational nature of interactions among firms within the ecosystem.

The research and technologies at the frontier of science that underlie the industry are not confined to local or national borders and we expected a network than spans multiple geographical regions, integrating a global array of various actors. Such a broad and international scope makes the task of defining and establishing clear

network boundaries non-trivial. Depending on the starting sample and inclusion criteria, the network will take very different shapes and significantly influence the interpretations of our analysis.

Moreover, because the aim of this thesis is to treat interorganizational networks as multi-layered, a number of different types of interactions will be recorded and categorized. Each type of interaction will form its separate layer, which adds to the complexity of defining types of interactions and actors to be included.

Lastly, the dynamic evolution of the network and layers over time further complicated boundary definition and setting. In the biotechnology industry, the emergence of new firms, liquidations or acquisitions, mergers of existing firms and possible evolution of collaborative structures over time will pose another challenge. Compared to a static network analysis covering one time period, defining the network and keeping to the same definitions consistently over the time period requires additional attention to data collection and management. The possibility of firms entering or disappearing, changing names, corporate reconfigurations, changes in legal structure are all variation in the data that could obstruct consistent labelling and identification.

For this thesis, a definition of the sample of firms was selected by using a definition supplied by the Swedish innovation agency, Vinnova, in 2013, that listed all Swedish firms, private and publicly owned, engaged in the research and production of biotechnological products or drug development with human applications. From this list, firms with foreign majority ownership were excluded. This included 319 *dedicated biotech firms* (DBF) of varying size and age, which set the seed for the network boundary definition. The 319 DBF's what set the seed for constructing and defining the network. It was decided that the network will have its boundaries one step in interactions outside the DBF's, meaning all actors direct interacting with DBF's will be included, but there will be no second step where that actor's relations in turn are investigated further. This definition is commonly accepted as a way of building ego-networks (Marin & Wellman, 2011) and in this thesis, we are combining 319 networks into a "network of networks".

4.1.2 Data sources

To capture attributes of nodes and ties, a multitude of data sources were needed. Information collected through these various sources was subjected to cross-referencing to triangulate events, avoid duplicate entries and to maintain data accuracy. Primary data sources consisted of annual and quarterly company reports, published either on company websites or downloaded through the *Retriever Business* database of Swedish companies.

Websites, where available, were mirrored and downloaded to preserve the information present at the time of data collection. This gave access to all publicly available information and documentation available on the website at the time of the mirroring. This included press releases, annual reports, quarterly reports, product catalogs and other marketing material. Video file formats were excluded in the mirroring process due to their large size.

Press releases and news articles were accessed through *Retriever Mediaarkivet*. The service covers Swedish business news and press release channels, news websites as well as local printed press. For each firm, a search was performed for the full firm name in all sources. Doubles were excluded as well as daily and weekly reports on the prices of company stock, for the firms that were publicly listed. The resulting list of documents were compiled into a single data file with dates and sources included for each news item.

Complete financial data, as reported in the firms' annual financial reporting, was downloaded and paired with the sample firms through the Serrano financial database. As previously mentioned, annual reports were collected in pdf format to include any notes or comments made by management within the financial report that would not be included in the financial data files.

4.1.3 Data types

The data was subsequently compiled into a unique and proprietary database of the total population of Swedish biotech firms during the years 2004 to 2013. The database at this stage consists of 360 companies, all types of events relating to them and company specific data including a broad spectrum of performance measurements. The database holds all types of partners (biotech, biomedical and pharmaceutical

companies, universities, financiers, regulatory institutions, commercial actors etc.), geographical regions of activity and all types of partner ties (see Table 1) during the period. In total, the database covers 2,868 partners and 8,966 ties. The database, which took five years to compile, at this stage contains a rich set of financial and qualitative data related to the events taking place.

As mentioned in the discussion on boundary setting, there are changes occurring during every period across the years being studied. Over this time period there are changes in the dataset, for instance by that companies have been terminated, merged, purchased, or that new companies have been started. The dataset has the corporate ID of life science companies as a unit of identification for companies, and any changes to this company ID has been recorded over the time covered in the database. In the years between 2004 and 2013, of the original 319 firms 38 were de-registered or dissolved as part of a merger or an acquisition event, 62 ceased operations due to bankruptcy or liquidation.

The project uses a database that covers events for Swedish biotechnology firms. The reason for choosing an event as the primary unit of empirical analysis is that exchange incur a cost, and an event is commonly a significant indicator of an exchange and potential investment by the firms. Event study methodology has been used in many areas of business research, such as Finance to study how events relate to market pricing (Wang & Ngai, 2020), in regulation (Carroll & Lamdin, 1993), management (Kang et al., 2010; Lee & James, 2007), Management Information Systems (Corbett et al., 2005; Hendricks & Singhal, 1996), IT outsourcing (Duan et al., 2009), marketing (Chen et al., 2009; Cobbs et al., 2012; Miyazaki & Morgan, 2001; Wiles et al., 2012) and international business (Barkema & Vermeulen, 1997). Event study has been used in the study of Biotech innovations (Powell, 1996). Events are commonly defined as recorded events, and what is recorded depends on the research being done. In the present research, we define an event based on relationship and network theory, and therefore, the events that we record are exchanges, including an:

- investment
- transaction
- potential investment
- collaboration

- joint development
- agreement

Examples of such events are:

- R&D events: research collaborations and technology co-development, joint clinical trials, participating in research consortiums, co-funding PhD students.
- Financial events: debt or equity transactions, public or private research grants, milestone, licensing or royalty payments, mergers and acquisitions, sale or purchase of technology assets or intellectual property, IPOs.
- Regulation & verification: interactions and applications with regulatory agencies regarding clinical trials, product certifications, intellectual property et cetera.
- Licensing agreements: both in- licensing, and out-licensing agreements.
- Organizational events: creation of joint-ventures, interactions with government agencies, new market entries.
- Commercial events: supplier, agent and distributor agreements and various other forms of commercial agreements

Descriptive statistics of the sample in terms of the type of network ties, number of ties and examples of ties are displayed in Table 1. The table shows a concentration of events in the commercial, financial and R&D types and these are the main categories of interest in our analysis in the following sections.

The events are transactions or types of exchange between actors, and these are biotech, biomedical and pharmaceutical companies, universities, financiers, regulatory institutions, commercial actors and other industry and non-industry actors. Event and network study methods are usually applied to analyze networks of relationships between actors, and in the present research, the actors are conceptualized as collective actors, and the events taking place are exchanges between these collective actors. Other social network analysis applications are on networks of individuals, but that is not the focus in the present research. The collective actor is defined as an actor that represents the collective of individuals in the firm. To analyze exchanges between collective actors follows in the tradition of previous network studies (Cook & Emerson, 1984; Anderson et al., 1994).

Table 1: Types of network ties, number of ties and examples of ties.

Type of ties	**Number**	**Example of ties**
Commercial	2056	Distribution, marketing, supplier agreements
Financial	2009	Debt and equity financing, M&A activity, milestone/licensing payments
Licensing	324	In/out-licensing agreements
Marketing & communication	333	Participation and presentation in investment meetings and research conferences
Organizational	404	New market entries, investment in facilities and equipment
R&D	1556	Clinical trials, research collaborations, industry-academia consortia
Regulatory	636	Patent and trademark activity, regulatory approvals

Table 2: Type of node, number of nodes and examples of nodes

Type of node	**Number**	**Example of node**
Biotech	362	Actors specialized in researching and applying biotechnology
Biomedical	717	Actors specialized in biomedical and medical technology
Big pharma	61	Large actors researching and producing pharmaceuticals

Research organizations	381	Universities, university hospitals
Finance	351	Venture capital firms, public research funds
Regulation/verification	60	National patent offices, drug approval agencies
Government organizations	126	National agencies, supranational unions
Life science	135	Actors engaged broadly in producing research and equipment for life sciences
Non-life science	127	Actors outside of the life science and biotechnology industry
Non-commercial	47	Non-governmental organizations, patient organizations, associations
Support organization	154	Incubators, technology transfer offices
Dedicated biotech firms (DBF)	319	Swedish biotech firms within the sample
Unspecified distributors/customers	28	Actors not fully identified for complete classification

4.1.4 Data processing

A thorough and systematic approach to data collection and classification was developed, to capture firm events in a structured and coherent manner, which was essential for later stage analysis. For each uniquely identified event the following information was recorded.

Start and end date. The beginning and end date of the event. If the exact date during the year was not specified, only the year was considered. For events that were considered transactional rather than longer term relational, or for some reason did not have a natural end date, it was considered to end in the same year.

Location of the event. The country where the event had taken place was recorded. In the case of international partner organizations, we further mapped their specific countries onto the following regions: Africa, Asia, Europe (EU & non-EU), Middle East, North America, Oceania, or South & Central America. The classification of a relationship as domestic or international was determined based on the description of the event in the source material.

Brief description of the event. To capture more detail and to add nuance when studying events in detail, now and in the future, each event included, if available, the description of what occurred. Most commonly this was in the form of texts from press releases or annual reports, in other cases the text was written manually based on our interpretation of what had occurred.

Partner organization. The full name of the partner was recorded. In a relational database it is essential to avoid duplicates and have the ties pointing to the right partner. After all events were recorded, the full list of partners were manually reviewed and corrected to ensure naming conventions and classifications were uniform across the sample.

Type of partner organization. In the same manner as event types, partner organizations were divided into 13 categories (see Table 2 for all node types). With one level of subcategories, organizations were classified into 202 possible types (not shown in Table 2).

Location of partner organization. The geographic location of the partner organizations was recorded and categorized based on their country of origin. Partner organizations registered in Sweden were classified as domestic, those based outside Sweden as international with the same coding structure as for events.

Using an iterative approach, a common coding scheme was developed to facilitate and ensure uniformity and accuracy when coding events. The coding scheme classified events into seven main categories (see Table 1) with two levels of subcategories (not

shown in Table 1). In total, this scheme allowed for 302 unique types of events to be classified.

4.2 Descriptive statistics

The network in this research is coded into different dimensions of called layers and this section describes the total network, as well as three network layers which only contain events of one category. In our analyses, we focus on the three categories: (i) R&D, representing interactions aimed at knowledge creation; (ii) financial, representing interactions aimed at securing external capital; and (iii) marketing, representing interactions aimed at bringing the product or service to market. Consistent with our earlier discussion, we find that these three relationship types are central to the social space created by the DBFs in our sample: they account for 5,946 or 77% of all interactions in our dataset.

The networks are longitudinal, and comprise the entire network of biotech and life science companies in each year. That means that nodes, such as companies, that have been started during the time period in which observations are made, have been entered into the database. Similarly, companies that have been terminated, have been deleted from the database. A considerable amount of manual coding labor has gone into making sure that the database comprises all nodes that currently exist in each time period. There is a variation in how active nodes are, and some actors may not be active at all in a time period, but if they are still registered, for example as registered corporations, then they are part of the database.

The total network statistics is displayed in Table 3. There is a notable growth in the size of the network over time, as can be seen in an increasing number of DBFs, nodes and edges. The network density (Wasserman & Faust, 1994) decreases over time, suggesting that as new actors enter the network, new connections are not made at a rate that maintains network density. Freeman degree centralization (Freeman, 1979) remains relatively similar over the years, suggesting that the structural properties remain relatively similar over the years, even though the size increases.

Table 3: Total network descriptive statistics.

Variable	Total	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Number of nodes	2868	437	647	923	1194	1507	1737	1976	2192	2452	2839
Number of edges	7745	575	995	1654	2501	3367	4096	4827	5631	6304	7098
Number of DBFs	319	130	173	225	252	287	297	295	295	289	292
Network density	0.0019	0.0060	0.0048	0.0039	0.0035	0.0030	0.0027	0.0025	0.0023	0.0021	0.0018
Network centralization	0.093	0.095	0.0074	0.057	0.059	0.070	0.071	0.076	0.094	0.102	0.091

To get a better understanding of the separate layers, the sample is partitioned into *financial*, *marketing* and *R&D* network sublayers in Table 4. A more advanced comparative analysis is done in the papers adjoining the thesis, but here we present descriptive statistics. Table 4 shows the financial network statistics, where it can be seen that the nodes, edges and DBFs increase over the years, meaning that the network increases in size as more actors enter and form ties within the industry. The density decreases from 0.008 in 2004 to 0.005 in 2013. The centralization of the network fluctuates over the time period, beginning at 0.17 in 2004 and ending at 0.17 in 2013 after stabilizing around 0.15-0.17 in 2009-2013. This result thus suggests that the financial network has stabilized and displays stable structural properties towards the end of the time period. Analysis of specific nodes, as well as visual analysis of the network graph, could provide further insights on which actors are central and what structure are formed around them.

Table 4: Descriptive statistics of network layers by year.

Layer	Variables	Total mean	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Financial												
	Number of firms	202.9	92	129	174	198	224	237	239	248	248	240
	Number of partners	424.1	123	187	268	350	420	468	529	598	640	658
	Number of interactions	1119.6	191	359	569	811	1071	1275	1472	1694	1822	1932
	Network density	0.006	0.008	0.007	0.006	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	Network centralization	0.14	0.17	0.07	0.09	0.11	0.13	0.16	0.17	0.16	0.15	0.17
R & D												
	Number of firms	131.4	49	68	99	122	139	156	160	174	172	175
	Number of partners	334.6	70	98	162	227	311	368	430	492	563	625
	Number of interactions	798.0	130	193	345	541	747	899	1056	1192	1377	1500
	Network density	0.009	0.019	0.014	0.010	0.009	0.007	0.007	0.006	0.005	0.005	0.005
	Network centralization	0.09	0.17	0.12	0.09	0.08	0.07	0.06	0.06	0.07	0.07	0.06
Marketing												
	Number of firms	146.1	51	77	104	133	161	170	183	191	196	195
	Number of partners	508.9	91	152	248	339	441	539	658	735	829	1057
	Number of interactions	946.8	135	238	411	591	795	986	1202	1437	1638	2035
	Network density	0.006	0.013	0.009	0.007	0.005	0.004	0.004	0.003	0.003	0.003	0.003
	Network centralization	0.08	0.12	0.07	0.07	0.06	0.09	0.08	0.06	0.08	0.10	0.11

Descriptive statistics for the marketing network can be seen in Table 4. The rise in number of nodes, edges and DBFs indicate a growing network size over the years. Although there is fluctuation in density and centralization, there appears to be a slight downwards trend in density and a slight upwards trend in centralization.

The descriptive R&D network statistics are displayed in Table 4. Again, the increase in network size is evident in the increasing number of nodes, edges and DBFs. As in the other layers, there seems to be a downward trend in density and an increasing level of centralization. As in the other networks, the number of actors in the network is increasing over the time period and edges between actors are not being made at a rate that keeps the density constant.

As mentioned earlier, analysis of the different network layers and their interconnectedness is analyzed more in detail in the papers, but what can be seen in these descriptive statistics is that there is a difference in size of layers, a growth in size of all network layers over the years, and it can also be seen that density and centralization differs within and between layers.

4.3 Constructing the network

The initial step in the construction of a social network is the creation of a relational database of all nodes and relationships. This database is what constitutes the input data files to the social network analysis tools in R. The database is structured to record detailed information about each interaction, including the nature of the interaction, the participating firms (nodes) and the characteristics of these interactions (events). The database contained all relationships between nodes for all years, with all the details of the nodes and relationships stored as attributes. These databases were created for the complete network of all interactions and for the three layers of interest. Every year is its own network, and for each layer one network was made that added all years into one network.

Due to the rich and complex nature of the data collected, a bespoke script was coded in R to accommodate and customize the wide variety of attributes of nodes and edges (events) and the operations applied to them. For each year, a list of nodes and a list of edges were loaded into the program and for each layer, eleven network graph objects

were created and prepared for analysis in a: one for each year and one for the agglomerated network across all years.

4.4 Network measures

Along with the descriptive statistics of the network layers, the degree distribution provides insights into the network's overall structure and helps identify whether a network is uniform (where connections are distributed equally across nodes) or skewed (where some nodes are significantly more connected than others). As seen in the descriptive statistics, the number of actors and ties increase over the time period across all layers and to better understand where new actors and ties are formed, the degree distribution is shown in Figure 1. As noticed by Barabási and Albert (1999) many real-world networks are far from evenly distributed in connectivity. Instead, the degree distribution follows a power law, meaning they are centered around a few highly connected actors and the number of highly connected nodes decreases exponentially and a significant majority of nodes are comparatively less connected (Lambertini, et al. 2014). Networks displaying this topology are referred to by Barabási and Albert (1999) as "scale-free" and the distribution can be represented mathematically by $P(k) \sim k^{-\gamma}$ where $P(k)$ denotes the probability of a node having k connections and γ being a constant, typically ranging from 2 to 3. Figure 1 suggests that all three layers in this sample appear to have a similar overall structure. These skewed distributions imply a non-random and hierarchical structure within the network, where the probability of attachment of new nodes is not uniform and random, but preferentially to nodes that are already well connected (Barabási & Albert, 1999).

The similar degree distributions across all layers clearly suggests similarities in network structure. A large number of nodes are involved in very few interactions, and a small number of nodes are extremely active and appear on the far right tail of the distribution. In this aspect, there are clear similarities in structure. However, the true benefit of applying a multi-layered approach becomes evident in the following sections when the attributes of edges and nodes are used to further analyze the characteristics of the different layers. In the following section, the network layers are visualized to increase the understanding of what types of actors participate and shape the networks.

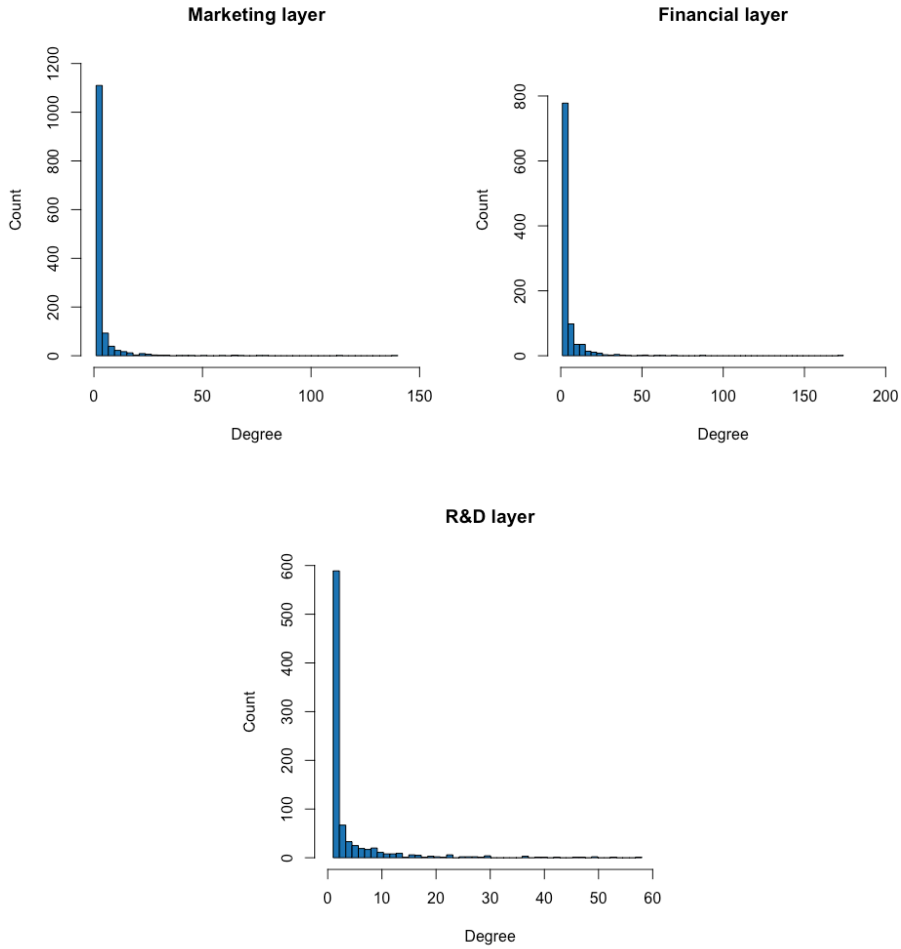

Figure 1: Degree distribution of three network layers.

4.5 Network visualizations

Analysis of the structural properties of the different sublayers, as well as observing other properties of individual nodes and edges, can be aided by plotting the network graph. Visualizing a network as a graph involves transforming the relational database that was constructed earlier into a graphical format, where the actors are depicted as nodes, and the relationships between actors are represented as edges. All 2,868 actors present in the sample are labeled as unique nodes and all 7,745 edges are assigned to their respective nodes. As the data spans the ten years between 2004-2013 the

resulting network visualizations was ten separate network graphs, each with their unique combinations of nodes and edges.

For the purposes of Paper I and Paper II, we bundle a number of categories together to focus our analysis and simplify visualization. From the original 13 categories described in Table 1, we combined categories and reduced the number of categories to 8 as follows: biomedical, biotechnology, life science, big pharma into *Incumbents*. Non-commercial and non-life science, together with unspecified customers/distributors into *Others*. All other categories remained the same. In Paper I and Paper II, the focus of our analysis is not on a level of detail that requires separation of different types of life science firms, but rather that they are active participants in the ecosystem and highlighting whether they are based in Sweden or abroad.

Using the free *igraph* library and package for network analysis in R (Csárdi & Nepusz, 2006), all network layer graphs were visualized for each of the years between 2004-2013. In Figures 2-4 the combined networks for each separate layer are presented and for clarity only include the top 30 percent of nodes, based on centrality. The *igraph* package allows for customization in how nodes and edges are visualized, here we chose to scale the size of the node based on degree centrality and selected the *graphopt* algorithm to plot the nodes and edges in a layout that minimizes overlap and clutter (Csárdi & Nepusz, 2006). For this project, we are mostly concerned about the existence and attributes of the partner firms, which is why we decided to emphasize partner colors and shapes and color DBF's grey. Furthermore, all DBF firms are also Swedish in origin, and it is international partners that are of interest here.

Financial layer. In Figure 2, we observe the financial layer, constructed by all financial ties across all years compressed into a single network. All partner types apart from regulatory and verification are present an as detailed in Table 2, we see relatively few international actors in this environment that is mostly made up of Swedish financial actors. The network has several central nodes, indicated by their larger size, which suggests they have a higher degree centrality. These nodes are the most connected within the network, potentially playing key roles in the flow of information or resources. In central positions, with the size of the nodes indicating large degree centrality, we find a number of government organizations, both domestic and international. Dispersed around the main component of the network we find a number of nodes scattered along the periphery, not connecting to the larger group of interconnected actors in the center. Although the network appears dense, by looking at Table 2 it appears to be a network that is relatively centralized around a number of central actors, but not particularly dense or interconnected. Central actors in this network do not seem to act as connectors or bridge makers to a great extent.

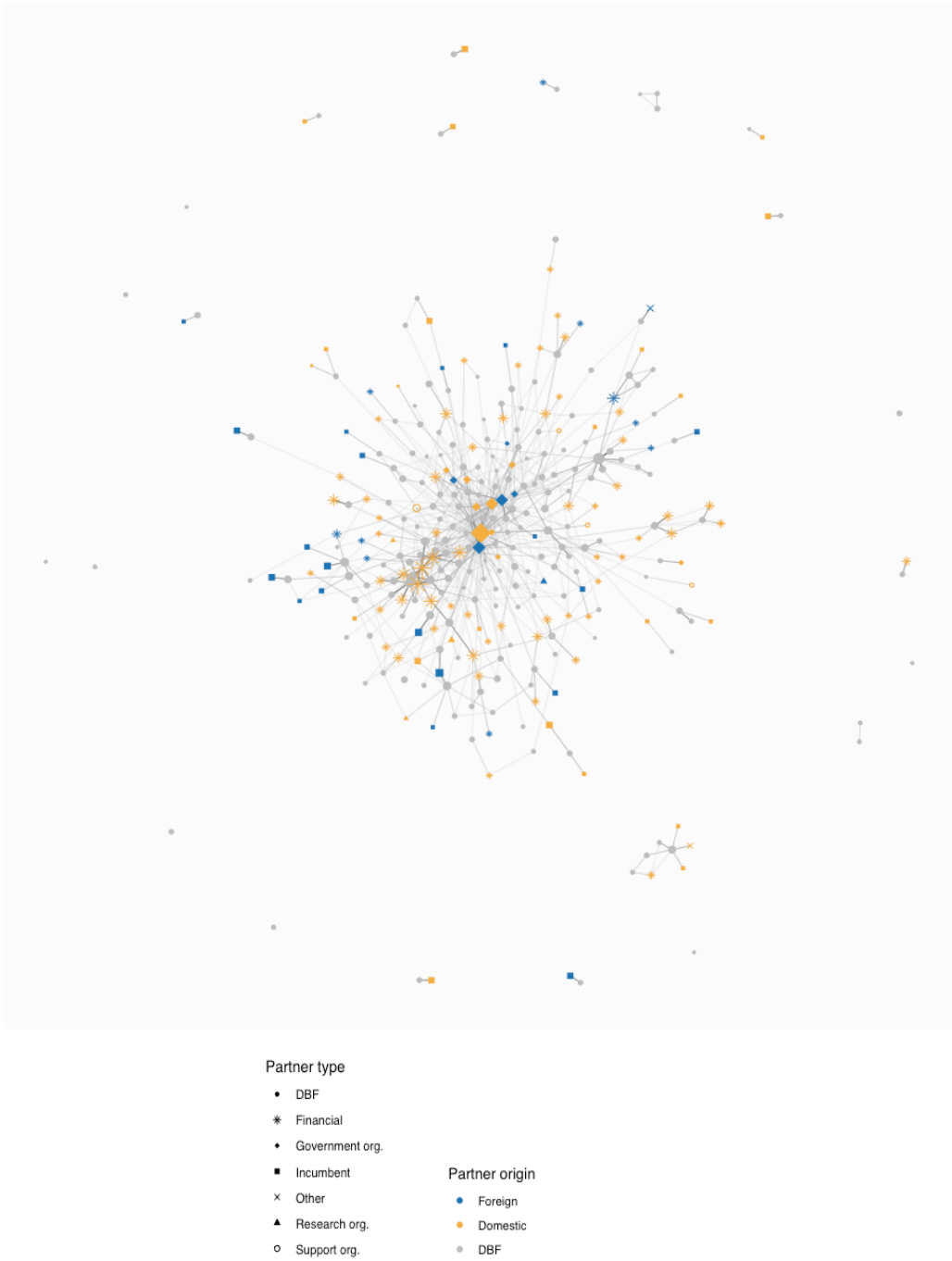

Figure 2: Financial layer of the interorganizational network. Top 30 percent of nodes based on degree centrality, 2004-2013.

Marketing layer. In Figure 3, all ten years of marketing ties are shown in one graph. Similar to the financial network, all partner types are represented except Regulators. In this layer, international partners are more prominent and in particular international incumbents. These are the firms and organizations engaged in the production or marketing of products, including distribution and agency agreements. Compared to the other two networks, as seen in Table 4, the network is relatively decentralized, with few clear central actors that tie the network together. Interestingly, a number of DBFs appear to foster a large number of international connections that are kept separate from the rest of the network. These appear as nodes with high centralization and many connections to it, but no significant integration with the larger surrounding network. As previously mentioned, these are firms acting in specialized products and services and one interpretation is that the marketing partners are equally specialized and not generally accessible as partners to every DBF.

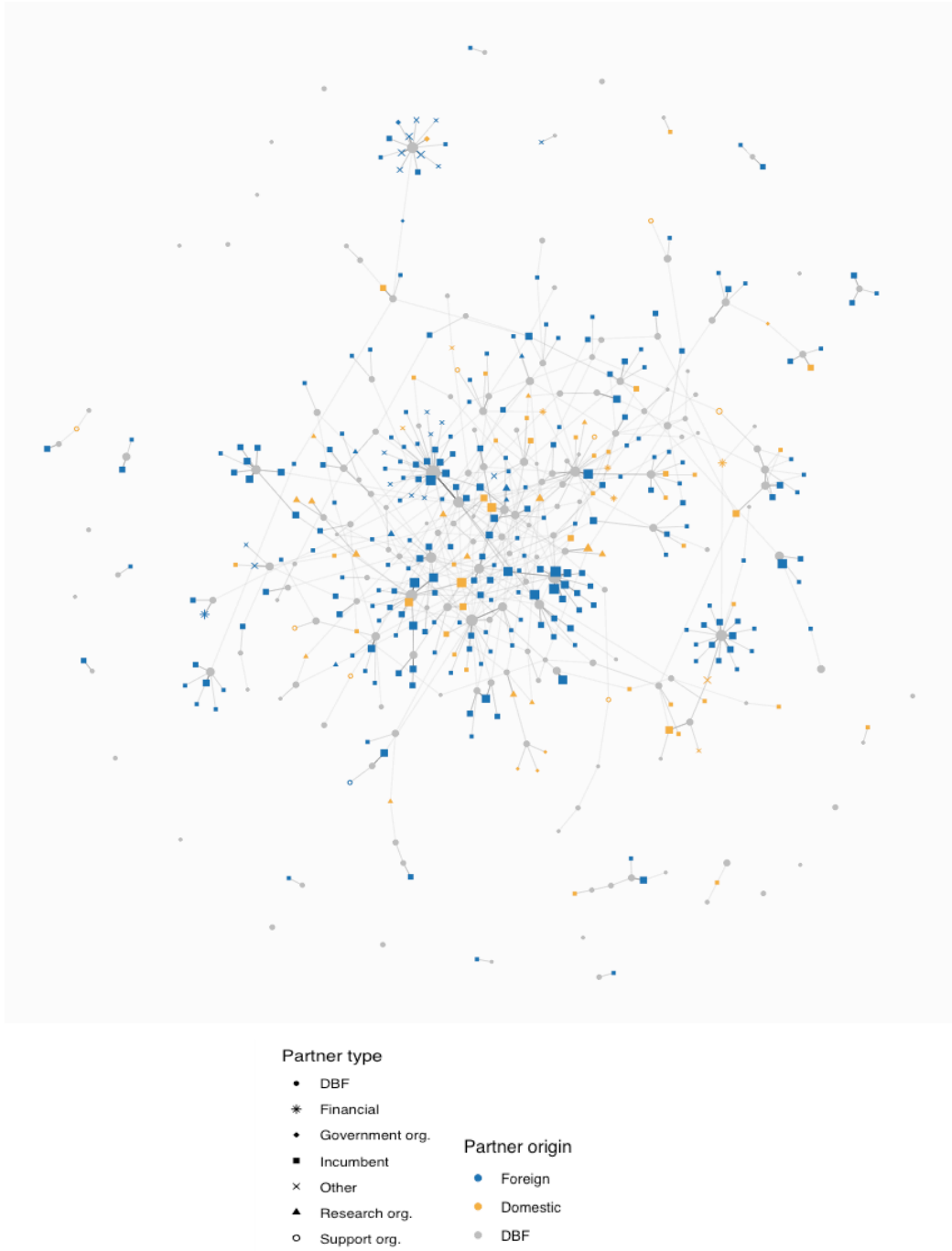

Figure 3: Marketing layer of the interorganizational network. Top 30 percent of nodes based on degree centrality, 2004-2013.

R&D layer. In Figure 4, all R&D ties for the ten year period is visualized in one graph. In this layer, there are no financial or support actors present, however the regulator class of actors are now present. Not surprisingly, the research organizations are prominent and central, with a number of domestic actors clearly occupying central positions in the R&D network. As seen in Table 4, the network displays a relatively high level of density, as seen by the level of interconnectedness between nodes. Compared to the marketing network, there are much fewer "islands" of DBFs isolating themselves in their own sub-ecosystem, suggesting that R&D at this high level does not occur in isolation, but in a number of organizations that are well-known and well-connected. Notably, there are also a number of international research organizations and incumbents that appear to be both central and interconnected.

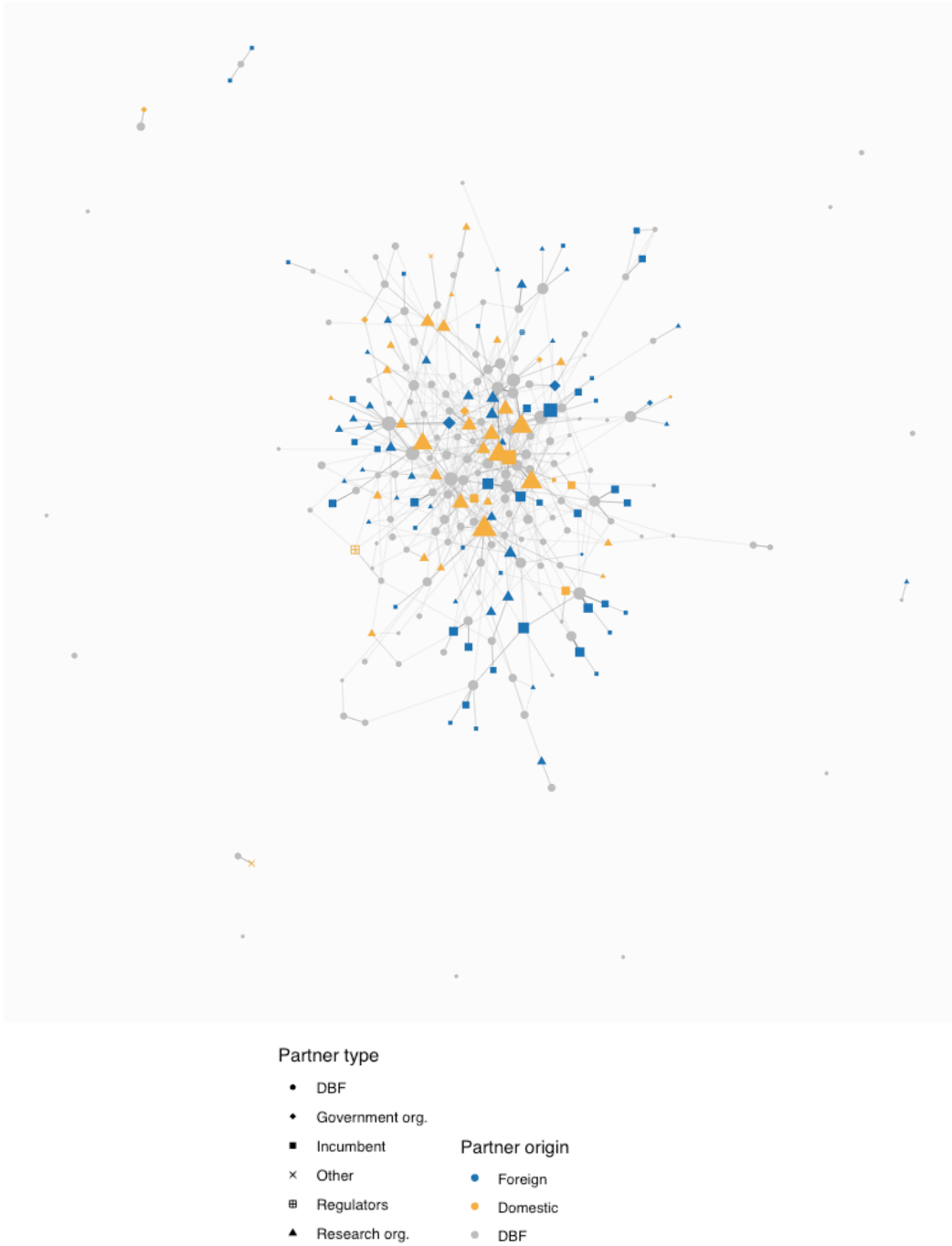

Figure 4: R&D layer of the interorganizational network. Top 30 percent of nodes based on degree centrality, 2004-2013.

4.6 Hypothesis formulation and statistical analysis

Our sample consists of panel data over time, and we hypothesize that there are effects of independent variables on a dependent variable at each point in time, over several time periods. Therefore, we employ a panel-regression model and estimate the effects of our explanatory and control variables in period t-1 on the dependent variable in period t at multiple points in time (for similar approaches, see Gilding et al., 2020; Powell et al., 1996). To account for the effect of variables that vary between individuals and over time (DBF-specific measures), as well as variables that are constant across individuals but vary over time (e.g. structural properties of the network, economic factors of the particular region), we employ a random effects model that considers both individual and time-dependent variations (Gilsing et al., 2008). As several firms in our sample were founded after 2004 (but before 2013), we include only those firms with observations for all variables and years in the panel regression analyses to balance our data. All panel regressions were computed using the package "plm: linear models for panel data" in R (Croissant et al., 2022).

4.6.1 Operationalizations and variables

Dependent variable. In papers I and II we measure *international network activity* of firms as the number of a DBF's interactions that involve a foreign partner. The network structure is a context from which activities of the firm follows, and we therefore introduced a time-lag on the dependent variable to observe how structure and activity in one time-period affect network activity in the next period (Powell et al., 1996). This was done in order to capture the effects of the existing network structure on the dependent variable. The scale of the time lag effect is in years, so the time lag added is one year. The time lag effect also reduces issues with endogeneity (Gilding et al., 2020). In papers III and IV, we operationalize the firms' resource base as the *logarithm of total assets* in year *t+1*. This is taken from the balance sheet in the annual report, as recorded in the *Serrano* database. Assets are commonly used in DBF research as a measure of firm resources and financial strength, rather than revenue, due to the fact that the time horizons for drug-developing firms are long and consists of extended periods of being pre-revenue (Owen-Smith & Powell, 2004; Powell, 1996; Whittington et al., 2009).

Network centralization. We use Freeman's degree centralization to capture *network centralization*. The concept of centralization describes the extent of centralization of edges around a small number of nodes in the network. A high centralization indicates a level of hierarchy in the relative influence of nodes, and the concentration of edges to a small number of nodes (Freeman, 1979). In higher centralization networks, a few nodes have a disproportionately large amount of connections, making these nodes more central to the network. In less centralized networks, connections are more evenly distributed between participants. This score has a range from 0 to 1, with 1 being the maximum.

Network density (edge density). The variable edge density quantifies the interconnectedness of a network. It measures the proportion of possible edges between nodes that do in fact exist in a network and for an undirected network, where the direction of the relationship does not matter, it is calculated as in Equation 1 as a ratio of the number of observed edges and the number of possible edges (Wasserman & Faust, 1994).

$$\text{Edge density} = \frac{2 * \#\, Edges}{\#\, Nodes * (\#Nodes - 1)} \quad (1)$$

Density is a structural characteristic of the network and one of many that can influence network opportunities (Alvedalen & Boschma, 2017; Boschma, 2005; Owen-Smith & Powell, 2004) Dense local networks with many connections close off entrepreneurial firms from other, more geographically distant partners, offer fewer opportunities to cross geographic boundaries, and may lead to lock-ins (Boschma, 2005; Whittington et al., 2009). Sparse local networks with fewer connections are rich in structural holes that facilitate boundary crossing and enable international network activity (Burt, 1992, 2004; Obstfeld, 2005).

Network diversity. The Blau diversity index measures the diversity of partners of an individual node, based on the different types or groups of actors they are connected with. The index calculated as in Equation 2 measures heterogeneity of firm level networks and is a measure of variety in group membership

$$\text{Blau diversity index} = 1 - \sum_{i=1}^{k} p_i^2 \quad (2)$$

where p_i is the proportion of group members in the *i*th category and *k* is the number of categories (Blau, 1977). A higher number indicates that the given node has a more diverse set of partner organizations. Conversely, a lower value indicates a more uniform set of partners, and the minimum score (0) represents a completely homogeneous network with respect to the categories of partners.

Network size (degree). Degree is a measure of the number of edges connected to a node and is equivalent to the edge count of a node. It represents the number of incoming and outgoing connections an organization has to other organizations in the network. It is a measure of the relative centrality of a node and high-degree nodes are considered to be more influential and occupy a central position in the network (Newman, 2010).

Network centrality. To capture *DBF network centrality*, we use betweenness centrality. Betweenness centrality is a widely used measure in social network analysis and captures how frequently a node lies on the shortest path between pairs of nodes in the network (Freeman, 1979, Owen-Smith & Powell, 2004; Scott, 2017). A node with high betweenness has a higher likelihood of being on the shortest paths when traversing the network, which suggests that it plays an important role in connecting different parts of the network. Because the shortest path is also likely to be the most efficient path, nodes with high betweenness are likely to play an important role in the transfer of resources and information.

High betweenness, therefore, indicates a position of possible influence, acting as a bridge or bottleneck in the flow of resources. It is also associated with holding a bridging position between different closely knit communities, where only a few inter-linking connections exist.
This measurement is unique for each firm and is calculated separately on a network level for each year. Compared to the other measure of centrality, degree centrality, it provides a different view of centrality in the network. Having a high degree centrality does not guarantee a high betweenness, and vice versa. A node can be highly central in

terms of betweenness, lying on the path between two large groups, but still have a relatively low level of degree in its position as a bridge, or connector, between groups.

International network experience. We also included the share of international ties in a DBF's network excluding interactions in the sub-layer of interest at time t-1 as a measure of international network experience (Powell et al., 1996; Whittington et al., 2009).

We measure the munificence of the regional EEs at time t-1 using the size of the local market and the strength of the local economy (Audretsch & Belitski, 2021; Schrijvers et al., 2023). These measures are calculated for each regional EE relative to the national average and are based on regional accounts of the corresponding NUTS-3 region. We also include the multiplicative interaction between the size of local market and the strength of the local economy to gauge the extent to which they jointly influence international network activity. Local network density at time t-1 is measured as the ratio of the number of actual to the number of possible ties in the four networks resulting from the network activity of DBFs located in each regional EE (Borgatti & Halgin, 2011; Scott, 2017; Tichy et al., 1979). It is calculated using the *igraph* package in R.

Finally, we controlled for *firm age* in years as well as *firm size* measured by the logarithm of total assets as alternative explanations of network behavior. While the logarithm of total sales is more commonly used to measure firm size, it is not well-suited for knowledge-intense sectors like biotechnology with long development cycles and high up-front research and development costs: here, a firm may exhibit significant growth and development without any sales.

5. Results

The thesis consists of four appended papers that build cumulatively on a shared longitudinal event-based relational database of Swedish dedicated biotech firms, as described previously. Taken together, the papers move from presenting how firms' network activity and ecosystem conditions shape the spatial reach of entrepreneurial ecosystems (Papers I-II), to explaining how firms mobilize and build a strong resource base through financing networks and network positions (Paper III-IV). Papers I and II establish that entrepreneurial ecosystems in biotechnology are supra-local and that international network activity differs across network layers. Paper III and IV shift the focus to the effects on resource accumulation of these network structures by examining the configurations of financing networks and brokerage effects within and across finance, R&D and commercialization layers. Table 5 provides an overview of the four studies, their core question, layer(s) analyzed, outcomes, methods and main contributions as well as how they advance the thesis' overarching argument.

Table 5: Overview of appended papers I-IV.

Paper	Core question	Layer focus	Outcome	Method	Main finding	Thesis-level contribution
I	How does firms' network activity restructure ecosystems and shape international engagement over time?	Whole network / regional entrepreneurial ecosystems	International network activity	Social network analysis + panel regression	Ecosystems are supra-local; more than half of ties involve international partners; ecosystem conditions shape international activity.	Establishes ecosystems as networked, cross-border systems shaped by firm activity.
II	How does international network activity differ across network layers, and what explains variation?	Finance vs R&D vs commercialization layers	International network activity by layer	Social network analysis + panel regression + ANOVA	Commercial and R&D layers are more internationalized than the finance layer; drivers differ by layer.	Shows why multilayer analysis is necessary: layers reflect different logics and constraints.
III	How do financing network configurations shape firms' ability to build their resource base?	Financing layer	Resource base (assets)	Panel regression	Inverted U-shaped effect of financing network size; international orientation is positive; government ties are negative; partner-type diversity is not significant.	Moves from activity to resource mobilization; identifies financing configuration as a mechanism for asset accumulation.
IV	How does brokerage within and across layers shape resource-base expansion?	Finance, R&D, and commercialization layers	Resource base (assets)	Panel regression with cross-layer interactions	Finance-layer brokerage has a direct positive association with asset growth; R&D and commercial brokerage matters primarily as a configuration (their interaction).	Demonstrates layer-specific and configuration-dependent positional advantages; links 'outside' finance to 'inside' innovation layers.

5.1 Paper I

Basu, E. M., Lindstrand, A., & Fichtel, J. (2025). Pushing the boundaries of entrepreneurial ecosystems: antecedents to international network activity of entrepreneurial firms. *Small Business Economics*, 65(3), 1363-1384.

The contribution of the PhD student is as follows:
The PhD student has been involved in research design, including development of template for which data to gather. The development of the research design has also involved conceptual and theoretical developments, where the PhD student has been involved. The PhD student has managed and collected data, including structuration of the database. In this research, the structuration of variables and observed cases in a database is advanced research. The PhD student is the primary person responsible for doing data collection, and he has performed data analysis, chosen relevant methods, and presented results. This has also involved theoretical and conceptual development.

In this paper, we adopt a networked view of entrepreneurial ecosystems and focus specifically on the network activity of entrepreneurial firms, or the interorganizational relationships they build to other ecosystem stakeholders to access and mobilize resources. The purpose is to study how network activity of firms restructures the networks within which they operate and what effect this has on international network activity over time.

Using the same longitudinal database described earlier, we narrow the focus to study firms present in four of the main biotechnology and life science regions in Sweden: Stockholm, Uppsala, Malmö and Lund and Gothenburg. From prior literature we posit that the network activity of actors in entrepreneurial ecosystems is not limited to the local actors in their region, but instead spans across regions and international borders.

Our quantitative analyses of the data using social network and panel regression analyses, offer insights into the temporal dynamics of interorganizational networks and their impact on the territorial boundaries of EEs. We find that the entrepreneurial firms in our sample collaborate across the territorial boundaries of EEs. Indeed, study

finds that a significant portion, more than half, of the network activities of these firms involves international partners, indicating a strong inclination towards global engagement. This aspect is emphasized, as it highlights the supra-local or international nature of entrepreneurial ecosystems, extending beyond just local or regional confines. Our regression analyses further indicate that the extent of international network activity is influenced by firm and ecosystem factors.

In particular, the conditions within local entrepreneurial ecosystems play a significant role. The study suggests that firms in ecosystems with larger local markets tend to be less internationally oriented, whereas those in stronger economic environments show a greater propensity for international networking. This finding is particularly interesting as it indicates that the local ecosystem's characteristics can significantly influence a firm's international networking behavior. Contrary to our hypothesis, the density of local networks did not show a significant impact on international networking activities, challenging some common assumptions in social network theory about opportunities and network behaviors.

Through this work, we add to the scholarly understanding of the microfoundations underlying the spatial configuration and dynamics of EEs and respond to recent calls for studies of the nature and evolution of entrepreneurial ecosystems that draw on new novel longitudinal datasets (Wurth et al., 2022). Our research suggests that the network activity of entrepreneurial firms creates interorganizational networks that span geographical boundaries and contribute to the cross-territorial integration of EEs over time.

5.2 Paper II

Basu, Eve-Michelle, Lindstrand, Angelika and Fichtel, Joakim. (20xx). Local, international or glocal? The network activity of entrepreneurial firms in multi-layered networks. *Will be submitted to Entrepreneurship and regional development.*

The contribution of the PhD student is as follows:
The PhD student has been involved in research design, including development of template for which data to gather. The development of the research design has also involved conceptual and theoretical developments, where the PhD student has been involved. The PhD student has managed and collected data, including structuration of database. In this research, the structuration of variables and observed cases in a database is advanced research. The PhD student is the primary person responsible for doing data collection, and he has performed data analysis, chosen relevant methods, and presented results. This has also involved theoretical and conceptual development.

The purpose of this study was to study variations in network activity between different layers of an interorganizational network. An interorganizational and international network of Swedish biotechnology firms was studied by analyzing multiple separate layers of ties. Patterns and drivers of international network activity within and across multiple network layers were investigated by estimating linear panel data regression models for our longitudinal relational dataset as well as ANOVA. The three network layers were also visualized by plotting the network graph to further the understanding of the structure and patterns of actors and ties within the separate layers.

The distribution of ties, presented in Figure 5, indicate a significant difference in international activity between the different layers. The marketing layer, including commercial activities with national and international partners, displayed the highest level of internationalization. 71 percent of ties related to commercial activities were found to be with non-domestic partners. The lowest level of internationalization is found in the financial layer, with firms engaging in financing activities mostly with local or national partners and only 27 percent of ties appearing to non-domestic partners. The R&D layer, which includes research collaborations, clinical trials and other research projects, falls in between the two other layers with 56 percent of ties being with international partners.

Further analysis of tie types across the time period 2004-2013, shown in Figure 6, reveals a pattern of increasing level of internationalization in the marketing and R&D, while the financial layer international activity remains at a steady, and relatively low level across the time period. Figure 6 shows the development of the internationalization of network activity, calculated by comparing interactions with international partners to those with domestic partners within a given year, over the 10-year period covered by our data.

Across all layers, the interorganizational networks formed by the DBFs in our sample display a rather internationalized industry with 51 percent of all interactions involving a partner located outside of Sweden. International networking activities with partners outside of Sweden are located primarily in three regions: Europe (56 percent), North America (23 percent) and Asia (11 percent).

In the R&D layer, both variables capturing network size, as well as international network experience remain consistent in sign, magnitude and were highly significant across all four linear panel regression models. They indicate that firms with a large R&D network, as well as a large network outside of R&D, and with more international network experience are more likely to engage in international R&D network activity in the subsequent period. Network density also had a significant positive effect, suggesting that a denser network facilitates international network activity.

In the financial layer, network size variables again have a significant and positive effect on international financial network activity across all four models. Centrality of the DBF within the overall network has a negative effect on its international financial network activity, whereas centrality within the financial layer does not have a statistically significant effect. The centralization, a structural characteristic of the network, of the financial layer has a negative effect on international network activity, suggesting a concentration of actors around a few central nodes has a dampening effect on the international network activity of actors.

Finally, in the marketing network, the firm size, size of the marketing network and international network experience all have consistent and positive effects on

international network activity across all models. Put differently, larger firms, with more pre-existing interactions with the purpose of producing and distributing their products to market, and with more international network experience are more likely to interact with foreign partner organizations. We also find that the position of the firm, meaning the centrality of the DBF, as well as structural properties of the network, influence the extent of international marketing network activity. In contrast to the financial layer, however, centrality within the network layer has a negative effect. The effect of the structural characteristics also differs within this layer, with density having a significant and positive effect on international network activity, and the interaction effect between density and centrality is significant and negative.

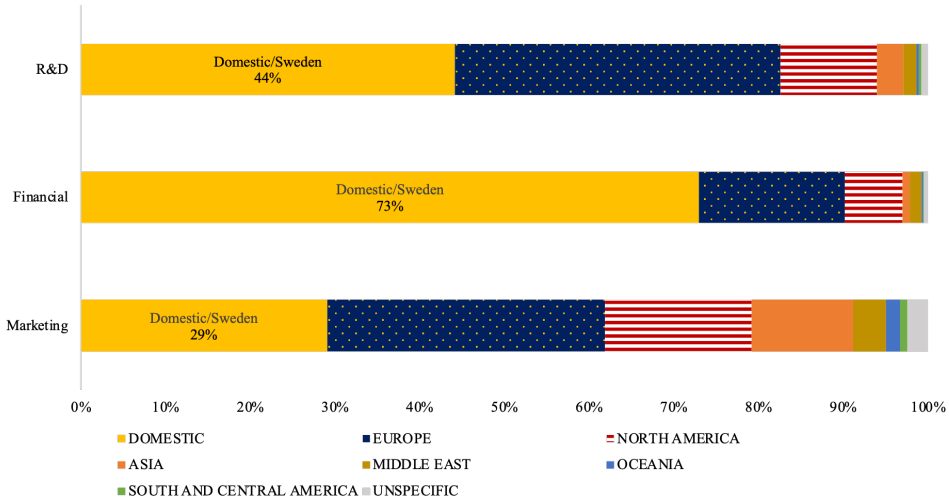

Figure 5: Geographic distribution of partner organizations by network layer (total across dataperiod; n=5,946).

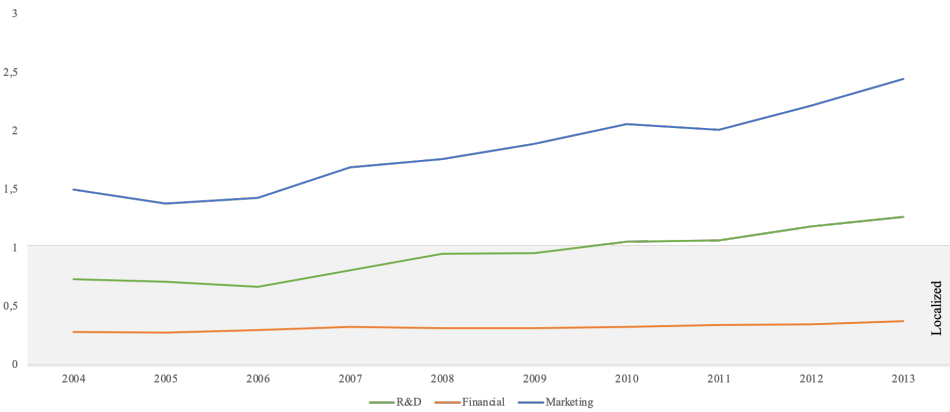

Figure 6: Internationalization of network activity by network layer (2004-2013; n=5,946).

5.3 Paper III.

Basu, Eve-Michelle, Lindstrand, Angelika and Fichtel, Joakim. (20xx). Networks of entrepreneurial finance. *Submitted to Entrepreneurship and regional development*

The PhD student has been involved in research design, including development of template for which data to gather. The development of the research design has also involved conceptual and theoretical developments, where the PhD student has been involved. The PhD student has managed and collected data, including structuration of the database. In this research, the structuration of variables and observed cases in a database is advanced research. The PhD student is the primary person responsible for doing data collection, and he has performed data analysis, chosen relevant methods, and presented results. This has also involved theoretical and conceptual development.

In this paper, we focus on entrepreneurial finance as a networked phenomenon and examine the effects of size and composition of financial networks on the growth of firms in the Swedish biotechnology industry. Prior research has studied the effects of specific sources of funding in isolation (e.g. venture capital, banks, or grants), entrepreneurial firms often build financial positions by building long term relationships with multiple types of financiers over team. The biotechnology industry is characterized by being capital intensive, having long development cycles and being reliant on a multitude of actors for outside resources and support. The purpose therefore is to investigate how the configuration of firms' financing networks relates to their ability to accumulate assets. Of particular interest are effects from network size, diversity of partners and international orientation.

Empirically, we draw on the same longitudinal event-based relational database on Swedish dedicated biotechnology firms (DBFs) as described in Paper I and Paper II over the period between 2004-2013. In this study, the financial layer is isolated and we analyze how firms' financing ties are structured across partner types and geographies. Firm-level financing ties were systematically coded by studying public sources such as annual reports, websites, press releases and news coverage and subsequently adjoined with firm-level financial data. Fundraising is conceptualized as a network activity and the financing network is defined as the set of ties it forms with financiers, potential or actual. To test our four hypothesis, we estimate time-lagged panel regression models

predicting the logarithm of total assets in the subsequent year. The analysis distinguishes between size effects (number of financing ties) and compositional effects (the diversity and internationalization of those ties) as well as four different sources of funding.

The results suggest that the relationship between financing network size and asset growth is curvilinear, specifically an inverted U-shape. This indicates that an increase in the number of financial ties is beneficial up to a point, after which additional ties begin yielding diminishing returns. This finding supports the hypothesis that network expansion is not uniformly advantageous but instead comes with trade-offs related to coordination costs and managerial attention. Furthermore, the findings suggests that the international orientation of financing networks is positively associated with asset growth, and that access to foreign capital and exposure to international markets provide benefits to the resource mobilization of firms. In contrast, diversity across financier types did not show any significant effects on resource base growth, indicating that simply broadening the range of funding sources does not immediately translate into stronger financial performance. Finally, and perhaps surprisingly, the study showed statistically significantly negative effects of having a high proportion of government actors as financial partners. This suggests that public funding relationships, while often designed to support early-stage research and specific efforts to reduce technological uncertainty, do not seem to directly translate into future asset expansion among the firms in the sample and may even lead to a reduction in the same. This result should not be interpreted as evidence that government funding is ineffective; rather, for the high performing firms in this sample it might indicate a mismatch of the objective and design of public funding schemes and asset accumulation as an outcome variable.

5.4 Paper IV

Lindstrand, Angelika, Fichtel, Joakim Basu, Eve-Michelle and Eriksson, Kent. (20xx). Brokerage in multilayered networks.

The PhD student has been involved in research design, including development of template for which data to gather. The development of the research design has also involved conceptual and theoretical developments, where the PhD student has been involved. The PhD student has managed and collected data, including structuration of the database. In this research, the structuration of variables and observed cases in a database is advanced research. The PhD student is the primary person responsible for doing data collection, and he has performed data analysis, chosen relevant methods, and presented results. This has also involved theoretical and conceptual development.

In this paper, we examine how brokerage in multi-layered interorganizational networks shapes the growth of innovative and entrepreneurial firms' resource base. While prior research has established that network position affects both performance and access to resources, brokerage is often treated as a broadly beneficial structural advantage within a single network. However, innovative firms are embedded in multiple, interdependent domains of relations that coordinate different stages of the full innovation process. The purpose of this study is therefore to investigate whether brokerage has different implications depending on the network layer in which it occurs, and whether brokerage positions across layers interact in shaping firms' asset growth.

Using the same longitudinal event-based relational database as in Papers I-III, we study the population of Swedish dedicated biotechnology firms between 2004 and 2013. The data contain 7,752 coded organizational interactions involving 319 DBFs and 2,549 partner organizations. Building on the multilayer perspective developed in Paper II, we construct cumulative networks for each year and distinguish three separate network layers that are essential for innovation: finance, R&D and commercialization. Brokerage is operationalized as the normalized betweenness centrality within each layer, capturing the extent to which a firm spans otherwise weakly connected parts of the network. To examine implications for firm growth, we estimate time-lagged random-effects panel regression models predicting the logarithm of total firm assets in year t+1.

The results show that brokerage advantages are neither universal nor uniform across layers. Brokerage in the finance layer has a positive and statistically significant association with subsequent asset growth, suggesting that intermediary positions among financial actors provide a direct pathway to building firms' capital bases. In contrast, brokerage in the R&D and commercialization layers does not independently predict asset growth when tested separately. However, we find a positive interaction effect between R&D brokerage and commercialization brokerage, suggesting that brokerage in the two innovation-oriented networks contributes to asset growth only when firms simultaneously occupy brokerage positions in both layers. No other interaction effects are observed. These findings suggest that returns to brokerage positions in innovation-oriented networks are configuration dependent. Bridging positions in knowledge development appear to generate growth benefits when coupled with bridging positions in downstream commercialization-oriented networks.

Through this work, we contribute to network research by demonstrating that the performance implication of brokerage depends on both the specific layer in which brokerage occurs, and the interaction between network layers. Rather than treating brokerage as a uniform positional advantage, the findings illustrate the importances of conceptualizing brokerage as being embedded in multi-layered network structures. The findings also inform entrepreneurial financing research by suggesting that financing networks may operate according to partially independent dynamics within the broader innovation ecosystem. Financial brokerage contributes directly to asset growth, while innovation-layer brokerage produces growth only when it links complementary stages of the innovation process: R&D and commercialization. Overall, Paper IV advances a multi-layered view of how entrepreneurial firms mobilize resources and build financial strength through interorganizational networks.

6. Conclusions and future research

This thesis explores how interorganizational networks within the Swedish biotechnology sector and its ecosystem partners across the globe form and evolve over time and how entrepreneurial firms' network activity and network positions shape access to resources and development outcomes. The thesis demonstrates that biotechnology entrepreneurship is deeply network-dependent and occurs in multiple network layers that differ in structure, internationalization and implications for firm development. It highlights the globalized nature of entrepreneurial ecosystems, which is particularly pronounced in knowledge-intensive sectors like biotechnology.

A first conclusion is that entrepreneurial ecosystems in biotechnology are not bounded by local geography but are better understood as supra-local structures that are constituted through interorganizational relationships that span regions and international borders. We find that more than half of our sample firms' interaction involves international partners, indicating that key resources, knowledge and opportunities are mobilized through cross-border interactions and collaborations. The findings suggest that the characteristics of local entrepreneurial ecosystems significantly influence a firm's international networking behavior. This interplay between local conditions and international outreach adds a new dimension to the discussion on entrepreneurial firm behavior, emphasizing the role of local ecosystems as a foundation for international expansion. At the same time, the international orientation is not uniform across network layers and the results of the thesis consistently point towards systematic variations between R&D, commercialization and financing networks. R&D and commercialization appear substantially more internationalized than financing networks and remain so during the entire time period of this study. This indicates that firms seek expert knowledge and downstream marketing partners internationally while relying to a greater extent on domestic partners to build and secure financing relationships.

Our findings also offer insights into how the position of entrepreneurial firms within multi-layered networks influences their network activity. Generally, our findings suggest that entrepreneurial firms occupying more central network positions are less likely to form financing and marketing relationships with international partner

organizations. This supports the notion that informational advantages and coordination costs can deter central actors from exploiting network brokerage opportunities (Burt, 2004; Obstfeld, 2005). However, our analyses point to well-connected entrepreneurial firms with international network experience and higher growth ambitions as the spiders in the net driving EE internationalization. These firms likely benefit from increased opportunities to form new relationships across the territorial boundaries of their local EE resulting from their central position within the network (Burt, 2004; Whittington et al., 2009) and from networking and internationalization knowledge they gain through international network activity over time (Lindstrand et al., 2011; Lindstrand & Melén Hånell, 2017). Both facilitate collaboration across territorial boundaries. Having a larger network was seen to contribute to international activity across all layers and the impact of this on the success of commercialization and subsequent performance of the firm remains a topic for future studies.

A second conclusion is that network structure matters not only for where, but also for how they build the resource base needed to sustain long and uncertain development cycles. Paper III shifts the focus from international networking activity towards the expansion of the firms' resource base as an outcome variable and highlights the firms' financing networks as a central mechanism in this process. The finding that finance network size displays a curvilinear relationship with asset growth is consistent with the idea that there is such a thing as over-embeddedness. Network connections require attention and time for them to create the benefits of learning, visibility and legitimacy, and the tradeoff is apparent after a point where the costs of coordinating a bundle of network relationships outweigh the benefits. The access to non-domestic capital for Swedish biotech firms is shown to be important, as the analysis shows that international orientation of financing networks is positively associated with subsequent asset growth. Interestingly, as seen in paper I and II, the financing network was however the least internationalized, suggesting opportunities for international financiers to explore opportunities within the Swedish ecosystem, as well as for entrepreneurs to expand outward, beyond the domestic capital markets. Paper III also suggested that ties to government actors (Swedish as well as regional and international) are negatively associated with asset growth, which raises the question of

the alignment of goals in funding design, scale and scope relative to asset accumulation as a measurement of firm performance.

A third conclusion relates to the network positions and conditions under which positional advantages translate into development outcomes. Paper IV showed that a brokerage, previously thought of as a uniformly advantageous position, is layer-specific and configuration dependent in multilayered interorganizational networks of entrepreneurial firms. It is directly associated with asset growth in the financial layer, indicating that occupying an intermediary position among financial actors can provide opportunities for funding, information and legitimacy that translate into expansion of the resource base. Brokerage in R&D and commercial network layers, by contrast, does not generate benefits independently. Instead, only when a brokerage position is occupied in both layers simultaneously are there effects on asset growth, which suggests some required level of coordination and bridging between knowledge and commercialization activity. These results imply that the innovation process is shaped by both an outside domain of capital mobilization in the finance layer, and an inside domain of innovation development in the R&D and commercialization layer where growth outcomes depend on achieving alignment across domains rather than brokerage in one single layer.

In summary, this thesis advances research on entrepreneurial ecosystems and intraorganizational networks by showing that (i) ecosystems are constituted through supra-local network activity, (ii) intraorganizational networks should be studied as multi-layered structures rather than as single aggregated networks, and (iii) both financing network configurations and multilayer brokerage positions are central mechanisms through which biotechnology firms mobilize resources and progress toward commercialization.

6.1 Limitations and future research

As with all research, this thesis is not without its limitations which can point to opportunities for future research. First, its focus is on Swedish biotechnology firms. Sweden is a small and open economy with unique economic and institutional

characteristics, and the innovation landscape might not mirror those of other countries, particularly in varying institutional and cultural contexts. Future studies could expand this research to include biotechnology firms in diverse geographical settings, enhancing the universality and applicability of the findings.

Second, the relational database is constructed from information found and coded from public sources. While this approach provides a broad scope and depth of data sources and longitudinal coverage, ties that are not publicly disclosed may be underrepresented. Informal ties, company board or academic connections and other relationships that are likely to occur and persist in a small economy (and even smaller biotechnology sector) are more easily detected through an interview-based study and could further strengthen the dataset.

Third, the thesis operationalizes outcomes primarily through international network activity and asset growth. These measures are meaningful and common for biotechnology, but growth is multidimensional and is not easily captured in a single metric. Future research could examine whether the results hold for other outcome variables and research on entrepreneurial firms would benefit from the continued development of composite metrics that capture a broader perspective of firm growth.

Finally, by applying social network theory and methods to the study of entrepreneurial ecosystems and their internationalization processes, the paper contributes methodologically to both the fields of entrepreneurship and international business. It offers a new lens to examine how inter-firm networks transcend geographical boundaries and facilitate internationalization. In this thesis, the network layers are studied largely as separate networks, although part of one large network. We have not explicitly studied what actors are present across layers and how their positions and roles evolve over time in a “network of networks”. In future research, applying novel models for analyzing dynamic multi-layered network and find network metrics that span several layers, as well as multilayered community detection (see e.g. Magnani, Rossi & Vega, 2021 or Magnani et al., 2021) which may be an interesting extension of our work.

7. Implications for managers and policy

7.1 Implications for managers

This thesis shows that biotechnology entrepreneurship is not only shaped by what firms do internally, but also by where they are positioned in interorganizational networks and which relational domains they prioritize. A practical implication is that managers and support organizations should treat networking as a multi-layer strategy with different objectives, partner types and success criteria for R&D, commercialization and financing.

First, international networking should be viewed as a strategic capability rather than an optional add-on activity. Firms in this industry rely on access to specialized knowledge, market channels and capital that are not always available locally. This thesis shows that while international ties are common in R&D and commercialization, it is significantly less common in financing. For managers, this implies that being experienced and active internationally in the scientific community or in business and market development does not automatically translate into being international in the search for funding. Firms could therefore build an explicit financing internationalization strategy. This could involve the identification of foreign investor communities, building credibility over time and treating financing across borders as a relationship-building rather than transactional, much like what seems to be the case in other networking domains.

In paper III, there are signs of diminishing returns on the size of the financing networks. Beyond a point, the costs of coordinating and maintaining ties seem to outweigh the benefits that a large network of financier brings. This suggests that fundraising is not merely a matter of meeting more investors without a strategy. Instead, there are benefits to evaluating financing ties not only by the capital they provide, but also the attention they demand, the complexity they introduce, and which doors are opened to additional credible financiers through their networks. Paper IV builds on the notion that position, not only size, matters in the financial network. Firms may benefit from cultivating a role that connect otherwise separate financial audiences

rather than being too closely tied to a close-knit local circle. By contrast, brokerage in R&D or commercial networks were not shown to be associated with asset growth. Firms benefit when they span both network layers, suggesting that the coordination and connection of knowledge development to downstream market development plays a key role in the innovation process.

7.2 Implications for support actors

Incubators, science parks, technology transfer offices, accelerators and regional development actors are all part of the ecosystem surrounding not only biotechnology firms but most high tech and knowledge intensive firms and all do their part to improve the chances of success and return to their respective stakeholders. This thesis implies that support should be designed as layer-specific capacity building rather than emphasize generic networking. The evidence presented here suggests that it is important to be aware of which network layer is being strengthened and developed. Based on the low levels of international funding in general, and the positive effects of international financial ties in particular, there should be opportunities to invest in efforts to connect Swedish firms to international financing communities. For entrepreneurial and well-connected financial actors already active in Sweden, the lack of international actors also presents an opportunity to take on a brokerage role between Swedish entrepreneurs and international financiers and facilitate cross-border activities to mobilize capital.

7.3 Implications for policy

From a policy perspective, this thesis suggests that financing remains a bottleneck for science-based entrepreneurship but that the relevant question for policy is not only the quantity of available funding, but also how funding shape firms' financing and growth trajectories. The negative association between government funding in paper III should be interpreted with caution but it raises an important issue about the impact of government funding programs on fast-growing firms. One interpretation is that government funding stabilizes technological development without providing the complete and necessary capitalization for long term development cycles and

subsequent acceleration and market launch. This implies a need to evaluate whether policy initiatives and instruments are aligned with the outcomes (e.g. capitalization, R&D progress, commercialization, employment, firm survival) policymakers want to stimulate.

Finally, this thesis demonstrates the practical value of social network analysis as an analytical tool to deconstruct ecosystems into layers and find the effects of structure and position. It is a tool that can be used by policymakers and managers of both firms and ecosystems to monitor and diagnose the health of the ecosystem and identify risks and opportunities by identifying key actors, brokers and structural gaps. Used in this way, is a useful and scalable approach for evidence-based ecosystem development.

8. Declaration on the use of generative AI

Generative AI (ChatGPT, OpenAI, version as of mid-2026) was used to improve R-based data visualization workflows and to assist with the language and formulation of parts of this “kappa”/comprehensive summary. All generated material was thoroughly reviewed and revised by the author, who bears full responsibility for the final content.

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