QUANTITATIVE APPROACHES TO THE NETWORK PROBLEM IN PROGRAM DESIGN AND EVALUATION (CASE STUDY: ENTREPRENEURSHIP)

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Submitted to Saïd Business School
in Partial Fulfillment of the requirements for the degree of
Doctor of Philosophy
at the

UNIVERSITY OF OXFORD
April 2015

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Title: DP World Chair for Entrepreneurship and Innovation at Saïd Business School

Abstract

Many billions of dollars each year are spent in pursuit of economic and social development goals. The field of program evaluation aims to measure the efficacy of these programs and allocate funds to achieve optimal results. However, current research on program design and evaluation tends to focus on determining causality through complex statistical methods, neglecting intermediate measures of data, such as network metrics. Similarly, research in computational social science has focused on generating hypotheses and validating theory rather than economic development applications.

This thesis develops a novel technique for using computational social science to design and evaluate social and economic programs. A framework for program design and evaluation using network metrics is presented, along with two case studies that illustrate the use of this technique. In the first, we consider Start-Up Chile, an economic development program whose goal is to foster networks between Chileans and international entrepreneurs, using network metrics to evaluate its ability to facilitate connection between Chilean and non-Chilean entrepreneurs. Second, an agent-based model for designing entrepreneurial incubators is developed, with novel conclusions for more efficient design of economic development programs.

Acknowledgements

I would like to begin my acknowledgements by thanking my supervisor, Dr. Linda Scott. My deepest gratitude goes to you for everything you've done for me. Your encouragement and support, in these final hours, has been life changing. It will never be forgotten.

I would also like to thank the Said Foundation and Green Templeton College for their generosity throughout my DPhil and their help in funding conference attendance and other necessities. The staff at the College and at Said Business School were tireless in their support of all of their students and I am incredibly grateful for their help. In particular, Kate Goodman and Kate MacDonald at SBS and Marina Prosperi at Green Templeton College made everything possible with their hard work, attention to detail, and care for all of us.

My gratitude also goes to the Academy of Management for the chance to present materials related to this thesis twice, and for the honor of being awarded Best Paper Award for a doctoral student both times. The generosity and support of the Fulbright Committee has also touched my life. The opportunity to learn about entrepreneurship in another environment shaped my thinking and led to the structuring of my thesis around the subject of program design and evaluation. It was the opportunity of a lifetime and I am endlessly grateful for the chance to have been a part of it.

To Zac Apte, the most real of imaginary friends.

To my fellow DPhil students: I have been inspired by you, challenged by you, and moved by the passion you bring to making the world a better place through scholarship.

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Chapter 1 – Introduction

> One must divide one's time between politics and equations. But our equations are much more important to me, because politics is for the present, while our equations are for eternity.
>
> —Albert Einstein
>
> Quoted by Ernst Straus in Seelig, *Helle Zeit, dunkle Zeit,* 71

New Applications for Computational Social Science

Many billions of dollars are spent each year on economic and social development programs, from foreign aid to domestic job creation programs. Approaches to program evaluation are generally focused on better understanding cause and effect, for example, using randomized controlled trials to disaggregate results and determine their causes (Duflo, 2006). However, the question of what precisely is measured during these trials has been sorely neglected.

This thesis aims to measure the results of social and economic programs in a more efficient, timely, cost-effective, and powerful way. By using network measures as intermediate metrics, we can quickly and easily evaluate the progress of programs and determine how well they are performing while there is still time to change course. Furthermore, by using network metrics to design programs, we can build a model of the desired outcomes and compare them to actual results in an automated fashion, iterating quickly on the program's structure to achieve better results.

The data for these new metrics can be collected automatically, as part of processes with which many recipients are already familiar. The ubiquity of social networking software in both professional and personal life has made massive quantities of data available about all of us, for both good and ill. There can be much risk in this accumulation of data, but there is also much promise in its use to take better measurements of our individual lives (and of our collective social lives as well), and learn more quickly from them. The nascent *Quantified Self* movement involves individuals tracking data about their health to learn more about their habits and make positive changes; similarly, by using network data and tools, organizations can measure the success of particular programs quickly and make adjustments to their plans, and then iterate and test again.

Network measurements can be built seamlessly into the functioning of an organization and then used to monitor and encourage social relationships that are of benefit to the individual as well as the whole. There are numerous social programs that rely on building networks as an important component of their activities and as crucial to their success: for example, education (e.g., retention at educational institutions), acculturation (e.g., reducing culture shock), and poverty alleviation (e.g. social capital transfer to the poor through "Big Brother"-type programs). In entrepreneurial incubators—the focus of this thesis—both the organization and its members want to form connections that support the growth of the company as well as the institutions of which they are part.

Computational social science, originated in the 1970s in its modern form, has wide reach.[1] Networks have been used in a variety of fields to measure the effect of social relationships to prove or disprove hypotheses. In public health, networks have been used to gain an understanding of the social transmission of health conditions like obesity and heart disease (Christakis & Fowler, 2007). In fields as diverse as military strategy (Mac Ginty, 2010), animal behavior (Sueur, Jacobs, Amblard, Petit, & King, 2011), and stock price valuation (Bollen, Mao, & Zeng, 2011), networks are useful in analyzing relationships and measuring correlations. In entrepreneurship, they have been used to measure access to capital, information flows, gender equity, and regional advantages (Acs & Audretsch, 2006). These diverse uses of networks point to a new application: program design and evaluation.

[1] Note: the terms *computational social science* and *mathematical sociology* are used interchangeably in this thesis, along with *modern computational techniques* (as opposed to regression-based and other parametric statistical techniques).

It is the aim of this research to add computational social science techniques, such as social network analysis and agent-based modeling, to the program evaluation toolkit. These tools are both less costly and more timely than traditional surveys and interviews. Of key importance is that these techniques can be used ex ante and/or contemporaneously with program participation. Intermediate metrics are of paramount importance as long-term metrics are often difficult to gather and, by their nature, are gathered long after the program has been completed (CGD, 2006).

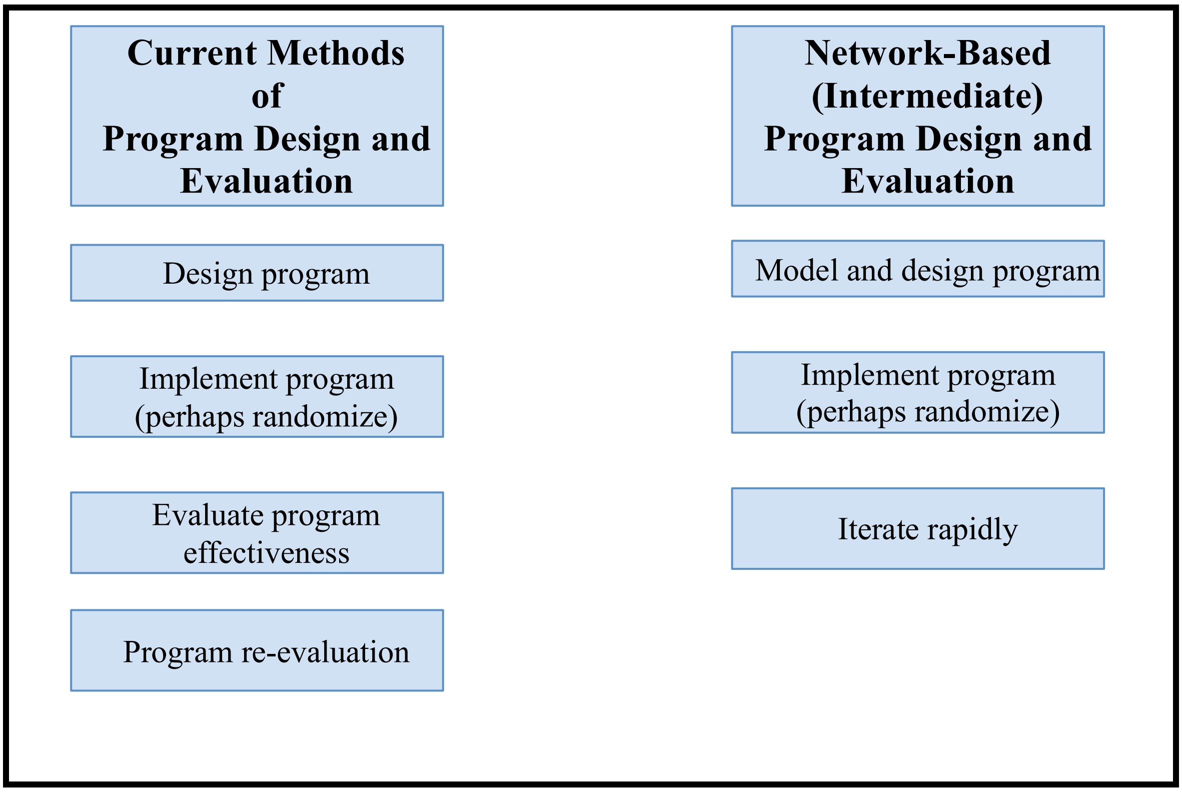


Figure 1. Process of intermediate measurement vs. outcome-based measurement.

The "Evaluation Gap" in Economic Development

Recent advances in economic and statistical methods for impact evaluation have catalyzed acceptance of evaluation as a tool for effective policymaking and program management (Duflo, 2006). Investors and lending institutions such as the World Bank, national governments, regional development banks, and foundations have begun to require impact evaluations as part of their loan or grant requirements. Other agencies note that these assessments enhance accountability and transparency and help policymakers assess program scalability and sustainability.

Impact evaluations—studies that assess the social and economic effects of specific programs—have the potential to substantially enhance our understanding of how to spend limited economic development funds (Levine & Savedoff, 2006). Moreover, impact evaluations can help development and other economic aid organizations evaluate their programs and lay the groundwork for future interventions. Many researchers have noted the difficulties that organizations face in evaluating the effects of their efforts and the political, social, and financial issues that can hinder efforts to produce effective impact assessments (Khandker, Koolwal, & Samad, 2010).

The practice of program impact assessment is extremely fragmented, and many authors have decried the lack of common standards in measuring the impact of programs, whether for programs related to corporate social responsibility, international development, or poverty alleviation (Khandker et al., 2010). Termed the *evaluation gap*, this problem plagues international aid programs and domestic initiatives alike. It is the hope of this researcher that adding network measures will provide a unifying base for more effective evaluation of social and economic programs.

Adding network metrics to the evaluation process would allow practitioners to gather early evidence for hypotheses and test them with current data, a quick and simple check of program effectiveness. Another advantage of network metrics is that the process does not need to disrupt program implementation or burden staff with additional responsibilities. Data collection can be performed automatically, without the intervention of program staff.

The process of gathering these measurements—while providing better specificity over time and allowing for greater flexibility—does pose higher upfront costs as institutions integrate these measurements into their current frameworks. Additionally, institutions might be reluctant to be evaluated in a new way that could potentially reveal deficiencies in their organizations (Vaessen & Leeuw, 2010). It is hoped that these potential concerns will be outweighed by the benefits received as administrators come to understand how this data can help build more effective programs. For programs whose participants are technologically savvy, use of social networking software like LinkedIn and Facebook is quite common. Every participant has her own computer and strong personal and professional reasons to expand their network. In the case of social and economic development programs aimed above the bottom billion, especially, these strategies can be quite easily adopted.

Finally, it is important to note that interim measures (such as network metrics) are not a substitute for outcome measures. Rather, they are intended to supplement existing evaluation methods and to allow for rapid iteration before other types of data—which may be time consuming to gather—becomes available. Outcome measures can still be used to evaluate the final result of the program and to tie intermediate measures to long-term ones to determine causality.

Motivating Case: Start-Up Chile

Start-Up Chile is the motivating case for this study for a number of reasons: 1) incubators are a particularly apt example of an economic development program with the aim of transferring networks; 2) the participants in Start-Up Chile are computer-savvy professionals who make extensive use of online social networks (such as LinkedIn) to form relationships that are comparatively easy to measure with network analytic techniques; 3) Start-Up Chile is a very prominent incubator, yet is unique in not aiming for a return on investment in monetary or intellectual property terms, instead aiming for a "return in networks" based on the value of the networks brought back to Chile; 4) the incubator structure leads to networks with clear boundaries both of participants (those admitted to the program), and start and endpoints (the beginning and end of each session) ; and 5) because of

Chile's relative geographic isolation, it is easier to delineate which network ties are more likely to be because of the incubator (i.e., most entrepreneurs in North America and Western Europe have few pre-existing ties to the Chilean entrepreneurial ecosystem).

Incubators in developing or emerging countries face a special set of issues based on the need for economic development, the transition from a manufacturing to a service- or innovation-based economy, and the lack of a mature entrepreneurial ecosystem (OECD, 2013). Some researchers have argued that social networks are even more important in emerging markets, where new ventures face greater difficulties raising capital and establishing credibility, and thus need the support of existing networks (Perez-Aleman, 2005; Ter Wal & Boschma, 2009). Furthermore, extreme social stratification and the resulting dense social networks among the wealthy and powerful—which can be exclusionary to the rest of the population—make formation of new networks even more important to spur broad-based innovation. For these reasons, many emerging countries have established policies to promote the creation of new clusters and to strengthen existing ones (see e.g., van Dijk & Rabellotti, 2005).

Start-Up Chile is an economic development program founded by the Chilean government in 2010 with the goal of bringing international entrepreneurs (and their valuable networks) to the country to support the development of an entrepreneurial ecosystem in Chile. Funded with $40 million USD, this incubator represents a new type of economic development program: one designed to help the domestic economy by giving money to foreigners. Start-Up Chile focuses on high-growth early-stage technology startups that seek angel or venture funding and are intended to grow to massive scale, often before achieving profitability. Like many other regions of the world, Start-Up Chile aims to replicate the success of the Silicon Valley ecosystem by creating Saxenian-like (1994) networks of regional advantage.

Start-Up Chile has received extensive international press in publications like *The Economist* and *The New York Times* and spawned imitators around the world. Thousands of entrepreneurs have applied and the acceptance rate has dropped with nearly every admit class. This leads us to several important questions: Does the program work? How would one know? And what would make it work better?

Research Objectives

Entrepreneurial incubators and many other social and economic development programs rely on transfers of social capital to achieve their ends. In fact, some programs are designed specifically to facilitate the development of networks among participants. Until now, these networks have not been used to evaluate or design programs. Further, network metrics and other methods from computational social science are not widely used.

Therefore, this research aims to fill the gap in the existing literature on program evaluation and computational social science by addressing the following question:

> *How can techniques from computational social science be used to design and evaluate social and economic programs?*

Research Approach and Methodology

This thesis includes two case studies. The first evaluates Start-Up Chile's efforts to integrate the networks of international entrepreneurs with those of domestic ones in order to create an entrepreneurial ecosystem. The second develops a model using agent-based simulation of network metrics as a guide to designing an entrepreneurial incubator. The first case study uses data gathered from entrepreneurs' LinkedIn profiles; the second is an agent-based model that uses a custom-designed simulation to examine the effects of network size, interconnection rates, and helpfulness on total social capital gained by entrepreneurs within the incubator.

Thesis Outline

Chapter 2 provides background on entrepreneurial incubators and develops an understanding of the structure and impact of entrepreneurial incubators. Chapter 3 reviews the literature relating to networks, entrepreneurship, incubators, and program evaluation (while reserving a methods literature review for Chapter 4). Chapter 4 reviews the literature on network metrics and describes how the first case study was implemented. Chapter 5 describes the origins and structure of the Start-Up Chile incubator, the empirical work completed for the first case study, and the results. Chapter 6 details a second case study, an agent-based model for use in the design of entrepreneurial incubators, reviewing the related literature and describing the methods used in the simulation. Finally, Chapter 7 contains discussion, conclusions, and directions for future work.

Chapter 2 – Background on Entrepreneurial Incubators

Brief History of Entrepreneurial Incubators

The first business incubator was a privately owned, for-profit business started in Batavia, New York in 1959 with the goal of increasing local economic development through entrepreneurship. Over the next 30 years, incubators expanded to include innovation centers for technology transfer, local and regional government efforts to foster economic development, and private investors' efforts to streamline the new venture investment pipeline (Bhabra-Remedios & Cornelius, 2003).

Initially, growth of business incubators was slow; by 1984, there were only 26 such centers in the United States (Hackett & Dilts, 2004). However, by 2003 there were over 1,000 incubators each in the USA and Asia, and 700 incubators in Western Europe, with the largest percentage (35%) in the UK. There are also incubators in developing nations such as Turkey, Nigeria, and Brazil. In all, by 2003 there were over 3,500 incubators in operation worldwide (Lalkaka, 2003). Since 2005, incubators with a network focus have grown even more rapidly, with over 2,000 new programs ("Getting up to speed," 2014).

The American National Business Incubation Association (NBIA) defines a business incubator as an economic development tool designed to accelerate the growth and success of entrepreneurial companies through an array of business support resources and services. As noted in the work of Bruneel, Ratinho, Clarysse, and Groen (2012), business incubators have evolved through three generations to provide successively greater support to entrepreneurs. In the first generation, they provided access to office space, business machines, and other physical goods. Then, they provided access to business services such as the services of attorneys and accountants. The present generation offers access to networks of mentors, entrepreneurs, and formal structures for transferring knowledge, connections, and experience.

Table 1

Key Resources Offered by Incubators

- An environment of peers, including social inputs, resources, and support
- Discounts on rent, services, equipment, etc.
- Legitimacy and branding as a member of the incubator
- Financing or help in arranging financing

Note. Adapted from “The Networked Business Incubator—Leveraging Entrepreneurial Agency?” by A. Bøllingtoft and J. P. Ulhøi, 2005, *Journal of Business Venturing*, *20*(2), p. 270. Copyright 2005 by Elsevier.

There is some confusion between the terms *incubator* and *accelerator* in the literature. This thesis uses the term *incubator* exclusively. First, *incubator* is more commonly used for long-term, cohort-based programs, as opposed to programs like Start-Up Weekend (a three-day program that is designed to start projects rather than lead them to the funding state) or virtual accelerators that are primarily online and don’t create the same personal social connections as the in-person cohort model described below. Second, *incubator* is a more neutral term that does not imply that the programs must accelerate (as opposed to decelerate) the business. Moreover, *incubator* is a much broader term, commonly interchangeable with *technology park* and other terms that precede the current boom in entrepreneurial support programs since 2005. This requires us to differentiate what we shall call *network-focused incubators* from the older models based on provision of non-network resources such as office space.

Network-Focused Incubators

The format for the current generation of business incubators was developed in 2005 by entrepreneur Paul Graham and a team of angel investors who started a program named after an obscure mathematical function: *Y Combinator*. Y Combinator’s model provides a seed investment (originally $10,000 USD per person, now $120,000 USD per team) usually to fund the development of an initial product prototype, as well as to provide training, mentorship, and social connections. Y Combinator encourages high-growth, early-stage technology startups to apply, noting that "We can probably help any startup that hasn't already raised a series A round from VCs." (Y Combinator, FAQ) They seek high-growth, technology-based startups in a variety of fields, including energy, education, robotics, healthcare, transportation, and entertainment. On their Requests for Startups (a play on the standard Request for Proposals process) website, they indicate: "Many of these areas fall into the 'breakthrough technology' category, but the great majority of the startups we fund will continue to be the sort of Internet and mobile companies we've funded in the past." (Y Combinator, Requests for Startups).

The network-based incubator model has been a tremendous success in many ways. The total value of Y Combinator start-ups alone is approximately $50 billion. Individual companies, such as Dropbox and Airbnb, are both valued at more than $10 billion. More than 2,000 entrepreneurs have participated in the program. Current acceptance rates hover around 2% (Chafkin, 2015).

Since 2005, over 2,000 incubators have imitated this format, including Start-Up Chile, the focus of the first case study of this thesis. Using the criteria developed by Miller and Bound (2011), we define network-focused incubators (i.e., those on the Y Combinator model) by the characteristics as shown in Figure 2.

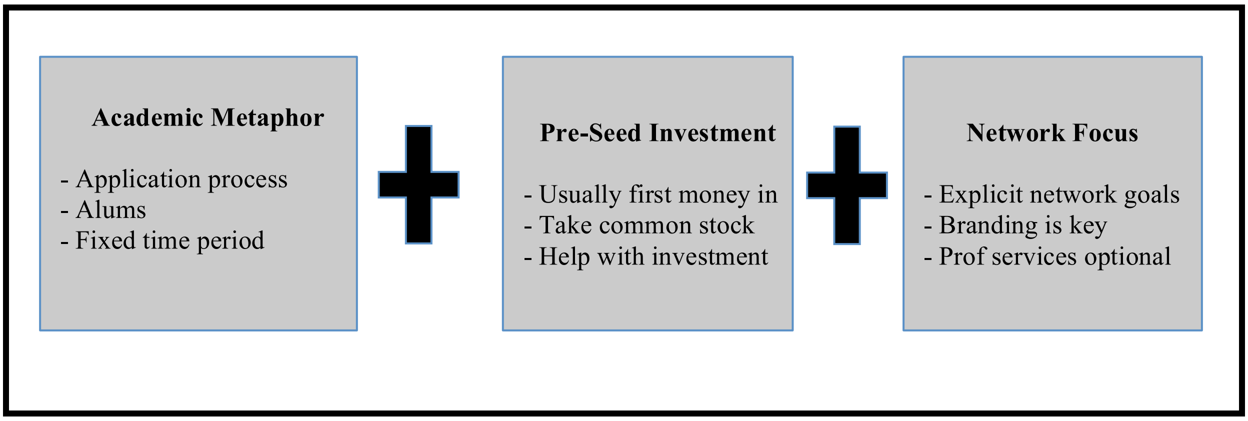


Figure 2. Characteristics of network-focused incubators. Adapted from *The Startup Factories: The Rise of Accelerator Programmes to Support New Technology Ventures*, (NESTA Discussion Paper), by P. Miller and K. Bound, 2011, p. 9. Copyright 2011 by NESTA. Retrieved from NESTA website: http://www.nesta.org.uk/sites/default/files/the_startup_factories_0.pdf.

The Incubation Process

Y Combinator uses the unifying metaphor of an academic program. Prospective entrepreneurs submit an application, go through rounds of interviews, and are subsequently admitted into a class (becoming *admits*). Prospective members often travel great distances to live for a temporary period in a new location (often a setting of great mystique to entrepreneurs, like Silicon Valley, New York, London, or the capital city of their country). They are expected to work exclusively on their start-up, to make close friends with their fellow entrepreneurs, and to leave the incubator transformed, if not funded. Participation in an incubator is designed to lessen the loneliness of the entrepreneurial journey and to build strong bonds that will help the entrepreneurs throughout this venture and the rest of their careers. In return for this mentorship and training, Y Combinator receives 7% of the company's equity. After they graduate, entrepreneurs become *alumni* of the program.

These explicit connections to a network of peers, as well as successful entrepreneurs, angel investors, and other advisors, create strong bonds within the incubator. In addition to connections to mentors and business professionals, entrepreneurial cohorts provide connections between peer teams that support each other with help ranging from problem solving on technical issues to feedback on interactions with potential customers, investors, and suppliers. Given that this new type of incubator is primarily focused on providing a network as opposed to other resources such as professional services or money, it is an ideal setting for research on program evaluation using network metrics.

Using the metaphor of the college application process starts a process of identity transformation in admits who then emerge from the process thinking of themselves as *Y Combinator*- or *Start-Up Chile*-branded entrepreneurs. This instills a sense of loyalty to the peer group—much like classmates at university—and to the larger group of alumni over time. The process of incubation is illustrated in Figure 3.

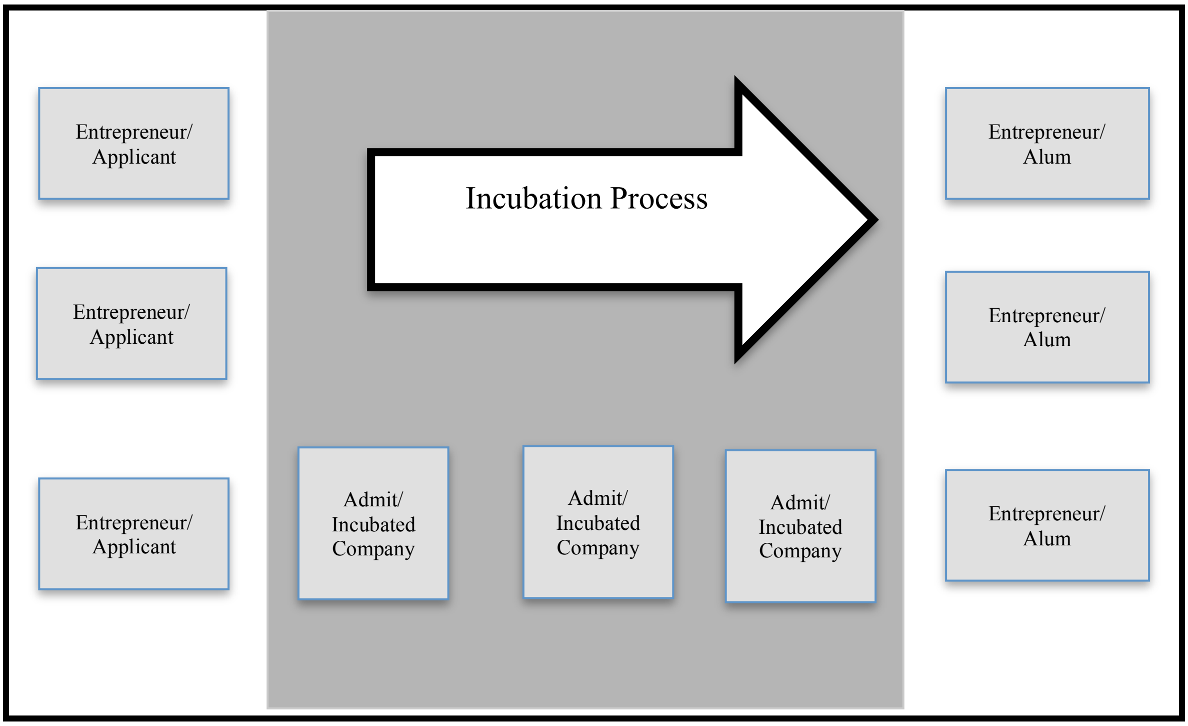


Figure 3. Overview of the incubation process. Adapted from "A Systematic Review of Business Incubation Research," by S. M. Hackett and D. Dilts, 2004, *The Journal of Technology Transfer, 29*(1), p. 57. Copyright 2004 by Kluwer Academic Publishers.

Types of Incubators

Y Combinator is a for-profit institution started by angel investors, but many of the programs that have followed its lead are not. The cohort-based method can be used to achieve disparate goals: for example, economic development, university technology transfer, or cultural transformation of an economic district. Table 2 gives examples of each type of incubator and its sponsoring organization.

Table 2

Types of Incubators

Type	Purpose	Sectors	Example
Economic development	Regional development	All	Start-Up Chile
Technology commercialization	Build businesses based on technology	Commercialization of (usually university) intellectual property	Stanford StartX
Social entrepreneurship	Triple bottom line returns	Non profit	The Hub
Profit	Seed fund	All	Y Combinator

From an economic development perspective, entrepreneurial incubators are attractive to policymakers. They are easy to create, widely recognizable vehicles for building entrepreneurial networks and transferring knowledge about best practices for entrepreneurs. Starting a network-focused entrepreneurial incubator often requires no more than an application process and a meeting place for entrepreneurs, as well as investment capital. With a relatively small investment, policymakers hope to gain great economic rewards from stimulating job and venture creation through incubators.

Chapter Summary and Preview

In this chapter, we discussed the history and present form of entrepreneurial incubators, with particular focus on network-focused incubators. In Chapter 3, we review the literature about networks and entrepreneurship, as well as the current state of program design and evaluation as it relates to economic and social development programs.

The following literature review surveys how network measures are used in social science research, in particular in entrepreneurship and entrepreneurial incubators. An overview of how social and economic programs are currently measured follows, as well as a discussion of this work's contribution to the field. Specific discussion of network metrics, including definitions and how they are applied in the Start-Up Chile case study, is reserved for Chapter 4. Figure 4, below, situates the present research in the context of economic development research.

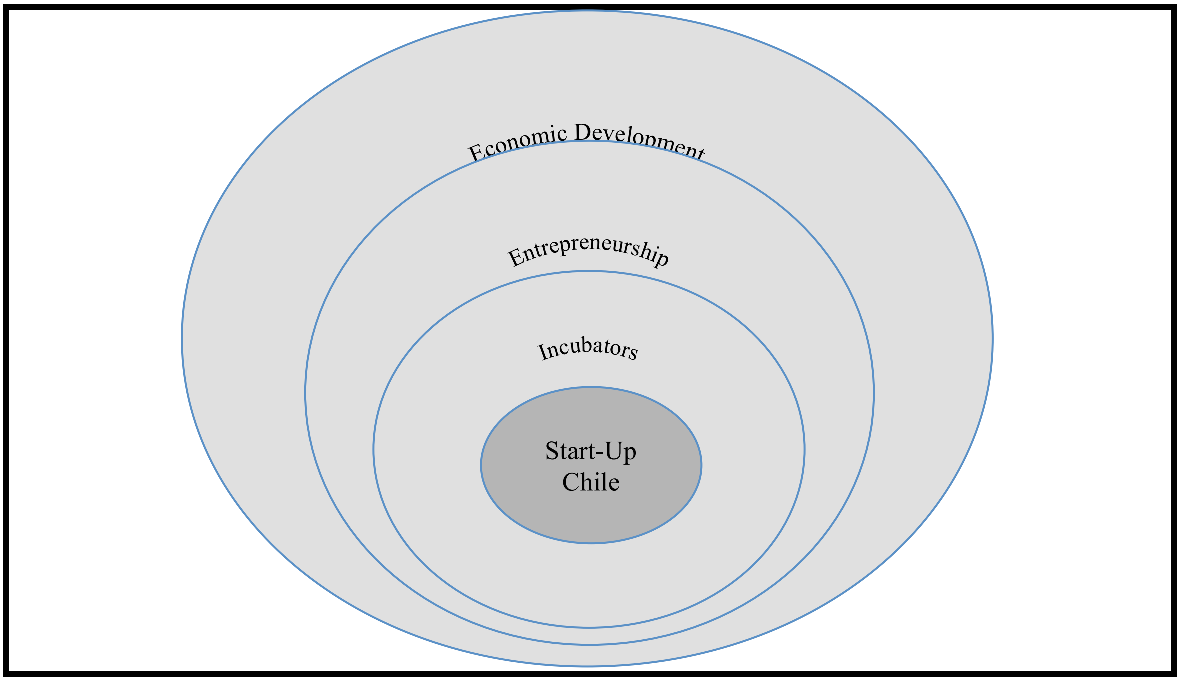


Figure 4. Situating this thesis in the context of economic development research.

Social Capital Theory

The theoretical basis that underlies this dissertation is social capital theory, based on the concept of *embeddedness*, which posits that economic relations are embedded in social structures that influence and are influenced by economic relations. Researchers such as Adler and Kwon (2000), Kenis and Knoke (2002), and Lin (2002) have increasingly focused on this intersection of economics and sociology, as simple models of *homo economicus* have proved inadequate to describe and predict human behavior.

Social capital is composed of the social networks, ties, and structures that help individuals get access to information and knowledge (Scott, 2012). Defined by Adler (2002) as "the goodwill that is engendered by the fabric of social relations and that can be mobilized to facilitate action" (p. 17), social capital has informed the study of education, public health, political science, and economic development (Jackman & Miller, 1998; Portes & Sensenbrenner, 1993; Woolcock, 1998).

General benefits of social capital.

Social capital has many benefits in economic activity as shown in Table 3. Providing information, control over, and access to resources, as well as trust and engagement, social capital is valuable in many processes, both within and outside of entrepreneurial or business settings.

Table 3

Benefits of Social Capital Transfer

Benefit	Description
Information	Social capital facilitates access to broader sources of information and improves quality, relevance, and timeliness.
Influence, control, and power	Social capital allows those who have it to control its flow to others and to influence the connections that are formed in the network.
Trust, solidarity, and engagement	Social capital can permit lower monitoring and transaction costs due to increased trust among members of the network.

Note. Adapted from "Market, Hierarchy, and Trust: The Knowledge Economy and the Future of Capitalism," by P. S. Adler, 2002, *Organization Science, 12*(2), pp. 215–234. Copyright 2002 by INFORMS; *Social Capital: A Theory of Social Structure and Action*, by N. Lin, 2002. Copyright 2002 by Cambridge University Press.

How social capital benefits entrepreneurs.

New organizations lack institutional ties that would allow them to obtain information they need about potential partners. Instead, their founders often have relevant personal ties from networks related to their education, employment, or previous entrepreneurial ventures (Hsu, 2007). Personal ties between employees within different organizations can also reduce uncertainty by encouraging the transfer of information about each organization across the organizational divide. In the entrepreneurial context, the value of the information that flows through the network about hiring or press opportunities, private evaluations of the quality of specific mentors or funders, and so forth can be extremely high (Podolny, 2001). New ventures, in particular, succeed or fail based on their access to helpful information networks (Greve & Salaff, 2003; Shane & Cable, 2002).

Furthermore, founders' ties can reduce the uncertainty that a new organization and its potential partner might have about each other. There are several reasons this can be the case. First, potential partners can benefit from their knowledge about the founder's personal traits and how relevant those characteristics might be to the newly formed organization (Broschak, 2004; Rosenkopf & Almeida, 2001). In addition, new ventures whose founders have ties to a potential partner have less uncertainty about the potential partner's capabilities as well as the partner's ability to contribute to future tie formation.

Much research supports the idea that the network ties of founders are important for building capacity in terms of hiring employees, accessing capital, finding customers, and optimizing online and offline sales for new ventures. For example, Doz and Williamson (2002) studied how alliances can act as accelerators of entrepreneurial activity, both by making additional entrepreneurial activity possible and by accelerating the pace of the activity, depending on the stage of the company (i.e., idea, experimentation, or venture).

Stam, Arzlanian, and Elfring (2014) performed a meta-analysis of 59 studies, finding that social capital had a significant and positive correlation to new venture performance.

Networks of entrepreneurs contribute to group solidarity as they promote an identity that can be based on type of product or customer (e.g., hardware, media, biotechnology, finance), other group affiliation (e.g., Stanford University alumni, Indian-American entrepreneurs), location (e.g., start-ups in Detroit), or other criteria. These identities make possible greater group cohesion, leading to stronger ties among entrepreneurs and thus greater flow of social capital to individuals and greater social capital aggregation overall for the group. Incubators represent one way to seek these benefits of solidarity, but there are many others: industry groups, alumni organizations, and even philanthropic societies.

Networks and Entrepreneurship

Major areas of research.

Hoang and Antoncic (2003) reviewed several perspectives on networks and entrepreneurship. Traditionally, entrepreneurship research has focused on the personal characteristics of the entrepreneur with an intellectual framing from the discipline of psychology. More recently, the scholarly community has begun to draw heavily from economic sociology, focusing on the effects of economic embeddedness, organizational emergence, and institutional structures. The study of networks has been an integral part of this work, allowing an understanding both of the entrepreneur and the environment in which he or she operates. This focus on networks concentrates into in three major areas of research, as shown in Table 4.

Table 4

Areas of Network Research

Method	Description
Network content	Types of resources and the access they enable
Network governance	How resource distribution networks are managed
Network structure	Organization of the relationships in the network

Note. Adapted from "Network-Based Research in Entrepreneurship: A Critical Review," by H. Hoang and B. Antoncic, 2003, *Journal of Business Venturing, 18*(2), pp. 165–187. Copyright 2003 by Elsevier.

Networks and entrepreneurial incubators.

Network formation has long been identified as an important aspect of the incubation process (Aernoudt, 2004; Phillimore, 1999). Hansen, Chesbrough, Nohria, and Sull (2000) argued that the best incubators offer an extensive network of business connections that forge both marketing- and technology-based relationships. Incubator management facilitates venture access to this incubator network, which allows member entrepreneurs to move on to the next stage of financing (Scillitoe & Chakrabarti, 2005). In the context of incubators and incubation, there has been a limited amount of research focused on the social aspects of incubation, although social capital has been identified as a valuable, intangible capital associated with business incubators and the incubation process.

There is much research to support the notion that networks are important to entrepreneurial success. In a frequently cited model, Larson and Starr (1993) describe a process of network building that changes over time. At the time of company formation, entrepreneurs benefit from diverse weak ties that provide information on the entrepreneurial landscape and from strong ties that provide encouragement. This is the stage at which incubators, which provide both diverse connections and weak ties as well as a bonding experience that builds strong ones, could possibly add value.

Despite these advantages in theory, evidence on incubators' effect on start-up success is mixed. For example, Mian (1997) looked at the effect of incubators on employment growth and other factors, and found both successes and failures on three types of performance criteria. Similarly, Colombo and Delmastro (2002) looked at incubators' effect on relationship building and other measures, finding that entrepreneurs in incubators had better connections but not better outcomes. These connections can be to management (Rice, 2002) or to a broader network of relationships, as found by Hannon (2005). There is dissenting work as well: for example, Tamasy (2007) found that incubators had no effect on start-up success.

The literature is unclear on whether incubators do a good job of building these ties and on whether those ties lead to a measurable difference in monetary or other outcomes. Mixed results on this question arise from several factors. First, there is wide variation in incubators, even within network-type incubators that share the college admissions metaphor and structure. Some incubators are driven by the charisma of a star founder, others by their geographical location, others by offering more money or access to specific resources. Second, what is meant by monetary success also varies by time and location. Silicon Valley startups can be valued more highly than those in other locations given similar business metrics. Similarly, economic cycles can affect entrepreneurial success in ways entirely uncorrelated with networks as financial crises or booms can affect the timing of financings or acquisitions. Finally, the psychology of the individual entrepreneurs may also have an outsize effect, especially in smaller incubators. More research into the structural position of entrepreneurs within networks may be helpful better understanding these effects.

Program Design and Evaluation

Program evaluation.

The lack of effective evaluation and assessment for social and economic programs has been termed the *evaluation gap* (CGD, 2006) and the *missing link* (Hill & Hupe, 2002). As noted by Hill and Hupe, the subtitle of the highly influential 1973 book, *Implementation, How Great Expectations in Washington are Dashed in Oakland; or Why It's Amazing that Federal Programs Work At All*, has been considered by many as an accurate representation of the frustrations of those who seek to implement policy prescriptions. This ongoing battle between those who take a top-down approach (implementing policies to meet broader social goals determined centrally) and those who take a bottom-up approach (implementing policies based on experience on the ground in a particular situation) illustrates the lack of informational interchange between planning and implementation. Evaluation is often viewed as an expensive, occasionally necessary evil to be dealt with long after program implementation.

Not only is there a gap between evaluation and planning, but policymakers also do not generally use methods from computational social science (other than regressions) in either role. An appraisal of the program evaluation literature reveals that network methods are rarely (if ever) used to evaluate completed or ongoing programs. Evaluation instead is tied at best to randomized controlled trials, mixed methods of evaluation, and meta-evaluation. In fact, the leading guide to program evaluation by Stufflebeam and Shrinkfield (2007) does not mention the word *networks* even once in the context of measurement, despite the prevalence of social network methods in the social sciences for decades (as detailed further in Chapter 4). The U.S. National Science Foundation, Centers for Disease Control, Department of Education and many other U.S. government institutions use either the Program Evaluation Standards of the Joint Committee on Standards for Educational Evaluation, or the Guiding Principles of the

American Evaluation Association (AEA) to guide their efforts, which do not reference social network analysis or computational social science methods at all. Vaessen and Leeuw (2010), among others, lament the disconnection between advances in social science and their use in policy evaluation.

Program design.

The literature on program design tends to be concerned with the origin of the policy prescriptions instantiated in the structure of economic development programs. Of major concern is the divide between theory and practice: that is, policies that are primarily driven by economic theory and those that are primarily based on experience. This mirrors but does not replicate the top-down vs. bottom-up approach described by Hill and Hupe (2002). Network metrics such as those proposed here can connect these two approaches to merge theory with practice in an iteration loop.

Another concern, as Cartwright and Hardie (2012) have noted, is that what works in one location may not work in a different geographic, cultural, or economic milieu. The ability to move over evaluation methods from one setting to another is key to implementing similar programs in different locations while still making sure they have similar results. This is noted as one of the limitations of randomized controlled trials: programs still need to be measured in a new location even if they have been proven in the previous one. Better metrics could aid in comparability of measurements from different sites. One advantage of network metrics is that similar tools can be used in different locations.

Social impact assessment.

A different stream of research on evaluation methodology comes from organizations that aim to measure social impact. Social impacts may be internal or external to the organization or intended recipients of the intervention. Some common methods of social impact assessment are featured in Table 5. This table includes impact assessment methods in use by large organizations such as the World Bank, World Health Organization, and the United Nations, drawing on disparate data and collection methods that aim to measure programs from a stakeholder approach rather than a needs assessment approach. These approaches are more likely to be predictive and to take into account a broader swath of stakeholders than traditional evaluation approaches.

Table 5

Selected Methods of Social Impact Assessment

Method	Example organization	Description
Millennium Development Goal Scan (MDG-scan)	United Nations	Measures value added by the program in terms of job creation and community investments.
Poverty Social Impact Assessment (PSIA)	World Bank	Examines the distributional effects of programs, with particular emphasis on the poor and vulnerable.
Stakeholder Value Added (SVA)	European Commission (InPro)	Measures a company's net value after satisfying all stakeholders
Social Return Assessment (SRA)	Government of China	Assesses blended value of NGOs and for-profit companies
Social Costs-Benefit Analysis (SCBA)	World Health Organization	Weighs current and future social advantages and disadvantages of each program

Other assessment of incubators.

Different types of incubators measure their efficacy in disparate ways. For example, Start-Up Chile is part of the general evaluation of its parent department, CORFO, the Ministry of Innovation of Chile. As such, Start-Up Chile is evaluated by sector growth, job creation, and other measures of economic development in Chile (as described more fully in Chapter 5).

For-profit incubators often use ranking systems from business magazines. These nonacademic measures of incubators are often based on perceived reputation, location, average acquisition per start-up, and so forth. *Forbes Magazine*, for example, ranks incubators based on enterprise value, measuring the “exit prices or last priced equity valuation,” amount of venture funding and proportion of companies that have raised it, and the “percentage of their companies that have been acquired or gone out of business” (Geron, 2012, para. 4).

Another popular methodology for measuring incubators (developed by researchers at Northwestern University) focuses on similar characteristics: 25% of the ranking is based on how much funding companies received after completing the program, 25% is based on the amount of money that start-ups receive and how much equity it costs, and the remaining 50% is determined by the success of the companies that emerge from the accelerator (Gruber, 2011). These are excellent measures if incubators are to be judged as profit-making ventures for seed funds, but not for programs that aim to achieve other purposes, such as creating networks to stimulate economic development.

Focusing on current company success is a shortsighted approach for organizations that have goals other than immediate return on investment. Incubators can add value to an entrepreneur, who may go on to future ventures with a better network, even if the present venture is not a success. An entrepreneur with a better network may achieve economic development or technology commercialization goals in the future even if they completely fail at this particular venture. In fact, it is likely that there is a trade-off in many situations between building a network and focusing solely on the profitability of the particular venture at hand.

This is even clearer in an environment where the cost of starting ventures is lower, such as with internet-based ventures that simply require access to a laptop and a server to get started. It's easier to *pivot* (fundamentally change the business model of company), start a new venture in the same space, or even completely change business areas while still keeping the network intact. The entrepreneur's personal networks survive the particular business, leading to a shorter and more effective preformation phase for the next venture pursued by the entrepreneur. To account for these factors, networks would be a valuable component of industry rankings (as well as program evaluation), in addition to rankings based on qualified financing events and exits.

Gaps in the Literature

Program evaluation of economic development programs has previously depended on broader measures such as job creation, economic output, patents, and so forth that are often measured years after the program is completed or the innovation has occurred. It is proposed that network analysis will allow a finer grained and timelier understanding of the success of social programs (especially those that are designed to build networks, like incubators) and will thus enable better evaluation and more rapid feedback on the success of programs. Our novel approach uses existing measures of networks that are well known in the literature to evaluate and design economic development interventions such as entrepreneurial incubators.

Vaessen and Leeuw (2010) have spoken of the need for a rapprochement between evaluation and social science:

> Just as evaluation studies provide a useful reality check on economic policy advice derived from macro-doctrines, the toolkit of the social sciences could greatly enhance the rigor of evaluations by challenging their methods, elucidating their practices, and enriching their content." (p. 65)

It is the aim of this thesis to close this gap between computational social science and policy evaluation.

Chapter Summary and Preview

This chapter surveyed how network measures are used in social science research, in particular in the study of entrepreneurship and entrepreneurial incubators. Beginning with an overview of current measurements of social and economic programs, we then discussed how program evaluation and design are currently performed, as well as the opportunities for a synthesis through applying social science research techniques to program design and evaluation. Chapter 4 will discuss networks and their metrics, including definitions of network terms and how they are applied in the Start-Up Chile case study.

Social Network Analysis

In order to understand complex and emergent phenomena, such as the formation of social networks and the transfer of social capital, we need new methods of data analysis that make good use of advances in computational social science. As noted by Gilbert (2004):

> Survey data has severe limitations if we take seriously the idea that societies are complex and their features are emergent. Survey data… treats individuals as isolated 'atoms' and pays little attention to the impact of people's interactions with others (p. 4).

Network analysis has several advantages over survey and interview data that make it ideal for studying emergent phenomena such as the transfer of social capital in entrepreneurial incubators. First, it allows us to simultaneously see the individual and the whole at the same time. We can examine each individual and note his or her position within the whole simultaneously. We can also look at how the whole compares against a previous state or against an ideal and measure the aggregate of individual relationships to track the emergence of a network over time.

In addition, network analysis allows us access to an entirely new data type. Network data was initially used to test specific hypotheses about how networks were involved in the transmission of information (Granovetter, 1973), and how not just networks, but individual positions within the network, are important to achieving goals (Burt, 1992). However, networks can be used for more than hypothesis generation and testing; they can be used as a tool of policy evaluation as well.

The roots of computational social science have been traced to the study of networks as far back as the thirteenth century (Freeman, 2011). In its more modern incarnation, the social philosopher Comte hoped to found a new field of social physics or *sociometry* based on measuring human relations (Borgatti, Mehra, Brass, & Labianca, 2009). From the 1930s to the 1970s, the use of modern social network analysis grew rapidly. The use of matrix algebra and graph theory to better understand the connections between people in turn made possible mathematical innovations in understanding relationships. The interdisciplinary nature of social network analysis allowed researchers to see connections between and among disciplines that led to deeper understandings and commonalities across fields as diverse as anthropology, psychology, geography, political science, and biology.

In the early 1970s, Harrison White of Harvard built the first explicit center of social network analysis, which standardized the tools available in the field and led to a universal recognition of the value of this type of research (Freeman, 2011). His students included Mark Granovetter, who coined the now common phrase *the strength of weak ties* in a seminal paper that showed that job seekers were more likely to find a job from people they didn't know very well (*weak ties*) than from people they were close to (*strong ties*). Barry Wellman's (1988) work shaped our understanding of network communities and influenced the study of social capital in multiple disciplines (Borgatti et al, 2009).

By the 1980s, social network analysis had become an established field within the social sciences, and in the 1990s, applied mathematicians and physicists such as Duncan Watts, John Kleinberg, and Alberto Barabasi explored new mathematical techniques for computing metrics based on networks. Watts and Strogatz (1998) described small world networks using online data. A year later, Barabasi and Albert (1999) contributed a stronger mathematical understanding of degree centrality. Since 2000, thousands of papers that develop mathematical theory, debate statistical standards, and apply network methods to test hypotheses have been published.

This chapter begins with some definitions of network and network terms. Next, it discusses the methods used in the case study of Start-Up Chile in Chapter 5, from ethical review to data collection to social network analysis techniques, as well as common analytical issues in network research. Specific methods that relate to the agent-based model (as opposed to networks more broadly) can be found in Chapter 6.

Definition of a social network.

. Social networks are formally defined as a set of nodes that are tied by one or more type of relations (Wasserman & Faust, 1994). Social network analysis is the mathematical representation and analysis of this kind of data to better understand social relations.

Networks have been imagined as both dependent and independent variables in relation to social processes. That is, they both influence the outcome of social processes (as causes) and are reflective of that process (as effects). Much research has attempted to sort out whether networks are independent or dependent. For example, Hoang and Antoncic (2003) examined how networks affect the entrepreneurial process (independent variables), as well as how entrepreneurial processes and outcomes influence network development (as dependent variables). This thesis takes as its starting point the idea that networks are both an influence on social behavior and a result of social processes. We take an agnostic approach to this question, by observing networks—whether they result from or cause social processes—and using them for policy evaluation.

Nodes and ties; edges and links.

Networks are modeled using nodes to represent actors in the network, and lines that connect them to represent the relationships or *ties* (or *edges* or *links*) between actors. Actor attributes are measures associated with the nodes, and the full set of actor attributes is the network composition. The pattern of all the ties between actors is the network structure. Two actors (nodes) and the relationship (tie) between them form the simplest possible network, known as a dyad (Wasserman & Faust, 1994).

The notation for representing networks comes from graph theory, in which a graph is an ordered pair, $G = (V, E)$ composed of a set, V, of vertices or nodes together with a set, *E,* of edges. This notation is extremely flexible, and allows easy analysis of complex data by mapping these ordered pairs onto a network space.

These nodes can be any two entities that have a relationship to one another: concepts, computers, human beings, or scientific publications. The connections can represent any relationship: Friendship, co-publication, colocation, membership, and so forth. In the Start-Up Chile case study, the nodes are entrepreneurs, and the links are professional relationships, as identified through connections on LinkedIn.

Edge weight.

A *weighted network* is a network where edges have weights assigned to them. This is sometimes stated as the *thickness* of the edges relates to how well connected the nodes are to each other. Newman (2004) summarized the value of measuring edge weights for more complex computations involving community structure and cliques within networks. Unfortunately, LinkedIn does not permit access to data that can help determine edge weight (e.g., messages between users, location data from meetings). Therefore, this study did not use edge weight to measure ties among the entrepreneurs, and the network is thus an unweighted network.

Bi-directional ties.

Networks are called *digraphs* if the relationships are unidirectional, or simply *graphs* if relationships flow equally in each direction (Bandyopadhyay, Rao, & Sinha, 2011). Real world relationships can be of either type or a mixture of the two. For example, the connection between a non-famous person and a famous person only flows in one direction: the non-famous person knows of the famous one, but not vice versa (Wasserman & Faust, 1994). In this study, all relationships are assumed to be reciprocal due to the nature of connections on LinkedIn; in other words, if entrepreneur A is connected with entrepreneur B, then entrepreneur B is equally connected with entrepreneur A. Since these are peer relationships, one would assume that it is a fairly accurate representation of their real-world connection.

Multiplex ties.

Ties can also be multiplex, meaning that the nodes have multiple connections. For example, entrepreneur A may be the sister of entrepreneur B as well as a fellow incubator member, meaning that they have two types of ties: familial and professional. Both may have gone to the same business school as well, leading to three types of ties that can be measured separately for tie strength, size of the resultant networks, and so forth.

In the Start-Up Chile case study, ties are not multiplexed. We assume that the LinkedIn (professional) connection is the salient connection. This is a useful assumption as we are measuring how many ties are formed between Chileans and foreigners who come to Chile as part of an incubator, who in most cases would not have met before. (Participants were asked whether or not they had connections other than as incubator members with other participants. None of the participants in our sample had these sorts of ties; if they had, they would have been excluded.)

Network Metrics

Scholars have defined social network structures at three different levels: single nodes, dyadic ties, and whole networks (Scott, 2000). The first case study focuses on the connections between different groups (Chileans vs. non-Chileans), meaning that we are focusing on the whole networks of each group as compared to the other group. We did not examine the position of individual nodes (e.g., to determine which entrepreneurs had a more advantageous position versus others) or specific dyadic connections (e.g., to determine which entrepreneurs were bridging structural holes). These metrics could easily be analyzed using similar methods if the goal of the social program were, for example, to position Chilean entrepreneurs advantageously in the network or to make a denser network overall through bridging of structural holes. The network characteristics examined in the Start-Up Chile case study are described below in detail.

Network size.

Network size consists of the total number of nodes connected within the network: an extremely simple calculation that consists of just adding up the number of nodes. In this case study, the network size was simply the number of entrepreneurs who participated in the study. We also measured the network size of their secondary connections (that is, the number of people to which each entrepreneur is connected). The formula for first-degree network size is:

$$\sum n$$

The formula for the second-degree network is given by:

$$\sum n + \sum m - \in$$

This is the summation of the first-degree nodes plus the second-degree nodes, minus epsilon, where epsilon is number of duplicate nodes, excluded so these are not double-counted (Wasserman & Faust, 1994). In the Start-Up Chile case study, we counted to the second-degree network both because it is more meaningful for determining the value of social connections and because LinkedIn only allows access to nodes' second-degree connections.

Network density.

Network density is the proportion of direct ties in a network relative to the total number possible. This is measured by the ratio of the number of actual ties in a network divided by the number of all possible ties. Density is useful in understanding how closely nodes are connected together by ties and thus gives a measure of how different groups compare to each other in terms of their interconnection rate (Scott, 2000; Wasserman & Faust, 1994). The density, D, of a network is defined as a ratio of the number of edges, E, to the number of possible edges, and is given by the following equation:

$$D = \frac{2E}{N(N-1)}$$

Figures 5 and 6 show two networks with five nodes each, which differ greatly in density because of the lack of interconnections in Figure 6. Network density can also be confirmed visually in most network visualization diagrams since a denser network will simply look denser when using standard visualizations (such as the Fructerman-Rheingold layout), as we will see in Chapter 5.

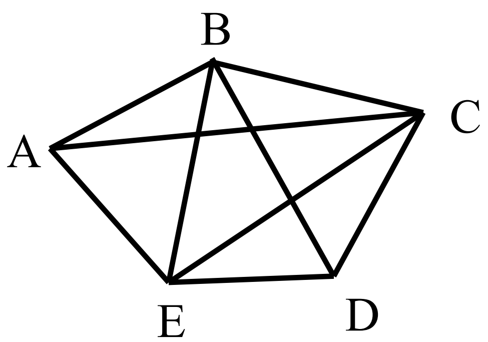


Figure 5. High-density five-node network graph.

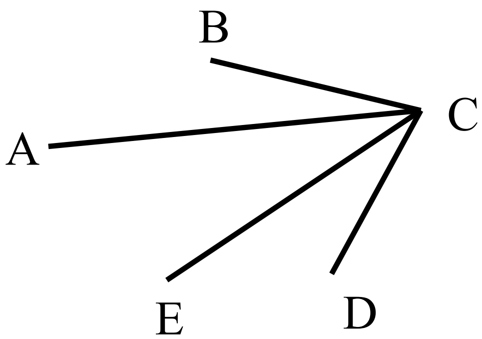


Figure 6. Low-density five-node network graph.

Clustering coefficient.

The clustering coefficient is a measure of the likelihood that the nodes that are connected to a single node are themselves connected. For example, in Figures 5 and 6, the clustering coefficient is higher in Figure 5 than in Figure 6. The difference between clustering coefficient and density is that clustering coefficient is a node-level measure (which we aggregated across the two networks for this case study), and density is a network-level measure.

Clustering coefficients can be either local or global. The local clustering coefficient of each node measures how close its neighbors are to being a clique (a graph in which all possible nodes are connected). The neighborhood, N_i, for a vertex, V_i, is defined as its immediately connected neighbors, where k_i is the number of vertices in the neighborhood N_i of a vertex:

$$N_i = \{v_j : e_{ij} \in E \ \wedge \ e_{ji} \ \in E\}$$

The local clustering coefficient, C_i, for a vertex, V_i, is given by the proportion of links between the vertices within its neighborhood divided by the number of links that could possibly exist between them. An undirected graph has the property that e_{ij} and e_{ji} are considered identical. Thus, if a vertex, V_i, has k_i neighbors, the number of edges is given by:

$$\frac{k_i \,(k_i \ - 1)}{2}$$

Thus, the local clustering coefficient for undirected graphs (such as those used in the Start-Up Chile case study) can be defined as:

$$C_i = \frac{2\ \lfloor\{e_{jk}: v_j, v_k \in \ N_i, e_{jk} \ \in E\}\}|}{k_i(k_i - 1)}$$

As an alternative to the global clustering coefficient, the overall level of clustering in a network can be represented as the average of the local clustering coefficients of all the vertices, *n:*

$$\overline{C} \ = \frac{1}{n}\sum_{i=1}^{n} C$$

Watts and Strogatz (1998) developed this measure in the context of determining whether a graph is a small-world network. A *small-world network* is one in which most nodes are not neighbors of one another, but most nodes can be reached from every other by a small number of hops. In the context of a social network, this provides an elegant mathematical description of the phenomenon noted by Granovetter (1973) above, namely that strong ties can be more important than weak ones to achieve social goals. In the Start-Up Chile case study, we compute the average clustering coefficient of each group (Chilean vs. non-Chilean) in order to measure the relative cohesiveness of each group.

Centrality and centralization.

Centrality refers to a group of metrics that aim to quantify the importance or influence of a particular node or group within a network. There are many methods for measuring centrality, including *betweenness centrality*, *closeness centrality*, *eigenvector centrality*, and *degree centrality*. The simplest of these is degree centrality. In undirected networks in which direction of interaction is not examined, *degree centrality* is defined and measured by the total number of direct links with other nodes. In directional networks in which ties have specific directions (e.g., sending versus receiving information or advice in networks), degree centrality can be separated into in-degree, which is the number of direct linkages from other actors to the focal actor, and out-degree, which is the number of direct linkages from the focal actor to other actors (Wasserman & Faust, 1994).

There are numerous measures of centrality. *Betweenness centrality* refers to the extent to which a node mediates the geodesic paths' centrality connecting pairs of other nodes, and can be measured as the number of shortest geodesic paths between other nodes in which the focal node lies in the middle. *Eigenvector centrality* captures the number of ties but adjusts for the importance of each tie centrality with the centrality of the contactor and considers both direct and indirect links (Bonacich, 1987). Closeness centrality measures the ease of connection between the focal node and all other nodes (Freeman, 1979). In this case study, we use betweenness centrality, the simplest and most common of these measures.

The *centralization* of any network is a measure of how central its most central node is in relation to how central all the other nodes are. Centralization measures calculate the sum in differences in centrality between the most central node in a network and all other nodes, and then divide this quantity by the theoretically largest such sum of differences in any network of the same size. Thus, each centrality measure (betweenness centrality, eigenvector centrality, etc.) has its own centralization measure.

Defined formally, if $C_x(p_i)$ is any centrality measure of point i, if $C_x(p_*)$ is the largest such measure in the network, and if:

$$\max \sum_{i=1}^{N} C_x(p_*) - C_x(p_i)$$

is the largest sum of differences in point centrality C_x for any graph with the same number of nodes, then the centralization of the network is given by:

$$C_x = \frac{\sum_{i=1}^{N} C_x(p_*) - C_x(p_i)}{\max \sum_{i=1}^{N} C_x(p_*) - C_x(p_i)}$$

Structural holes, weak ties, and other positional measures.

While network size, density, and centralization measure network level constructs, other patterns in the network structure influence each individual’s access to resources. For example, the brokerage opportunities provided by structural holes in the network constitute entrepreneurial opportunities in and of themselves (Burt, 1997b). Occupying a bridging position provides an opportunity to wield power or to influence those who are otherwise unconnected to the broader network (Krackhardt, 1995). Given this opportunity for diverse, non-redundant contacts, spanning structural holes can also increase the focal actor's exposure to novel information.

Moreover, networks can create social capital by serving as *prisms* (Podolny, 2001) that focus the attention of important outsiders (e.g., investors) on status, prestige, or other forms of value that can lead to venture capital funding (Stuart, Hoang, & Hybels, 1999; Stuart & Sorenson, 2001), a form of signaling. This case study did not focus on the position of individual actors within the social network, but rather on measuring interconnections among groups of entrepreneurs.

Data Collection

Background.

The Internet has made possible new kinds of data collection methods in the social sciences. Instead of relying on surveys and interviews, researchers can analyze and collect tremendous amounts of data in order to deeply answer questions ranging from the patterns of friend formation (e.g., Backstrom, Huttenlocher, Kleinberg, & Lan, 2006) to which organizational structures lead to more innovation (e.g., Wineman, Kabo, & Davis, 2009).

Internet data collection was first used to automate previous data collection methods such as surveys. Research methods in the late 1990s were focused on the switchover from mailing surveys through the post to sending them through email (Weible & Wallace, 1998). As late as 2004, emailing surveys to participants was considered a state-of-the-art research technique (Granello & Wheaton, 2004) to be justified with specific examples of its validity and comparability to existing techniques (Schillewaert & Meulemeester, 2005). Some researchers have expressed doubts about online surveys as recently as 2007 (Lefever, Dal, & Matthiasdottir, 2007).

The first papers to use online social networking data (e.g., from Facebook) to analyze existing sociological concepts, such as the formation of social capital (Ellison, Steinfield, &

Lampe, 2007), the presentation of oneself online (DiMicco & Millen, 2007), and privacy (Acquisti & Gross, 2006) were published in 2006 and 2007. Thereafter, there was an explosion of papers on every conceivable subject using Facebook, LinkedIn, MySpace, ASmallWorld, and dozens of other smaller social networks as data sources.

Convenience sampling.

Our study consists of a convenience sample of entrepreneurs from Start-Up Chile. Recruitment of subjects was accomplished through solicitations in private Facebook groups for Start-Up Chile entrepreneurs, email from the researcher and from Start-Up Chile, and direct interaction with interviewees who were known to the author. These solicitations asked for participants to go to a web page and click on a link to access a custom web application.

An important issue in data collection is choosing whom to include in a network sample. There are two basic issues: (a) selecting which nodes to study, and (b) defining the scope of possible relationships between these nodes. If the research focuses on specific dyadic ties, it is less important to capture the whole network. Conversely, if the network is being analyzed as a whole, it's important to capture as much of it as possible.

Laumann, Marsden, and Prensky (1989) delineate two types of network boundaries: self-reports (the realist approach) and industry or other phenomena (the nominalist approach). Incubators are a particularly good example to use in measuring networks because, since their goal is to create a network, they themselves define where the network begins and ends by accepting an incubator class. Thus, this case study follows the nominalist approach more closely. There are still some edge cases, such as speakers or mentors who are not part of the official network but nevertheless may have a great impact on the participants through force of personality, fame, wealth, or other factors.

As noted by Carpenter, Li, and Jiang (2012), studies of networks that are easily defined by factors outside the network do not require boundary specification, making the work of choosing participants much easier. Simple random sampling and opportunity sampling based on information ability are the most straightforward sampling methods and have been used widely, starting with Burt's (1997a) random sample of 170 out of 2,500 managers at a single firm and extending to Ahuja, Polidoro, and Mitchell (2009), in which sample firms were selected based on availability of information. In the case of Start-Up Chile, the network is defined by admission to the incubator program, so it is easy to determine the boundaries of the network.

There are advantages to more comprehensive methods that either sample the whole network or use the characteristics of the network itself (sociocentric sampling) to determine whom to include. Both whole network (Scott, 2000) and sociocentric sampling methods (Marsden, 1990) can often improve the reliability of network data, but are also more difficult to implement since they require access to information about the entire network, which may not be necessary or available (as in the case of the present study).

To determine the generalizability of our data to Start-Up Chile as a whole, we first looked for Start-Up Chile demographic information, but, unfortunately, Start-Up Chile does not publish information on the demographics of its participants. Next, we looked to the demographic characteristics of Silicon Valley as Start-Up Chile aims to attract a high-technology entrepreneurship population similar to other high-tech hubs (and draws from them for its participants). There are no overall surveys of the demographics of high-tech in Silicon Valley or other mature entrepreneurial ecosystems, although some companies, such as Google and Apple, make public diversity figures around gender and ethnicity only. Leading incubators such as Y Combinator do the same, with similar issues with gender parity and ethnic diversity (Minguia, 2015). Other researchers, such as Florida and Gates (2004) have collected data on (and argued for the value of) a diverse population for high-technology growth, examining the sexual preferences, bohemian traits, and foreign-born status of individuals, but not other factors. The demographic information gathered in this study (gender, age, educational attainment, and citizenship) is shown in Tables 6 to 9.

Ethics of network data collection.

Some concerns with the ethics of network data collection include participant privacy, the ability to gain IRB approval, and organizational cooperation (Kadushin, 2005). Many concerns have been raised about the import of already publicly available network information for research purposes. In our case, LinkedIn data is publicly available in the sense that a portion of each individual's network is available to anyone who browses a profile. However, LinkedIn only allows complete access through their API upon permission given by the user, which was gained from each user in this study.

Participant privacy was protected using various safeguards to reduce the likelihood of unauthorized access to the database. These safeguards included usage of the encrypted https protocol, user verification, and active escaping of all strings used in the dynamic generation of MySQL queries. To further reduce the likelihood of unauthorized access to participant data, the web application only has permission to write to the database and cannot make direct queries of the database.

IRB approval.

Institutional Review Boards (IRBs) emerged in the 1970s to oversee research on human subjects. While sometimes problematic in implementation (Schrag, 2010), IRBs aim to provide a framework for evaluating the ethics of a particular line of research inquiry and to make certain that checks and balances are put into place to protect subjects. Practices like informed consent and protecting the privacy of informants were intended to empower participants in light of earlier abuses in the medical and social sciences (Blass, 2004; Reverby, 2009).

Computational social science approaches often involve additional questions of ethics, as the amount of data to be collected can be unexpectedly large and often taken out of context (Ess, 2002). In this particular study, the data was collected from individuals with the knowledge that the data would be used for this particular purpose. The study was approved by Oxford University's Central University Research Ethics Committee (CUREC), the university Institutional Review Board.

Specific design elements were used to help ensure participant trust of the website. A simple, informal message explaining the study was used to request access, as shown in Figure 7.

> Hello Start-Up Chile entrepreneurs!
>
> Thank you so much for participating in this research to better understand the social networks of entrepreneurs!
>
> This research is conducted by Jessica Richman of Oxford University. Participants in incubators/accelerators can add data about their social networks so we can better understand how these networks are created and structured.
>
> You will be asked to login using your LinkedIn account, and information about your profile and your first-degree (direct link) contacts will be stored. This information will be kept confidential and only used for research purposes. For this first version, your network will simply be stored; in future versions, you will be able to visualize your network as well. If you have any questions about this research, please email jessica.richman (at) sbs.ox.ac.uk.
>
> Ethical review for this research is provided by CUREC.
>
> Thank you so much for participating!
>
> Jessica

Figure 7. Participant study solicitation.

Prominent display of the link to the ethical review by CUREC was used to inform the participants of the safeguards in place. A large colorful image at the header of the page was designed to make the webpage appear similar to already trusted professional webpages. Lastly, a large button was employed as the link to share the participant's LinkedIn data to provide visual cueing to participate in the study.

Boyd and Crawford (2012) noted the importance of accountability as well as compliance with explicit IRB rules. Accountability is a multidirectional relationship: there may be accountability to superiors, to colleagues, to participants, and to the public (Dourish & Bell, 2011). In accordance with this principle, network data was made available to participants so they could gain personal value from the insights generated by their participation. As this was a study of network level interactions, analysis of individual user networks was not necessary, lessening the impact on the privacy of participants as long as the raw data was not released.

Organizational cooperation.

Start-Up Chile initially cooperated with this study by allowing distribution of research recruitment through internal emails. Although turnover within Start-Up Chile itself prevented the fuller integration of the research tool with Start-Up Chile's management practices and internal evaluation, the initial cooperation was extremely helpful in recruiting participants. Later participants were recruited through community Facebook groups, LinkedIn, and direct emails.

Custom Application Development

Application description.

The custom webpage was designed to allow users to share the data from their LinkedIn professional network. It was written entirely in HTML and object-oriented PHP using the OAuth and LinkedIn API libraries for PHP. The script was designed to utilize dynamic generation of MySQL queries to record data about users into a custom MySQL database.

Amazon Web Services (AWS) was used to provide scalable and secure Internet hosting for the website. AWS provides a secured SAS70 Type II audited data center with industry-leading security practices, helping to ensure the protection of personally identifying information of the participants. An m1.large AWS instance running Ubuntu Linux was used as the web server for the study. Apache, MySQL, and PHP software packages were used to serve the content, process, and finally store the participant data. This so-called LAMP (Linux, Apache, MySQL, and PHP) stack of applications for web development based on open-source software is frequently used to ensure a stable, reliable, and secure service for the collection and management of data.

The website used to collect the data is shown in Figure 8. It is a simple one-page site designed specifically to optimize for participant sharing of their LinkedIn data.

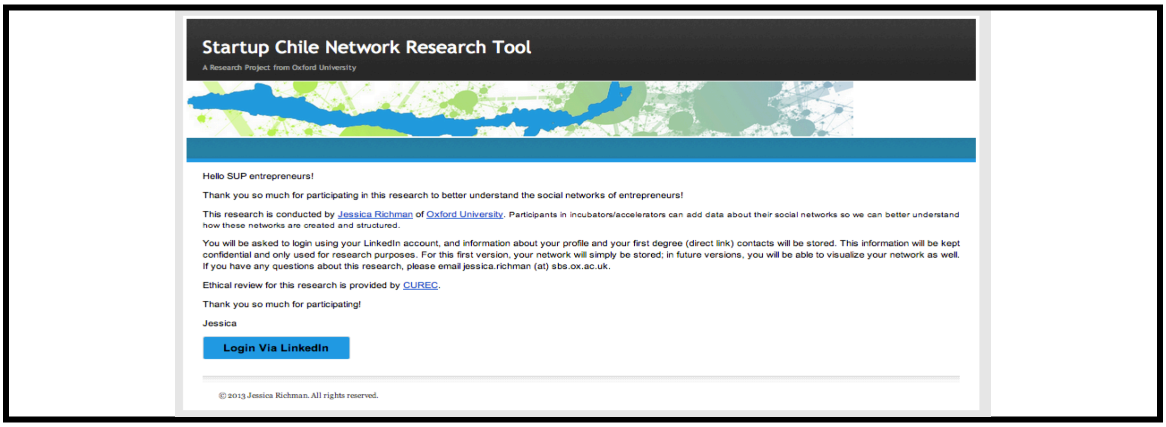


Figure 8. Screenshot of data collection website.

The LinkedIn Application Program Interface (API) was used to allow participants to share their data from their professional network on LinkedIn. After clicking the *Login Via LinkedIn* button on the front webpage of the web application, the participants were brought to a LinkedIn API login badge (see Figure 9).

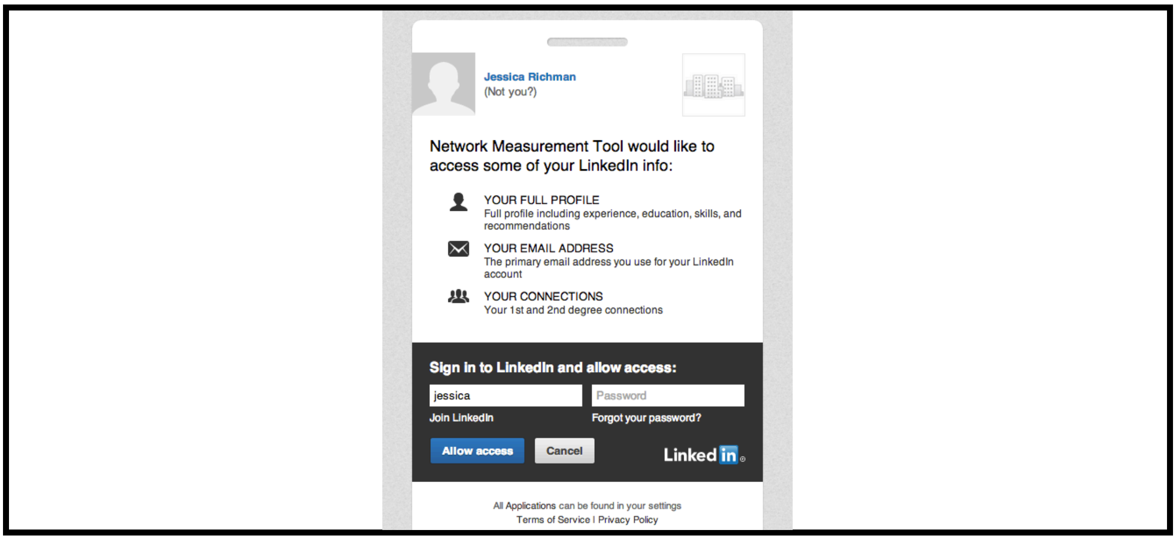


Figure 9. Screenshot of LinkedIn API access authorization.

After an individual entered his or her LinkedIn login credentials, participant data was downloaded from LinkedIn. The full user profile of the participant and the public user profiles of all of the user's connections were downloaded and stored in the database in JSON format. Information on which fields are available in the LinkedIn API is available in Appendix A.

Data structures.

The above data for every participant and each of their LinkedIn connections is stored in the database of the web application. Each participant's data is written into a single row of the database in the *participants* table. The data for each of the connections is written into the *connections* table in the database, referencing the user to which it is connected.

Network reconstruction.

Network reconstruction from the stored data in the MySQL database for analysis was achieved by issuing unique integer identification numbers for each entry in both the participants and connections database based on their unique LinkedIn identifier. Each connection in the connections table was then turned into a numerical pair; the connection identification number and the participant identification number (connection, participant). The complete list of pairs derived from the database represented the entire reconstructed network.

Further metadata about each participant and connection was extracted from the database using the numerical identification scheme so that it could be readily associated with the appropriate network node.

Network visualization.

Network analytics packages were used to visualize, cluster, and calculate network parameters on the network. A force-directed organization scheme utilizing the Barnes-Hut algorithm (related to Fruchterman-Rheingold algorithm, and used for large networks due to computational complexity) was used to apply an organizational layout of the data so that it could be visually understood. Direct calculation of network parameters were performed, as well as partitioning the network on metadata so that the parameters of sub-networks could be calculated.

Background Interviews and Surveys

Dominguez and Hollstein (2014) have pointed out the benefits of mixed-methods studies using both quantitative and qualitative methods to both provide background for and triangulate meaning in network studies. In this case, interviews and surveys were used to provide background for the proceeding social network analysis study.

Interviews.

From 2012 to 2013, interviews were conducted with the founders of 45 firms that had been accepted into Start-Up Chile. In addition, the research included attendance at many formal and informal gatherings in Chile, participation in many networking events, and collection of relevant documents. Sample firms were spread across all generations of Start-Up Chile, which at the time the participants were selected included 888 startups. Generation 0 was the first small pilot group that arrived in 2010; the last generation sampled here was Generation 7.

Each interview lasted from 30 to 45 minutes, and most were conducted by phone or video Skype. Interviews were conducted with firms that agreed to the solicitation in English, and the sample was chosen by snowball sampling from known Start-Up Chile entrepreneurs and from a solicitation on Start-Up Chile Facebook groups, email lists, and other online forums. This solicitation was in English, so there was likely some self-selection in favor of those who spoke English well (The effect of this was lessened by the fact that all Start-Up Chile application and onboarding materials are provided in English, and all business related to Start-Up Chile is conducted in English as well). Respondents were promised anonymity; therefore, the firm data for this study are aggregated to preserve anonymity.

LinkedIn allows developers to pull information about the company, education, and language of each participant. Whether or not an individual was a Chilean national was evaluated on the basis of their survey responses (if any), their education field (i.e., if they were educated at a Chilean university), their location field (which would define their location as a place within Chile), and the language fluency field (which would identify native speakers of Spanish).

Surveys.

The survey consisted of 19 questions asked through a Google Document Form. After the interview, each participant was asked to complete the survey. There was a 100% response rate for the survey, and 100% of the interviewees also participated in the network analysis in the following chapter. Response rates were so high likely because they completed the survey directly after the phone or Skype interview. This high response rate must be noted with the caveat that this was based on 45 participants who were asked to contribute to the survey; it does not represent a high response rate among the entire pool of 888 start-ups (selected questions can be found in Appendix C). Demographic details of the 45 participants are in Tables 6 to 9. These data are presented in four tables to maintain anonymity of participants. (Participants with more than one nationality were asked to choose a primary nationality.)

Table 6

Gender of Interview and Survey Participants

Male	40 participants
Female	5 participants

Table 7

Age of Interview and Survey Participants

18 – 25	9
26 – 35	17
36 – 45	10
46 – 55	6
56 – 65	2
65+	1

Table 8

Educational Attainment of Interview and Survey Participants

High school only	1
Some college	8
Bachelors Degree	13
Masters Degree	14
PhD or equivalent	4
Other graduate degree (medicine, law, etc.)	5

Table 9

Citizenship of Interview and Survey Participants

United States and Canada	14
Latin America (including Chile)	16
Europe	6
Asia	6
Australia and South Pacific	2
Africa and Middle East	1

Analytical Issues in Network Research

In this section, we discuss three analytical problems inherent in network research in organizational contexts: endogeneity, sample selection bias, and structural autocorrelation.

Endogeneity.

Endogeneity arises when predictors are correlated with the error term (Jackson, 2008), meaning that the predictive value of the network model is compromised. There are two primary ways that this occurs: measurement error and simultaneity (Carpenter et al., 2012). In network studies, particularly studies with network structure constructs, measurement errors arise when the network is misrepresented: It is either too large, too small, or otherwise biased in its representation. Simultaneity occurs when it is possible for causality to run in both directions (Bascle, 2008; Shaver, 1998) and is particularly salient for social capital research in which the causal relations between networks and individuals' outcomes are examined since the predicted outcomes may be the cause—rather than the consequence—of the network under study. In the present study, we make no causal claims about the relationship between networks and social capital transfer, merely using the relationship between the two to measure progress against policy objectives.

Sample selection bias.

Sample selection bias arises from nonrandom sample sets, which are widely adopted in network studies (Kilduff, Tsai, & Hanke, 2006; Scott, 2000). In the snowball sampling method, only actors connected to the initial actors are captured, and well-connected actors tend to be oversampled while those with small personal networks tend to be excluded (Carpenter et al., 2012). Furthermore, some network features under study also intrinsically rule out certain actors. As Winship and Mare (1992) suggested, "network density is observable only for persons with enough contacts for density measures to be computed" (p. 334). In this study, we use a snowball sampling method, which admittedly does not capture the full network and may contain biases. More detail on this is noted in the limitations section of Chapter 5.

Structural autocorrelation.

When observations of variables for different actors are not independent over time or through space (Certo & Semadeni, 2006), it creates autocorrelation, which can bias the standard errors of OLS regression and generate unreliable significance test results (Wooldridge, 2002). Actors in networks are interdependent and connected with each other, therefore making the observations of variables for actors in a network dependent on one another through different paths and directions. We do not make observations over time or space in this study, which reduces the risk of structural autocorrelation errors.

Chapter Summary and Preview

This chapter summarizes the methods employed in the Start-Up Chile case study, including definitions of network terms, data collection, ethical review, and specifics of programming the network tool. Limitations for the case study and the agent-based model are discussed in Chapter 5 and Chapter 6, respectively. Methods specific to the agent-based model are discussed in Chapter 6 as well.

Background on Economic Development in Chile

High-growth startups are desired by many emerging economies as an engine of economic growth. OECD (2013) noted that there are three interrelated gaps that face innovative entrepreneurs in emerging markets: information asymmetry between the entrepreneur, investors and customers; a knowledge and skills gap; and a funding gap. Entrepreneurial incubators are designed to address these gaps.

In particular, innovation has been a national priority in Chile, and is supported through innovation funds, research and development grants, seed capital, and other measures (OECD, 2013). Chandra and Silva (2012) have described a rich environment for business incubation in Chile, with 17 working incubators focusing on fostering innovative companies with high growth potential as well as economic impact in economically disadvantaged regions. Chile has the second highest number of incubators in South America after Brazil, which has over 400 incubators. Santiago Innova, the first incubator in Chile, was started in 1992 by the municipal government of Santiago. Others describe the public policy environment for entrepreneurial clusters in Chile as favorable as well (Romani, Atienza, & Amorós, 2009, 2013). With the goal of becoming the leader in the region in internet-based ventures, the Chilean Ministry of Innovation (CORFO), founded a program called Start-Up Chile.

The Start-Up Chile Incubator

Description.

Start-Up Chile is a program sponsored by the Chilean government that aims to bring world-class entrepreneurs to Chile to build an innovation ecosystem. Start-Up Chile uses the network-focused model of incubators based on Y Combinator. It uses similar rhetoric (*alums*, *admits*, etc.) to create a structure to bring entrepreneurs to Chile. Entrepreneurs are inducted into a *class* (called a *generation* in Start-Up Chile), remain in the country for six months, go through a series of stages (i.e., seminars on funding, growing users, etc.), and finally graduate when the founders have six months left on their visas so that they can remain in-country to get funding if needed.

The program is managed by CORFO, the Chilean Economic Development Agency, with funding from the Ministry of Economy, Development and Tourism, the Ministry of Foreign Affairs, and the Ministry of the Interior. Start-Up Chile launched in 2010, bringing 22 start-ups from 14 countries to Chile. The program provides participating start-ups with approximately $40,000 USD of seed capital and a temporary one-year visa. The selected start-ups join a six-month program in Santiago where they receive mentoring and access to elite social networks within Chile. Although the program has been open to Chileans since its second admitted class, most of the entrepreneurs are transplants from North America and Europe (a fact that has generated some controversy within Chile). Start-Up Chile takes no equity in exchange for the funding, structuring the payments as a grant that provides reimbursements for expenses incurred by the entrepreneurs while starting the company in Chile.

Start-Up Chile has been an astounding success by many measures. As of December 2012, CORFO, Start-Up Chile's parent department in the Chilean government, had invested $14 million USD in Start-Up Chile, with 888 entrepreneurs from 36 countries winning grants under the program, and more than 63,000 people participating in both public and private events (Von Igel, 2013). Thousands of entrepreneurs compete to participate in Start-Up Chile, with acceptance rates dropping in nearly every application cycle.

Start-Up Chile is quite prominent among international incubators, having generated much press coverage and even several academic papers on the program in its short life (Gonder, 2012; Melo, 2012; Wadhwa, 2012). *The Economist* dubbed Start-Up Chile *Chile-*

con Valley (a play on the phrase *Silicon Valley*) and touted its achievements ("The lure of Chilecon Valley," 2012), as did the *New York Times* (Lieber, 2014), CNN Money (Lobosco, 2014), and many other press outlets. A book has been written for entrepreneurs on how to make the most of the Start-Up Chile experience (Lustig, 2012).

As a trailblazer in new policy instruments in emerging markets, Start-Up Chile is being watched around the world to see how successful it will be at bringing entrepreneurial networks to Chile. To date, it has been copied throughout Latin America in Brazil (Cutler, 2013), Peru ("Startup Perú," 2015), and Colombia ("Innpulsa Colombia," 2015), with additional programs in the planning stages. Similar programs are planned in Southeast Asia as well (Singh, 2015).

Goals and evaluation.

The program's stated objective is to turn Chile into the premier innovation and entrepreneurship hub of Latin America by attracting entrepreneurs from around the world. Participants are expected to actively share their global social networks with members of the local Chilean entrepreneurial ecosystem. Admission is based in part on access to desirable global networks such as that of Harvard-trained MBAs or Stanford-trained engineers.

According to Start-Up Chile documents, there are three high-level policy goals for the incubator program:

1. Establish Chile as the innovation and entrepreneurship hub of Latin America
2. Change the national culture around risk; creating a demonstration effect
3. Build networks and international social capital

These policy goals are broader than many other network-focused incubators as they do not directly address return on investment and aim instead for what is essentially a network-focused result. The Chilean government does not own any part of the start-ups and thus does not receive any financial gain from their success; it instead wants to profit as the larger economy benefits from the network ties between foreign participants and Chileans. As Horacio Melo, former Director of Start-Up Chile noted, “By bringing entrepreneurs to Chile from all over the world, Start-Up Chile not only makes Chile better connected to the rest of the world, it also contributes to a cultural change that creates more openness toward entrepreneurship” (p. 19).

Further, even if Start-Up Chile wanted to measure its success according to traditional measures of return on investment, it would be nearly impossible. Since 2007, Chile has carried out a number of evaluations for its innovation programs. For incubators started in 2000, an evaluation was carried out in 2006, during which a major weakness was discovered: there were no performance-based evaluations (based on investment performance). Between 2009 and 2010, projects began to be prioritized based on their potential impact. CORFO set a deadline at that time to evaluate all programs by 2013, with a three-year time delay (OECD, 2013).

According to one source, of the 663 start-ups comprising the Start-Up Chile pilot and first seven generations, 12.7% have landed investment, totaling over $32 million USD (Stewart, 2013). However, estimates of investment received vary greatly—some interviews state $20 million USD (Van Edwards, 2013), while others give larger estimates for a similar period of time.[2] One difficulty in evaluating the success of Start-Up Chile despite its success at public relations is that it takes a very long time to evaluate the outcomes of small entrepreneurial ventures, even if evaluation methods were performed under ideal conditions.

Thus, Start-Up Chile is the motivating case for this thesis. It is a leading international economic development program whose goal is network formation. It is expensive to administer and somewhat controversial in domestic politics. Current measurements, even if

[2] Start-Up Chile was not able to give precise figures during personal interviews in 2013.

performed perfectly, are inadequate to determine its success. Moreover, current measurements are performed far after they can do any good.

In addition, the admission-based structure of Start-Up Chile makes possible iteration in between generations of admits. In this way, an evaluation of Start-Up Chile can be used as a model for future evaluations of programs that have a network-based component of their mission.

Networking infrastructure.

Following the incubator model, Start-Up Chile aims to foster camaraderie among its entrepreneurs. It has several advantages in doing so, as the entrepreneurs are thrown together in a foreign country for a limited period of time, somewhat like students coming together in a university dorm. To catalyze network formation, Start-Up Chile organizes events for orientation, weekly meet-ups, and speaker series with famous investors and entrepreneurs from around the world. Alumni hold events all over the world, from New York to Madrid, San Francisco to London. Another community bonding experience is the mandatory Return Value Agenda (RVA). The goal of the RVA program is to measure the entrepreneurs' contribution to the Chilean entrepreneurial ecosystem through organizing events, mentoring local entrepreneurs, hiring local employees, and other activities that encourage connections between the locals and Start-Up Chile entrepreneurs. Entrepreneurs have to accrue a number of points by participating in or initiating various activities. Points are doubled outside of Santiago to encourage Start-Up Chile entrepreneurs to leave the capital city and contribute to fostering entrepreneurship around Chile.

Once the foreigners leave after six months or a year, loyalty to Start-Up Chile is strong (Personal interviews, 2014). Alumni feel good about their experience, even if their venture failed. Many continue to be faithful and serve as informal ambassadors to both Start-Up Chile and to the country of Chile. Start-Up Chile's reputation also creates community.

Start-Up Chile (and its creator CORFO) is famous both within and outside of Chile. It has created buzz, as evidenced by the ranking of Santiago as an entrepreneurial ecosystem. This leads to a positive feedback loop for Start-Up Chile alumni and new recruits.

Start-Up Chile has instituted several structures for accelerating the ability of firms to connect individuals and enhance their networks. They created *tribes*, groups of like-minded entrepreneurs with similar subject-area interests (e.g., social enterprise, gaming, finance), linked each entrepreneur with a *padrino* or *madrina* (godfather or godmother) to provide mentorship and access to the Chilean business community, and established multi-generational pairings, which included access to entrepreneurs who were Start-Up Chile alums.

Table 10

Start-Up Chile Programs Intended to Build Networks

Tribe	Interest groups organized around specific verticals, such as hardware, gaming, finance, or social enterprise. Start-Up Chile staff encourages tribes, which operate across generations.
Padrinos and *madrinas*	A *padrino* (godfather) or *madrina* (godmother) is a Chilean volunteer from outside the program that has signed up to help Start-Up Chile foreigners become accustomed to life in Chile. They move within the Start-Up Chile ecosystem, sometimes investing in, joining, or founding Start-Up Chile companies.
Multi-generational pairing	Mentors are chosen from previous generations to help the current generation get started in Chile. Start-Up Chile also holds a week-long orientation at the beginning of each generation.

Note. Adapted from *Building international social capital at the Start-Up Chile accelerator* (SSRN-id2326003), by E. Carmel and J. Richman, 2013. Copyright 2013 by SSRN. Retrieved from Social Science Research Network website: http://ssrn.com/abstract=2326003

Interview and Survey Results

Before beginning the analysis of networks using computational social science techniques, interviews and surveys were conducted as described in Chapter 4. Some of these were general questions to learn more about the participants and test network model ideas for structuring the study. Others were asked to ensure that LinkedIn networks were indeed a good proxy for the actual connections of participants. As detailed below, participants were asked if networks were important to them and how often they used LinkedIn to track their networks (Survey and interview questions are listed in Appendices B and C at the end of this thesis).

Importance of networks to participants.

Several questions were asked to determine the importance of networks to participants to ensure that they (as well as Start-Up Chile) were motivated to put effort into network formation. A full 84% of participants stated that building an international network was a key factor in deciding to participate in Start-Up Chile, as shown in Figure 10.

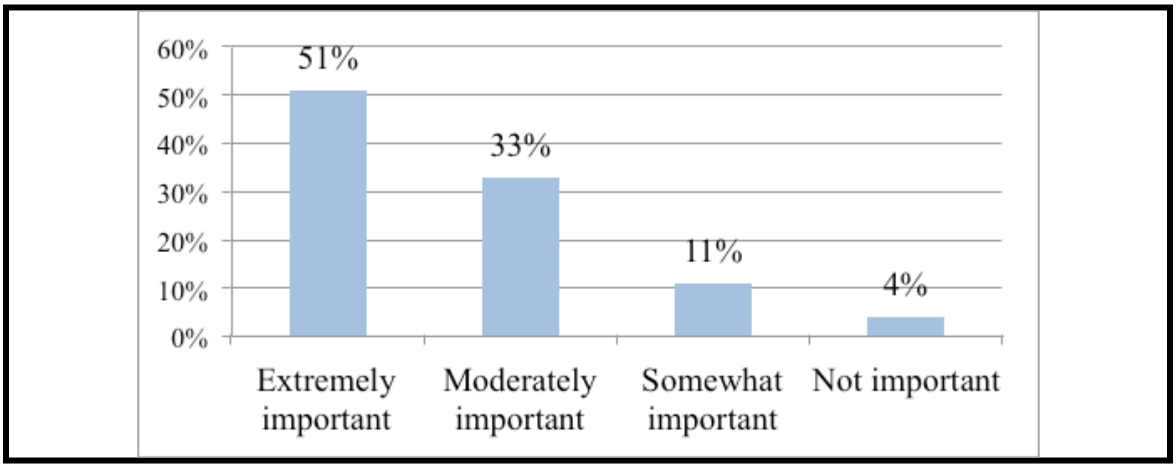


Figure 10. Importance of networks to Start-Up Chile entrepreneurs (N = 45).

Main objective in joining Start-Up Chile.

Furthermore, among such objectives as building a business, making a large amount of money, or having maximum social impact, building an international network was chosen as the top objective 29% of the time, as shown in Figure 11. Building an international network was ranked higher than making a billion dollars, having maximum social impact, and exploring Latin America combined. The only goal cited with greater frequency was to build a product or service.

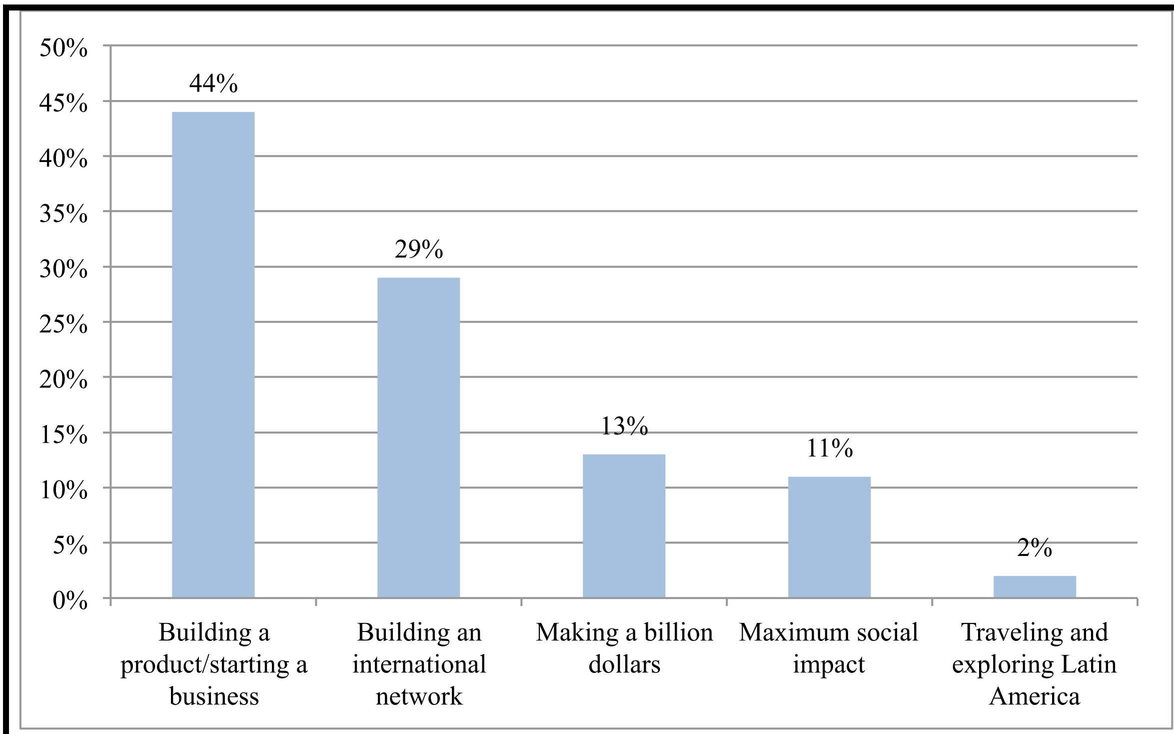


Figure 11. Main objectives of participants in Start-Up Chile (N = 45).

Previous attempts to build networks.

To gauge the seriousness with which participants approached network building, participants were asked how they had attempted to build their international networks before joining Start-Up Chile. These methods included traveling, attending conferences, other incubators that attract international participants, and MBA programs. These are represented in Figure 12 as a percentage of total responses, as participants could choose more than one option.

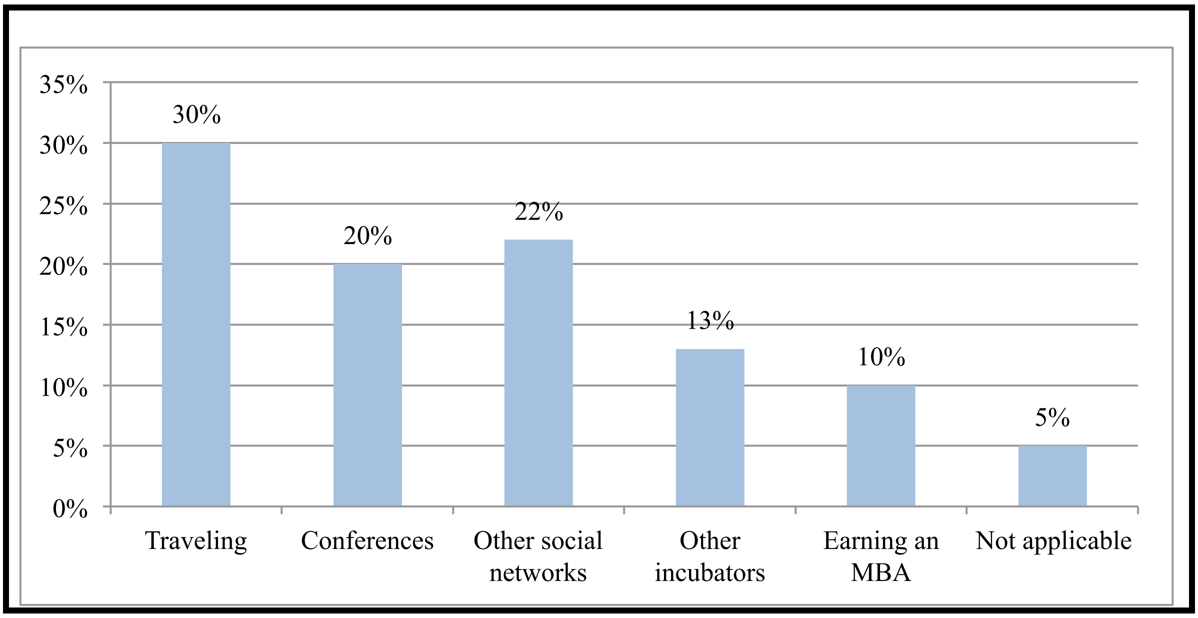


Figure 12. Attempts to build networks prior to Start-Up Chile (N = 45).

Use of online social networking tools.

Participants were also asked how often they used LinkedIn and for what purposes. Adoption of LinkedIn is, of course, key to determining whether or not it is a good proxy for real-world networks of participants. Figure 13 shows that 80% of participants use LinkedIn at least weekly (i.e., several times/week, weekly, daily, or multiple times/day), and 54% use it many times per week (i.e., the same group less the 24% that only use it weekly).

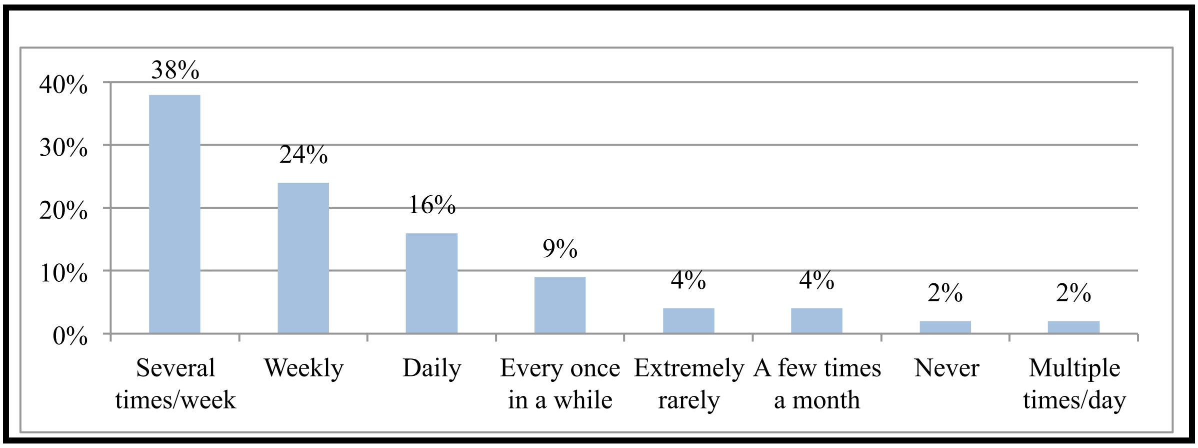


Figure 13. LinkedIn usage rates among Start-Up Chile participants (N = 45).

To ensure that participants were using LinkedIn for the purpose of forming international entrepreneurial connections, they were asked for what purposes they used

LinkedIn. Figure 14 illustrates that participants used LinkedIn for a number of purposes, including professional contacts, business development, and personal contacts.

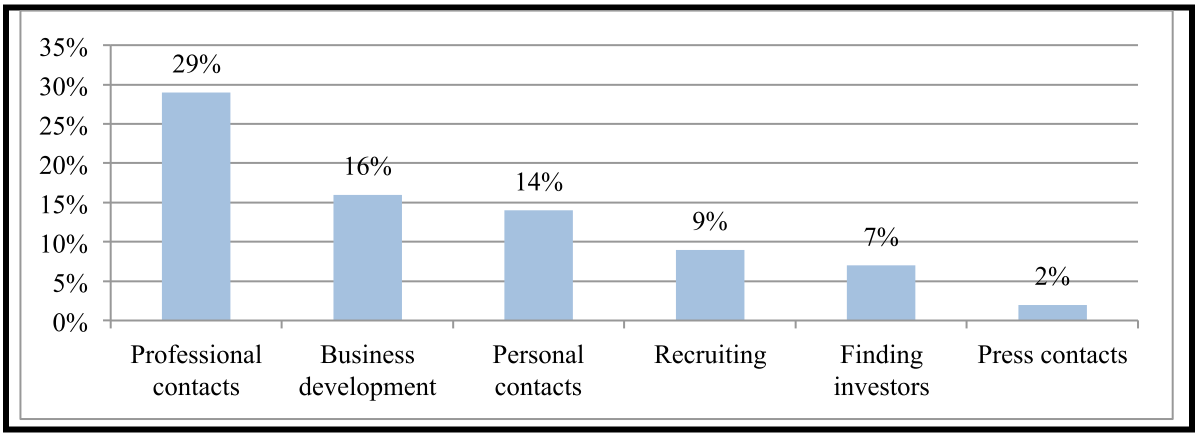


Figure 14. Purposes of LinkedIn usage for Start-Up Chile participants (N = 45).

Program Evaluation Results

The primary goal of Start-Up Chile is to connect Chileans to non-Chileans. Thus, we measured the connections of Chileans and non-Chileans in a variety of different ways using network metrics.

Connections among Chileans vs. from Chileans to non-Chileans.

Through both visual inspection (Figure 16) and measurement of the networks (Table 11), we determined that the sub-network of Chilean participants (Figure 16c) had a less centralized sub-network than that of the non-Chilean participants (Figure 16b). Network centralization for Chilean-only networks (194 nodes) was 0.198 (Table 11, Chilean column), whereas for non-Chilean-only networks (532 nodes) was 0.373 (Table 11, non-Chilean column), indicating a more centralized non-Chilean network.

After stripping away all nodes that were not Startup Chile participants to create sub-networks only including participants in Startup Chile (Figure 15) the network contained 24 Chilean participants and 47 non-Chilean participants (Table 11). Slightly more of the Chilean participants were connected to one another in the sample than to the non-Chileans, with a network density of 0.043 for the Chileans vs. .040 for the non-Chileans (Table 11). However, the non-Chileans that were connected had a far more clustered and connected network with a clustering coefficient that is more than twice as large, with 3.047 for non-Chileans vs. 1.853 for Chileans (Table 11). The comparison of the sub-networks in Figure 15 visually confirms this as well.

Connections among foreigners.

As shown in Figure 15, the ties of the Chileans to the foreign entrepreneurs (Figure 15a) are not as dense as the ties between the foreign entrepreneurs (Figure 15b). By comparing Figure 15a, 15b, 15c, one can see that the foreign entrepreneurs are more connected and central than the overall network or the network of only Chileans. This conclusion was drawn by measuring the network properties (Table 11) and can be seen through visual inspection and comparison of the single cluster created by the connections of non-Chilean entrepreneurs to each other (Figure 15b) and the two main clusters of connections of Chilean entrepreneurs to each other (Figure 15c).

Connections of Chileans to each other.

However, 43.4% of the Chileans were completely unconnected (Figure 15c) as compared 36.1% of non-Chileans who were completely unconnected (Figure 15b). Thus, while the network is connected overall, it is less likely for a Chilean to be connected to at least one other Chilean in the sample than for the non-Chilean participants to be connected with at least one other non-Chilean.

This is potentially an artifact of the cross-generational sample. Chileans are likely to remain in Chile after the end of their class, and are thus more likely to connect with others in the group later. It is also possible that Chileans within classes tend to seek out one another. This is another way of showing that Chileans are more likely to be connected to each other than foreigners are to each other.

Table 11

Network Metrics for Networks Connecting Chilean and Non-Chilean Start-Up Chile Participants Within the Program.

Network Metric	Chilean	Non-Chilean
Network size	24	47
Network density	0.043	0.040
Clustering coefficient	1.853	3.047
Centralization	.190	0.140
Heterogeneity	1.041	1.179

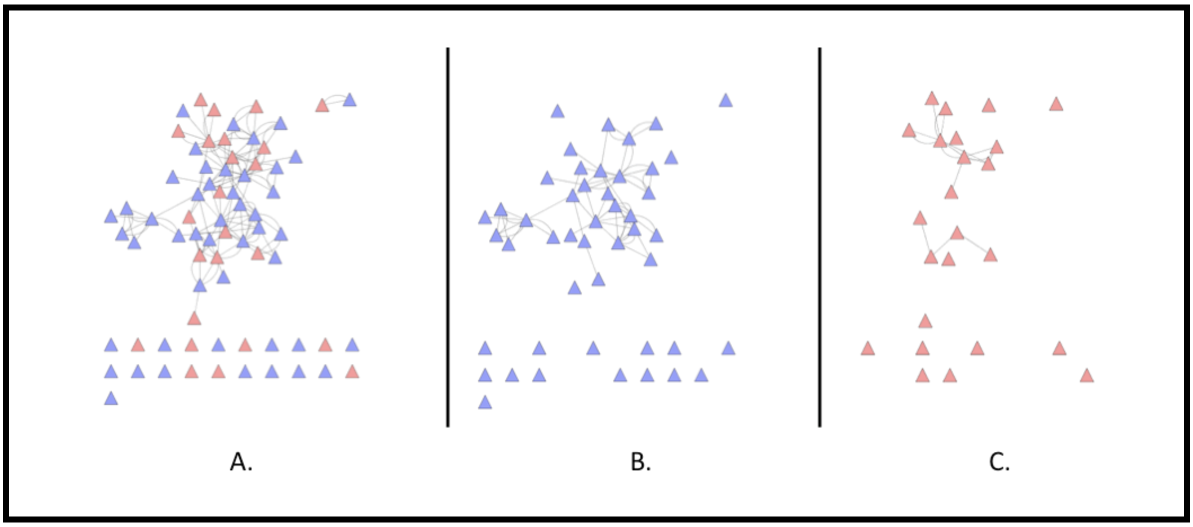


Figure 15. Networks connecting Chilean and Non-Chilean Startup Chile Participants Within the Program. Chileans are indicated as red triangles, while non-Chileans are blue. (A) is the complete sub-network of the sampled Start-Up Chile participants. (B) is the sub-network comprised only of foreign, non-Chilean participants. (C) is the network comprised of only Chilean participants.

Non-Chilean sub-networks are the most connected.

Examining the participant-connected sub-networks in Figure 16, the nodes including all the participants, and their neighbors that were connected to at least two participants in the sample (that is, second-order connections), the signal was far more dramatic. The clustering coefficient of the non-Chilean sub-network is 0.305, almost ten times greater than the 0.032 clustering coefficient of the Chilean-only sub-network (Table 12). Furthermore, the centralization of the non-Chilean sub-network of this participant-connected sub-network (0.373) was almost twice as great as the centralization of the Chilean only nodes (0.198). The non-Chileans were also 41.8% more topographically heterogeneous than the Chileans (Table 12). Non-Chilean entrepreneurs appear to be more central in this network than Chilean ones.

Table 12. *Network Metrics for Chilean and Non-Chilean Start-Up Chile Participants Including their Connections Outside the Program.*

Network metric	Chile only	Non-Chile only
Network size	194	532
Clustering coefficient	0.032	0.305
Centralization	0.198	0.373
Density	0.011	0.007
Heterogeneity	2.574	3.651

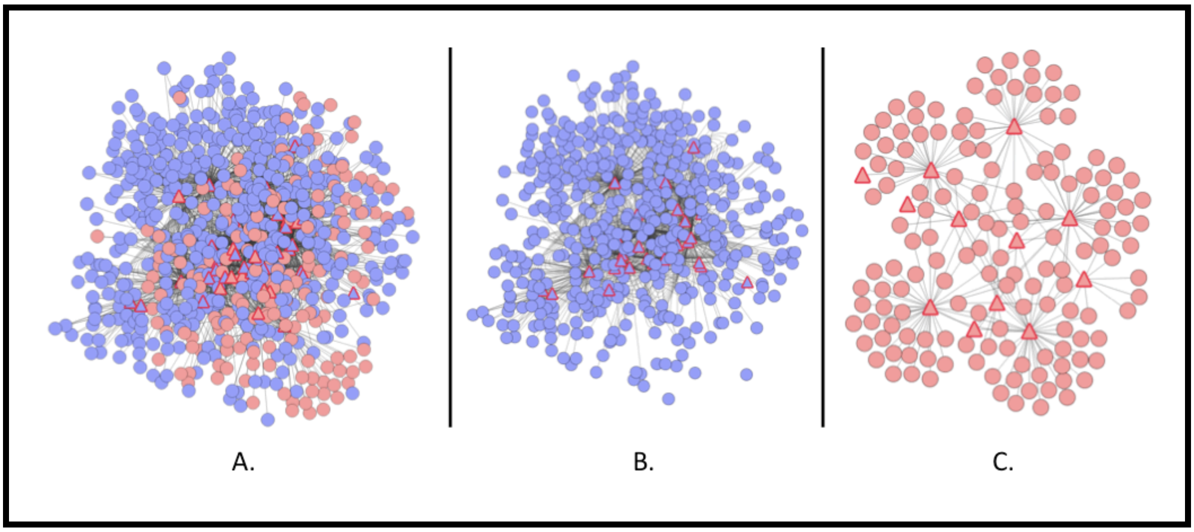


Figure 16. Networks of Chilean and Non-Chilean Startup Chile Participants Including Their Connections Outside the Program. Chileans are indicated as red triangles, while non-Chileans are blue. (A) is the complete sub-network. (B) is the sub-network comprised only of foreign nodes. (C) is the sub-network comprised only of Chilean nodes.

Results summary.

These network measures together illustrate that Start-Up Chile has not achieved its goal of interconnection between Chileans and non-Chileans. Chileans are more connected to each other, foreigners are more connected to each other, and foreigners are more central in the overall network of participants. What this means is that Start-Up Chile did not achieve its goal of connecting foreigners with Chileans. This accords with the results of the background interviews conducted with Start-Up Chile participants, many of whom had formed no meaningful connections with their counterparts. What these network results provide for us (and Start-Up Chile management) is an automated, repeatable way to come to this conclusion.

Limitations of This Case Study

This study has several limitations that can be addressed by future work. First, all generations of Start-Up Chile were examined equally, so entrepreneurs had time periods of differing lengths in which to build their networks. An entrepreneur from Generation 1 therefore had nearly two extra years to build their network than an entrepreneur from Generation 7. A random sampling method that separated the participants by generation and gathered more participants per generation would be helpful in removing this source of bias.

Next, this study looked at the overall structure of the network, but did not measure the state of the network before and after participation in Start-Up Chile. This is partly due to time constraints, as Start-Up Chile generations last for six months, and user participation would have to have been carefully timed to ensure that the network is gathered at specific time points.

Another limitation is that the networks captured are not the whole networks of participants in Start-Up Chile. Initially, Start-Up Chile leadership was cooperative in sending out notices about participation in the study. However, due to staff turnover, the same permission needed to be granted several times to complete the study and we were not permitted to sample beginning and end points of participation or to sample the entire network of an admitted group. In the end, both Start-Up Chile official communication and social media recruitment of participants led to the current structure of the participant cohort.

Finally, tie strength is an important measure when using social network data. LinkedIn only permits a binary *tie or no tie* status and does not allow API access to messages or other features that would indicate the thickness of the tie. The present data also reflect this limitation.

Chapter Summary and Preview

This chapter started with a detailed description of Start-Up Chile, including the program's goals and efforts to establish networks between international entrepreneurs and the local Chilean business community. We then discussed how LinkedIn is used by participants, and the result of two investigations comparing network measures between Chilean and non-Chilean networks. Finally, we discussed limitations of the study. Chapter 6 describes an agent-based simulation of an entrepreneurial incubator, including specific methods used, results, and limitations.

Background on Agent-Based Modeling

Agent-based simulation is a way of modeling complex systems by examining the interactions of individual *agents* who relate to each other based on their individual and group characteristics. Accordingly, the behavior of the agents is organized by simple rules, which give rise to complex phenomena through their interactions. Thus, agent-based modeling provides a way to understand social systems that is more nuanced than traditional top-down models of social or economic behavior. In particular, this method is especially suited to model the effect of networks, which emerge from the structure of their constituent nodes and ties (Bonabeau, 2002). In the present study, we use agent-based modeling to better understand the interactions of entrepreneurs within incubators, given characteristics of individual agents (entrepreneurs) and their environment (incubators).

Driven by the bottom-up behavior of its agents, agent-based modeling relaxes the assumptions of classical economics. Agents need not be rational, fully informed, or homogeneous, and the system itself does not need to tend toward equilibrium. Thus, agent-based models can lead to a deeper understanding of the chaotic and sometimes contradictory outcomes of human systems (Macy & Willer, 2002). At the same time, these models can often better predict real world outcomes than less flexible top-down models across disciplines. Applications are as various as the emergence of cooperation (Axelrod, 1997), the process of fomenting social instability (Epstein, 2002), and the spread of adolescent risk-taking behavior (Fujimoto, 2012).

Brief history of agent-based models.

One of the first social science agent-based models was created by early mathematical sociologist Sakoda in 1971. Entitled the Checkerboard Model, Sakoda's simulation relied on agents placed in cells in a checkerboard pattern, who moved in relation to their attitudes to each other (positive, negative, and neutral), leading to nonobvious groupings. Soon after Sakoda's model, the economist Schelling (1971) used similar methods to develop a model of housing segregation in which agents represented homeowners and neighbors. Schelling showed that housing segregation patterns emerge from self-organizing groups even though the individual agents were not acting out of discrimination. Epstein and Axtell (1996) took on the even more ambitious task of growing an entire artificial society through agent-based simulation by creating software called Sugarscape, which created a simple world in which agents act solely to gain and protect sugar. From these simple motivations, Sugarscape agents fought wars, collected rent, and exhibited other complex economic behaviors as emergent properties of simple rules.

Although many economic phenomena have been analyzed in this manner, agent-based modeling has yet to be used to understand the ecological factors relating to entrepreneurship. Valdez (1988) termed the group of mentors, investors, advisors, and employees that cluster around entrepreneurs an *ecosystem*. Indeed, this term is often used to describe the effect of economic policies that encourage entrepreneurship—do they help to build the entrepreneurial ecosystem? Carroll and Khessina (2005) discuss entrepreneurship as an ecosystem that enables individual, enterprises, and the society to combine effectively for the cause of generating economic wealth and prosperity. This chapter applies the agent-based modeling approach to the ecology surrounding entrepreneurs, particularly to entrepreneurial incubators.

Agent characteristics.

Agents have several typical characteristics: They are self-contained, modular, uniquely identifiable, and autonomous. Typically, agents are active, initiating their actions to achieve their internal goals rather than merely responding to other agents and their environment. Thus, the following qualities of agents are considered fundamental to their ability to model complex phenomena (Macy & Willer, 2002):

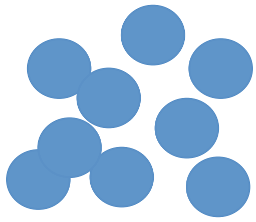
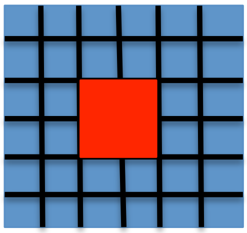
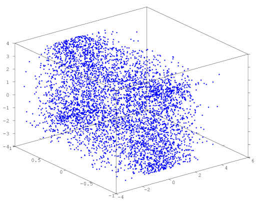
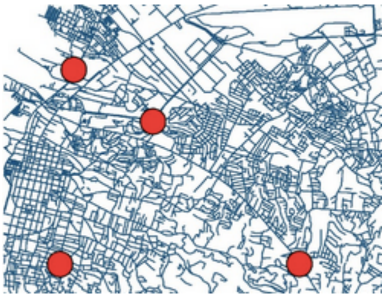
1. Agents are autonomous and self-directed. They are able to function independently and make decisions based on this information and the rules that they are given.
2. Agents have a state that varies over time. An agent's state consists of a set or subset of its attributes. The state of an agent-based model consists of the collective states of all the agents, along with the state of the environment in which they operate.
3. Agents are social. Agents have dynamic interactions with other agents that modify the behavior of one or more parties and/or the environment.
4. Agents pursue their own goals in an environment of limited information. There is no central authority that provides globally available information to all agents or controls their behavior in an effort to optimize system performance. Agents can interact with other agents, but not all agents interact directly with all the other agents all the time, just as in real-world systems.

Types of agent-based models.

According to Macal and North (2010), agent-based models can be categorized into five groups: (a) aspatial or *soup* models that do not require a spatial or network-based orientation; (b) cellular automata, in which agents are imagined within a grid, one agent per box; (c) Euclidean models, which are similar to cellular automata, but in three dimensions; (d) geographic information systems models, in which agents move in a realistic landscape; and (e) network models, in which the networks of the agents are the space in which they move and the measure of their final shape. Table 13 shows visual representations of each of these types of models. The present case study consists of a network model that does not have a geographic or spatial component.

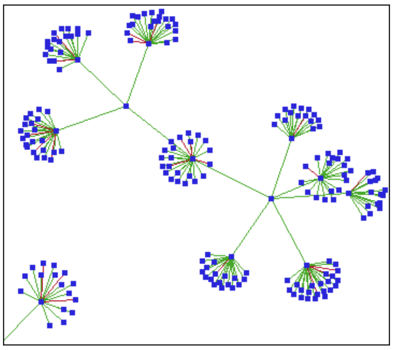
Table 13

Common Typologies of Complex Models

Type of model	Description	Visual example
Aspatial models	Model has no spatial or network representation	
Cellular automata	Agents within the model are imagined within a grid, one agent per box	
Euclidean space models	Like cellular automata, three or more dimensions	
Geographic information system models	Agents move within a realistic geo-spatial landscape	

(continued)

Table 13 (continued)

Typology	Description	Visual example
Network models	Agents are mapped within network, not coordinate space. Network models include both static and dynamic models. In static models, links do not change in the model. In dynamic networks, links (and possibly even nodes) are determined according to the rules of the model.	

Note. Adapted from Macal, C. M., & North, M. J. (December 2009). Agent-based modeling and simulation. In Winter simulation conference (pp. 86-98).

Components of agent-based models.

According to Gilbert (2008), agent-based simulations include four components: (a) nodes that have individual characteristics, (b) a way to transmit these attributes or their effects to others, (c) global parameters that affect the individual nodes, and (d) iterative simulation to reach an end state. The implementation of these characteristics in the present simulation is shown in Table 14.

Table 14

Components of Agent-Based Network Models

Attribute	Model
Nodes with demographic and behavior attributes	Helpfulness (h), individual connectivity (k)
Attribute transmission functions	Social capital transfer between participants in the form of connections
Population parameters that impact individual behavior and interaction	Incubator multiplier for connections (M)
Iterative simulation	Monte Carlo simulation

Parameters of the Model

Starting premises.

This case study models an emergent system based on an entrepreneurial incubator. Parameters are set at the beginning of the simulation, leading to unpredictable outcomes at the end of the incubation period. Each of the nodes has particular characteristics that define its behavior (the agent's attributes), while the incubator has rules that govern how it interacts with the participants. Only individual attributes of the agents are characterized at the beginning of the simulation, not the aggregate characteristics. For example, propensity to network is a property of the individual agents, but aggregate propensity to network of all agents is an emergent property not governed by the rules of the model.

It is important to note that we model the agents as entrepreneurs, not firms, since most seed-stage incubators admit individuals who may change many company-specific factors during the course of the incubator. That is, they *pivot* (completely change their business model or even their industry), add new employees or co-founders, or change the for-profit or nonprofit status of their enterprise. For this reason, we model the agents as entrepreneurs, not as firms.

The model assumes that each entrepreneur comes into the incubator with a network of some set value based on the people they know and their potential to be useful to the other entrepreneurs in the incubator. One entrepreneur may know a billionaire investor; another may know a good bookkeeper. The aggregated value of these connections is modeled in this simulation, and the connections between entrepreneurs fostered by the incubator can increase the value of the entrepreneur's network after the incubation period. Although it is possible that the incubator may decrease the value of the entrepreneur's network (such as if the entrepreneur makes a lot of enemies in the incubator, which could be modeled as negative network ties), this is not the most likely case. Since the primary purpose of the incubator—for both the participants and the organizers—is to build positive connections with people who will be helpful to start-ups, we will assume that the resulting effect on the entrepreneur's network will be positive, even if small.

Incubator variables.

In the simulation, the incubator is characterized by two main factors: the number of participants, N, and the incubator's overall encouragement to participants to network, M. In the real world, this encouragement can be implemented through specific attributes of the program, such as networking events, prizes for networking, explicit social introductions, and so forth. In the simulation, N can either be 50 or 100, common class sizes for incubators. M is a randomly generated probability between 0 and 1 that indicates how much the incubator induces the participants to form ties.

Participant variables.

Individuals are characterized by four state variables: (a) propensity to network (which we'll call *individual connectivity*), k; (b) propensity to help others in the incubator (which we'll call *helpfulness*), h; (c) mean number of connections, u; and (e) the standard deviation of the number of connections, s. The variables k and h are randomly generated probabilities between 0 and 1. The values for u and s are set in this simulation to the average amount of connections for professional networks as reported by LinkedIn, the most common social networking platform for professionals (Monro, 2011).

Individual connectivity (the propensity to form networks), k, is the likelihood of each agent to want to connect to others within the incubator. This is a native tendency within the agent to form ties with others. This characteristic can be tuned as a parameter in the model; the *connectivity multiplier* parameter is multiplied with the random value to increase or decrease the relative likelihood of tie formation. For any pair of possible connections, each connection the other member of the pair has is assigned a pseudorandom number drawn from a uniform distribution between 0 and 1. If this value is greater than the individual connectivity value of the participant with the connection, the connection is added to the other participant's network.

Similarly, helpfulness, *h*, is the likelihood of that agent to transfer one of their useful ties from outside the incubator to someone within the incubator. This characteristic can be tuned as a parameter in the model; the *helpfulness multiplier* parameter is multiplied with the random value to increase or decrease the relative likelihood of tie formation. Like the propensity to form networks, the helpfulness characteristic is assigned pseudo-randomly. So, for each pair, each connection the other member of the pair has is assigned a pseudorandom number drawn from a uniform distribution between 0 and 1. If this value is less than the helpfulness characteristic of the participant with the connection, the connection is added to the other participant's network. These state variables and their initial values are shown in Table 15.

Table 15

Parameters and Values of the Incubator Model

Variable	Hierarchical level	Name	Description	Value or range
M	Incubator	Incubator multiplier	How much an average member of the network people to meet over their native propensity to network.	A probability between 0 and 1
N	Incubator	Number of agents	Number of participants per incubator class	50, 100, or 500
k	Individual	Individual propensity to network	How likely a participant is to meet someone else in the incubator.	A probability between 0 and 1
h	Individual	Propensity to help	How likely a participant is to introduce someone to a person in their network	A probability between 0 and 1
u	Individual	Mean number of starting connections	How many connections the participants have on average to start	150
s	Individual	Standard deviation of number of starting connections	The standard deviation of the number of connections the participants have to start	75
n	Individual	Number of ties	Number of connections per person	Emergent
v	Individual	Value of connections	Sum of each connections of a node multiplied by their value	Emergent
V	Incubator	Overall value of connections	Sum of *v* for all members of the incubator	Emergent

How the Simulation Works

Ties are formed between the agents using a simple model. Each agent has a characteristic that represents their propensity to form ties; that is, the likelihood of this participant forming ties with any other person in the incubator. In any given run of the model, the likelihood that any two participants form ties is based on the product of their individual connectivity over the square root of the number of participants in the incubator, to adjust for the difficulty of forming ties with participants as the size of the incubator grows. This value is also tuned through multiplication with the incubator multiplier parameter. So, a more network-encouraging incubator will make it easier for even participants who are intrinsically less likely to form ties to do so.

Our model is informed by previous models of social interactions in networks. For example, Jin et al. (2001) modeled how likely two people are to meet in the shared social context of mutual friends. They use the function as follows, where z is the size of the individual's network, m are mutual friends, and f and g are probability distributions specific to the topology of the network.

$$p_{ij} = f(z_i) \cdot f(z_j) \cdot g(m_{ij})$$

Similarly, Skyrms & Pemantle (2009) model agents playing repetitive games within a social network in which agents learn from repetitive pairings with others. Our work here addresses a novel situation in which a newly formed group with no pre-existing intra-group ties comes together for the purpose of social capital exchange (governed by h) inside of a larger institution (which influences the process through M).

Mathematical foundations.

The following equations illustrate the mathematical foundations of the model. First, we generate the initial number of connections for a given individual from random numbers generated from a normal distribution. Normal distributions have the advantage of being analytically simple and of not specifying whether the numbers are correlated with each other or independent. Poisson distributions are often used to describe network connections in a random network (e.g., Barbour et al, 1992), while power law distributions are often used to describe scale-free networks (e.g., Barabasi & Albert, 1999). Using other distributions, such as the Poisson distribution, would have obviated the need to take the ceiling and absolute value of each point and depending on the underlying distribution, may contribute a greater understanding of simulation outcomes. A comparison of underlying distributions in an agent-based simulation and its results would be useful in future work.

$$n_i = ||\lceil X \sim N(u, \sigma^2) \rceil||$$

Then, we calculate the value of the connections that the participant already has. We assume that each entrepreneur comes into the incubator with a randomly varying number of connections (as above) and that these have a randomly varying amount of value to transfer to the other participants. Some people who an individual knows are extremely connected famous investors, while others are acquaintances from a previous job with no relevant skills. The following equation was used to model these various sources of value, where i is the participant and *o* is their connection with variable value according to the exponential curve.

$$v_{io} = X \sim PowerLaw(q, \lambda), \qquad q = 0, \lambda = 2.5$$

The value of incubator to each of the participants is the transfer of the existing social capital from participants to each other, based on their propensity to network, their helpfulness to others, and how much the incubator encourages networking. The equation below illustrates the likelihood of two participants in the incubator connecting.

$$p_{ij} = \frac{M \cdot k_i \cdot k_j}{N}, i$$

Given entrepreneur i, one can find the likelihood of them connecting with entrepreneur j by multiplying the individual likelihoods of their meeting converting to a connection (k_i, k_j) to generate the joint probability of connecting. Then, as the incubator determines to what degree entrepreneurs interact within the program, this quantity is further multiplied by M, the networking multiplier of the incubator. Finally, the total is divided by N, the total possible members in the network for the individual to connect with on that interaction.

This probability is then multiplied by the helpfulness of the transferor of social capital as below:

$$c_{ij} = p_{ij} * h_i , i \neq j$$

Finally, we come to the resultant value of the individual's network after the incubator, where v_o is the connection outside the incubator, and v_i is the participant in the incubator.

$$v_i = \sum_{o} v_{io}$$

After the ties are formed and the connections are transferred, the increase in enterprise value is calculated by subtracting the initial value of the network from the final value of the network after connections are made (calculated as above). A useful normalization can be achieved by taking the ratio of this difference over the initial value. This allows us to readily compare networks of different initial values. Similarly, to determine the value of the entire network of all participants, we simply add the sum of the value of each of their networks.

$$V = \sum_{1}^{50\ or\ 100} v$$

Monte Carlo simulation.

This model was run iteratively as Monte Carlo simulation so that statistics on the robustness of each result could be calculated. Monte Carlo methods are a type of computational algorithm that uses repeated random sampling to arrive at a distribution around the desired result. This is a way of verifying the robustness of a result by trying pseudorandom numbers to see if the same result occurs during many iterations of the experiment. In this study, each simulation was run 50 times, allowing the calculation of both mean value and standard deviation of the value difference, as well as normalized value difference for that set of parameters.

Assumptions of the Model

Motivations of the agents.

In this simulation, we assume that the motivations to form ties are both endogenous to the entrepreneur (in the form of *h* and *k*) and exogenous (in the form of the encouragement provided by *M)*. We assume that the incubators provide equal motivation to each agent in the simulation, although individual agents have their own motivations that vary.

Non-overlapping connections.

In this model it is also assumed that the nodes in the model only have non-overlapping connections (i.e., no one in the incubator knows anyone in common at the first-degree level). This is a simplifying assumption that allows us to model the formation of new ties in the incubator based on an initial random distribution and the increase in ties according to *h*, *k*, and *M*, without regard to existing network ties among participants. The model also does not examine embeddedness in larger network structures such as networks of college alumni, work colleagues, previous incubator cohorts, or networks based on ethnicity, gender, or other personal attributes.

Diminishing returns.

It is also assumed that connections are harder to create as the incubator grows larger. If this parameter were not included, the value of the final network would be so influenced by the size of the network that no other factors would matter. As a network grows, ties are more likely to become weaker and more tenuous, leading to an overall reduction in the strength of the network. Since the tie strength of each connection drops with each additional connection, the model includes diminishing returns to scale on network connections (see McFadyen & Cannella, 2004).

Social capital endogenous to incubator.

The model does not address any synergies that are possible between members that don't arise from preexisting social connections. The main mechanism of social capital transfer is to map connections from entrepreneurs to each other based on their helpfulness and varying social capacities at the beginning of the incubation period. This assumes that connections will go where they are most needed and that the amount of social capital is determinate at the beginning of the incubation period. We can imagine, however, that some social capital could come into being during the incubation period, such as through one of the members becoming famous (unrelated to their own or the incubator's actions), or marrying someone with tremendous social connections, thus adding massive amounts of weak ties during the incubation period. Because the incubation periods are so short (usually less than six months), we have not included this in our model.

Aligned interests of incubator and entrepreneur.

We also assume that the interests of the incubator and the participants are aligned in that they both want to see the value of the individual and aggregated networks grow as a result of the connections formed during the incubator. There may be some cases in which this might not be true, such as in the case of rivalries between members of the incubator that lead to a zero sum game of connections. For example, if there are two competing firms in the incubator, they may find it in their interest not to share connections with each other and the incubator may need to choose who gets preferential treatment. Incubators tend not to accept directly competing firms (at least in the same class of the incubator) in order to avoid these conflicts.

Results

The results of the simulation yield several nonobvious conclusions about the nature of incubators that contribute to the literature about incubators and may also be helpful to policymakers and administrators of incubators as well as participants: (a) bigger networks are better, (b) helpfulness is as important as starting capital, and (c) explicit network goals may be valuable in influencing the overall value of the incubator.

Bigger is better.

Briscoe, Odlyzko, and Tilly (2006) recounted the story of what has come to be known as Metcalfe's Law—commonly referred to as the network effect. Metcalfe, the creator of Ethernet, a protocol by which computers were networked in the first local area networks, hypothesized that while the cost of the network grew linearly with the number of connections, the value was proportional to the square of the number of users. In other words, the bigger the network, the more valuable, since the cost of adding new members grows linearly but the value grows exponentially. Since Metcalfe promulgated this idea, several caveats have become clear. The value of specific connections is important, as well as the strengths of the links between nodes. In our model, we specifically include a factor to degrade the formation of the ties as the network grows larger in order to generate more realistic results. After all, there is a point at which a set of participants in the incubator is so large as to be indistinguishable from the general population and to confer no specific network benefits from membership.

Nevertheless, the present study found that the larger the incubator, the more value the incubator had to participants and overall. Figure 17 shows that the size of the incubator correlates with higher overall value (calculated as above) despite reducing the value of each connection based on the size of the incubator. Overall incubator value was calculated up to 500 members, to illustrate that the curve continues to extend upward at a diminishing rate after 100 members.

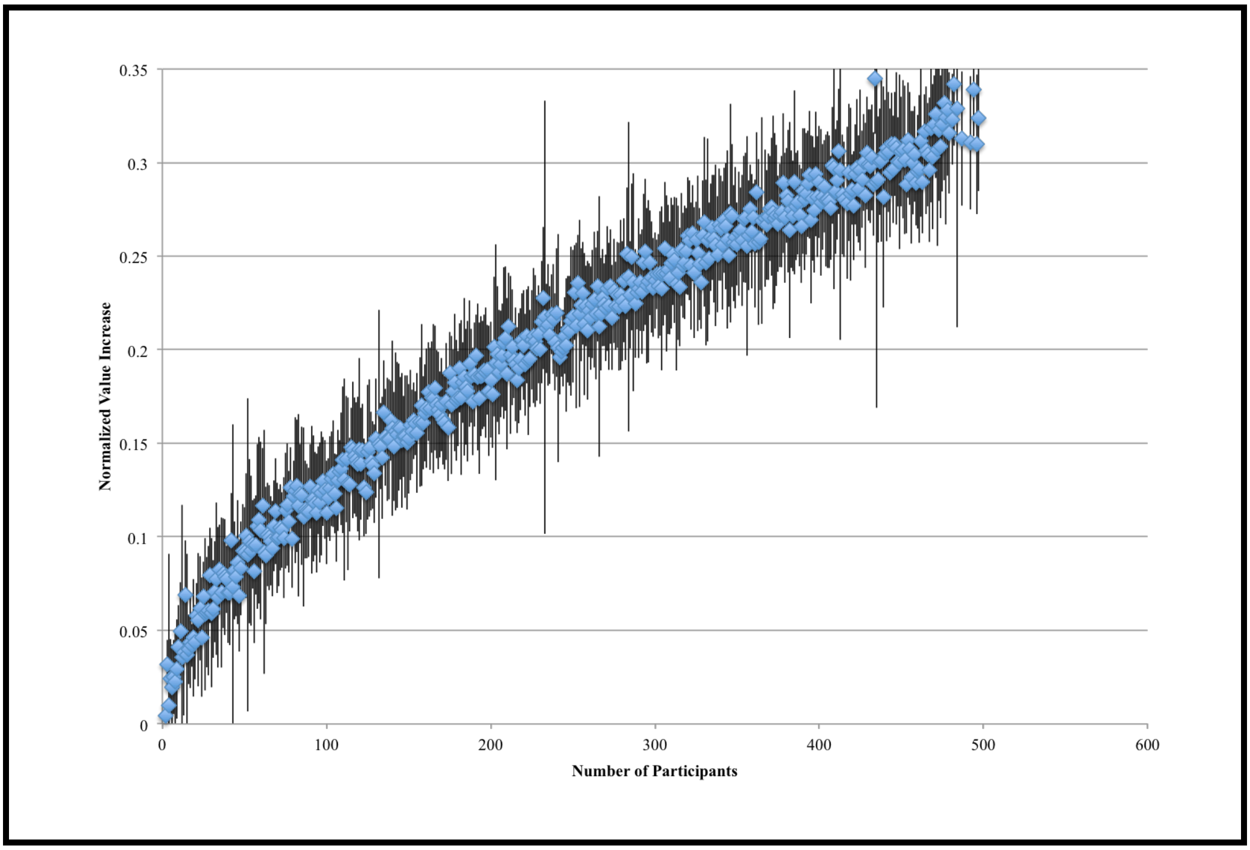


Figure 17. Effect of number of participants on overall incubator value.

Helpfulness matters.

Incubators often encourage networking events and mixers, but may overlook the importance of participants actually making the introductions that facilitiate the transfer of social capital between participants. This simulation shows the value of helpfulness, that is, the sharing of existing connections among participants. Many incubators hold explicit networking events and educational events, but none that we are aware of facilitate the direct transfer of social capital that occurs when participants introduce others to those in their broader networks. Encouraging helpfulness among participants (which, in the case of networks, really means the formation of relevant second-degree ties), can be set as an explicit policy goal.

Just like growing *M* (incubator encouragement of connections) has great implications when multiplied across all participants, selecting for *h* (helpfulness of the participants) has implications that multiply across participants. Figure 18 shows how the value of the incubator scales with regard to increases in the helpfulness of the participants. The more participants there are, the greater the impact of helpfulness.

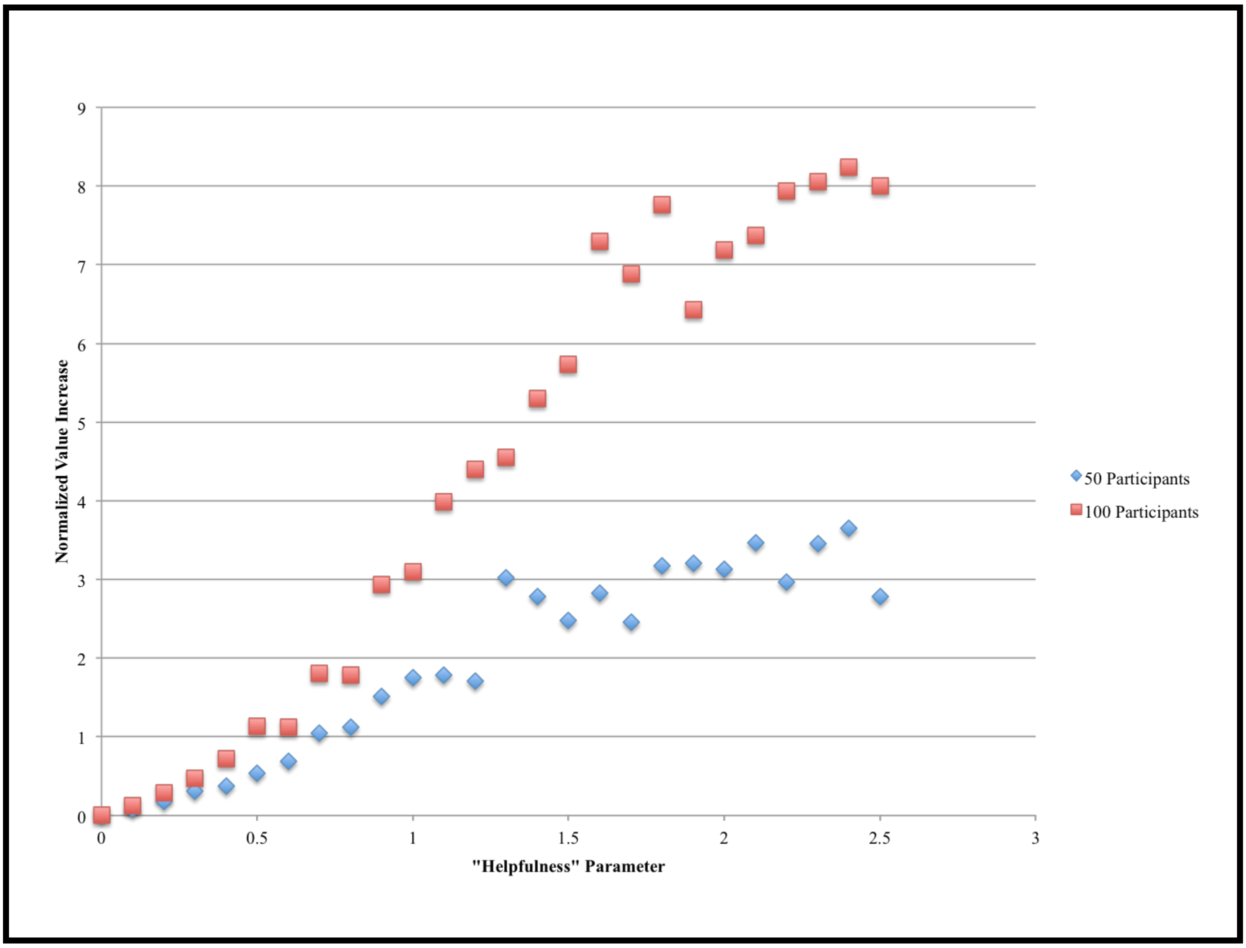


Figure 18. Effect of helpfulness on overall incubator value.

Explicitly encourage networking.

One of the factors that affects the value of the incubator is how much it explicitly encourages networking. If an incubator is even slightly more encouraging of connection (meaning that *M* is even slightly higher), there is a huge effect when multiplied by each of the participants in the incubator; the larger the incubator, the greater this effect. Incubators that encourage genuine networking—that is, forming of ties rather than attending events—or find ways to connect like-minded people instead of just putting people together in one room, will provide much more value to both the incubator and the participants.

Network criteria can also be used in selecting participants for the incubator. Some incubators, such as Start-Up Chile, already use network criteria, basing 30% of their admission decisions on the network of the applicant (e.g., an Oxford Business School graduate has a better chance of being accepted than one from a less prestigious school). However, they do not take into account the propensity to network of the participant—that is, their willingness to connect and share value with others in their network, prestigious or not. Measuring this kind of connectivity using LinkedIn data as described in the Start-Up Chile case study would allow for a more robust selection process and the ability to tweak admissions criteria rapidly in response to the needs of the network. For example, incubator sponsors could determine the type of network that is needed (more members from a particular country, industry, or network cluster) and admit participants who are particularly helpful in building out that network capacity.

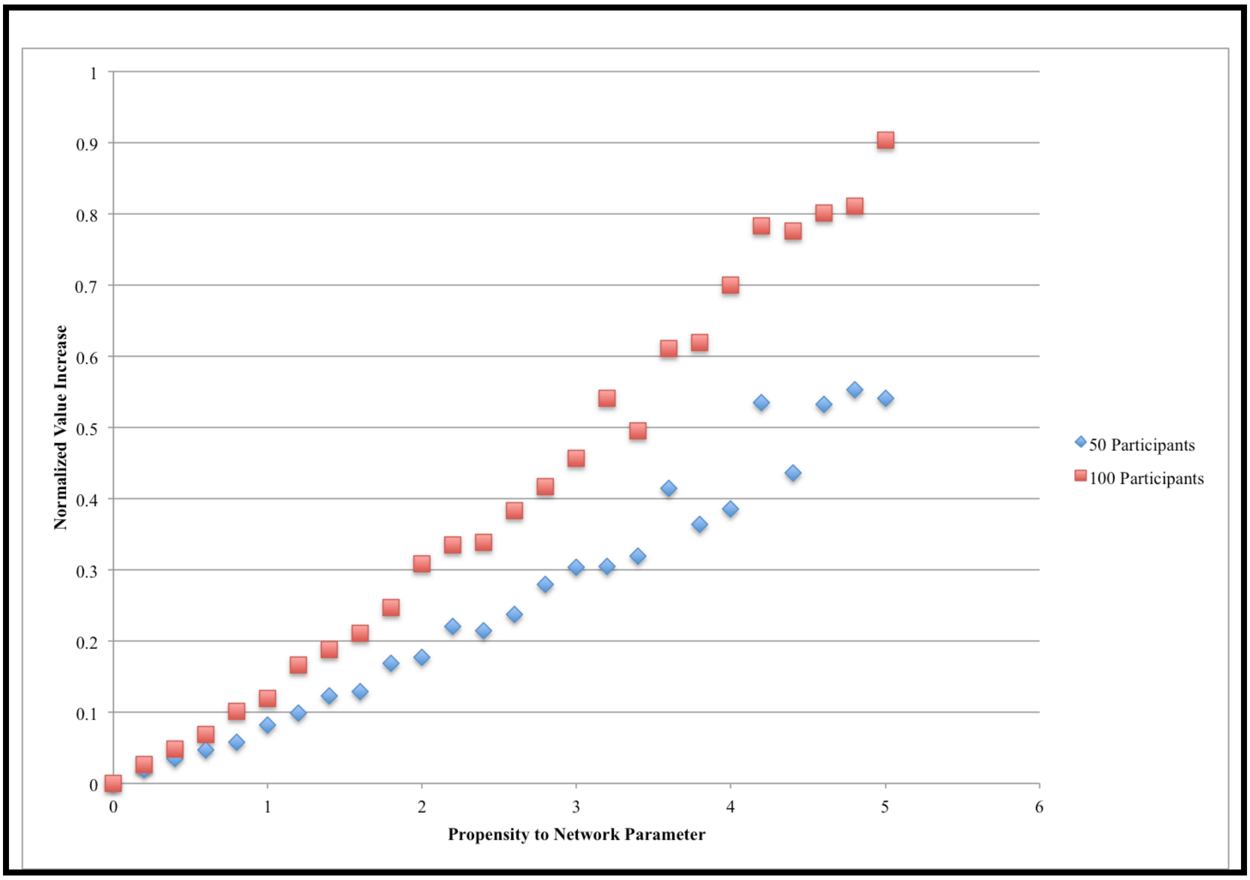


Figure 19. Effect of propensity to network on overall incubator value.

Limitations of this Model

Several important features of the model have been left for future research. Most importantly, future agent-based models of incubators should include a time component to show how networks decay over time. Relatedly, a model of the incubation period during which the participants are quite active in forming networks, and then the simulation of a dramatic drop off in network formation would provide a more complete picture of the incubation experience of participants.

In addition, this model assumes that nodes only have non-overlapping connections (i.e., no one in the incubator knows anyone in common at the first-degree level). A more complex model with existing first- or second-degree connections would yield a more granular outcome when using this type of modeling for program design.

It would also be of value to model nodes with varying characteristics. For example, dividing nodes into Chilean and non-Chilean in proportion to their frequency within Start-Up Chile could be helpful in modeling social capital transfer in that setting. Or, more broadly, this approach could be used to model foreign and domestic connections in incubators designed to encourage international exchange of any kind. High and low social capital nodes could be used to model transfer of social capital in incubators in which participants are quite varied in their initial endowments. To address theoretical questions about the networks of one-time versus serial entrepreneurs, a set of nodes with these attributes could be modeled.

Finally, future models should address questions related to the network as a whole, as opposed to at the actor or dyad level. For example, we do not focus on the centrality of any one node or network, nor do we measure network constraint—the extent to which an actor's contacts are redundant or have structural holes (Burt, 1992). This case study also does not address tie strength or multiplexity.

Chapter Summary and Preview

This chapter described an agent-based simulation of program design for an entrepreneurial incubator. First, we gave an overview of agent-based simulation, then detailed the specific methods used in this case. Next, we considered three nonobvious results of the simulation, and the limitations of the present study. Chapter 7 concludes this thesis by summarizing the advantages and concerns about using computational social science techniques to design and evaluate social and economic programs, as well as providing a framework for future work.

Chapter 7 – Conclusion

Summary of Key Findings

The research presented in the previous six chapters contributes to the existing literature on program design and evaluation in the context of entrepreneurship. Specifically, this thesis develops a novel approach based on network metrics that allows for rapid and useful evaluations of economic development programs to complement the predominant approach of randomized, controlled studies. This empirical work presents a proof of concept of the use of network measures to evaluate and design economic development programs.

In Chapter 5, the effectiveness of this approach was demonstrated using the example of Start-Up Chile, a $40 million USD economic development program designed to encourage international and domestic entrepreneurs to build networks in Chile. Instead of measuring job creation years after the program is complete, techniques from computational social science can—within a period of several months—show the efficacy of the program at achieving its stated objectives.

In Chapter 6, an agent-based simulation was used to design entrepreneurial incubators with network-related goals in mind. Nonobvious implications of program designs on networks were explored, including the idea that encouraging participants to network and be helpful is more important than the size of the network. Agent-based simulations of this type could be used to design other economic development interventions as well.

Research Contributions

This research has both theoretical and applied contributions. First, this work extends existing network literature by applying modern network analytic methods to the process of planning and evaluating economic development programs in entrepreneurship. As suggested by Jack (2010), research on networks should expand to more practical applications, of which this study is one. Additionally, this work contributes to existing organizational literature on social capital transfer in entrepreneurship with an emerging markets (specifically Chilean) example. In the computational social science literature, this thesis contributes an important application for both network analytic and agent-based techniques. Computational social science techniques can be used in many settings, not only to form and test hypotheses, but to measure the impact of programs in real time.

While the approach developed in this thesis was motivated by the case of Start-Up Chile, it is flexible enough to be applied to other entrepreneurial incubators and economic development programs more broadly. Programs whose aim is to modify existing networks or set up new kinds of networks can be planned and evaluated using the agent-based model developed in this thesis. For example, nascent entrepreneurial incubators in Brazil and Malaysia can use the resources developed as part of this thesis to approach the planning process in a more informed manner.

This is also true for programs with goals beyond economic development. For example, educational programs that aim to integrate students into social networks to reduce dropout rates, or neighborhood-based Big Brother or Big Sister-type programs that aim to reduce juvenile crime through social network formation can be measured using a similar approach. One can imagine replacing the existing survey-based measures of program success with network-based tools that are faster, easier to implement, and less costly.

The key findings of this research suggest that networks should be studied not only as a dependent variable to measure social interactions, or as an independent variable to influence outcomes, but also as a practical guide for real-time policy interventions. For example, if entrepreneurs' connections had been tracked in this manner in Generation 1 of Start-Up Chile, it would have quickly become clear that the desired networks had not been formed, well before it was possible to track other metrics such as job creation or start-up success. If progress towards these goals were not on track, changes could be made.

Policy Implications

A better system for measurement.

Network measurements can be gathered instantaneously by pulling data from LinkedIn, Facebook, Twitter, and custom-developed applications designed for the specific purpose of measuring the activities of the group. This instantaneous measuring allows more rapid iteration, using interim measurements to change the program for the next group of participants. In the case of entrepreneurial incubators, which have a fixed beginning and end point and a set of admit classes, the network measurements could be used to plan the next class based on measurements from the first class. These measurements can be used continuously throughout the program to make changes.

Network measures can also be combined with existing outcome measures to determine if networks are actually as important to the outcome as originally predicted. There is a vast body of literature relating networks to entrepreneurial success. By measuring networks contemporaneously with the program, as well as using traditional outcome measures, one can determine if these outcome measures and the networks that are supposed to produce them are actually correlated in any particular case. This creates a type of personalized medicine for economic development programs, allowing the common policy prescriptions to be tested in each setting, rather than relying on studies based in Silicon Valley, Boston, or London to apply to Kuala Lumpur, Belo Horizonte, or Santiago.

Much of the cost of program evaluation is due to the manual cost of surveys and interviews. If the program uses LinkedIn, Facebook, or other websites as the basis for the software application, the cost is simply of programming an interface to these websites. This thesis work includes this program, which has been released on Github (a programming aggregation site). Others are free to add to it, fork it (create new branches of programming code), or build their own network measurement platforms. If program designers want to build custom applications, they can do so for a fraction of the cost of traditional metrics that require interviews, surveys, and fieldwork.

The ease, speed, and low cost of network measures makes it possible to perform these measurements even in developing and emerging markets, where other types of measures are often difficult to implement. This *appification* of social measurement is a natural outgrowth of commercial applications that are used in the developed world to track everything from fitness to habits to social connections. Using these same tools at the population level to track network development performs many of the same functions for the goal of greater social and economic progress.

Network measures are more granular than traditional outcome measures not only because they are continuous, but also because they facilitate and automate the creation of subgroups that can be addressed with specific remedies for problems in social program design. Automatic clustering algorithms, for example, can be used to better understand subpopulations that might not be benefiting from the overall economic program. In the case of entrepreneurial incubators, these subgroups might be Chilean entrepreneurs, female entrepreneurs, entrepreneurs who enter the program without as many social connections, or other groups that might not be responding as well (or, conversely, super-responders) in the program. Automatic clustering can be used to better understand what these groups might be and provide alerts to program designers.

Information benefits can extend to participants.

Participants themselves can use the feedback from the data to improve their own behavior, especially if their incentives are aligned with the program designers. For example, entrepreneurs who want to network with others can use the same tool to judge their own network formation process and to ensure that they are forming the networks that will be key to their success. In the case of incubators, entrepreneurs often travel long distances, sacrifice time with family and friends, and give up large amounts of equity in their start-ups. They spend many hours networking and trying to cultivate useful contacts. Entrepreneurs are thus motivated to make the best of their networking opportunities, and having free tools to measure this can be an important benefit of the program itself. As detailed in the Start-Up Chile case study, we provided the entrepreneurs with a map of their network as part of the study design.

Concerns and Limitations

Poor fit for particular programs.

Network analytic methods are a particularly good fit for programs that rely on network connections to facilitate program objectives, and where there is a clear connection between network and program outcomes, such as programs that rely on network formation as the outcome (such as those related to socialization, acclimation, etc.). The looser the connection between the networks measured and the desired outcomes, or the greater the uncertainty about the connection, the less likely this analytical method is to be useful. For example, programs in which the focus is specifically on individual learning, specific economic objectives achieved individually, or on ephemeral contacts that are difficult to measure would not be well suited to this method.

Indiscriminate vs. targeted connections.

When using online network data, it is important to recognize that online networks are not a perfect proxy for real-life networks. There are several reasons for this. First, people may not use tools in the same way. Some people may connect indiscriminately, while others may only connect online with those with whom they have formed deep interpersonal connections. In addition, online usage may not correspond to their real-life levels of networking. That is, people who make a lot of connections in real life may record these connections poorly in the online tracking tool, or those who make few connections may record connections that were extremely brief or were not meaningful.

Participants may have different conceptions of what a connection is or means, leading them to overestimate or underestimate the value of a connection (Ellison, Steinfeld, & Lampe, 2007). A LinkedIn connection to a famous venture capitalist may not mean very much if they are in turn connected to hundreds or thousands of early-stage entrepreneurs. There is much literature that tries to map the relationship between online networks and real networks as well as the latent social interactions within online networks themselves (e.g., Jiang et al., 2013). This bias in use must be taken into account when using the data that results from network measures.

Incomplete use of the network tool.

Participants may not use the tool enough, with the result that there is not enough data to draw meaningful population-level results even if the results are meaningful when applied to the individual user. Or, certain subpopulations may use the tool more than others, therefore biasing the results towards particular groups that may not be representative of the whole.

There can be temporal issues as well. Users may log in only at the beginning of the program, or only when prompted by the organizers (or the tool), and thus the time relationship between the network tool and the real-life networking occurring may lead to biased results. Users may record their connections far after they are made, rendering time-based measurements inaccurate. For example, users may collect business cards at a networking event only to enter them in the networking software months later. This issue can be helped by making entry of new connections easier, such as by using applications like Bump—which connects users when they bump their phones together in real time—or Evernote, which allows automatic entry of LinkedIn connections based on photos of business cards.

People may also use the tool only to track certain types of connections, thus biasing the results. For example, if entrepreneurs only track connections with other entrepreneurs, as opposed to potential employees, customers, or funders, the overall picture of their networks will be inaccurate.

Specific cultural issues may also play a role if the networking application is at the interface of two cultures (say, Chilean vs. American or European entrepreneurs) and each of the cultures uses the tools differently. This can bias results in a way that is difficult to identify. For the present study, we asked users to explain their LinkedIn usage patterns in interviews and surveys at the time that their data was gathered in order to get an overall sense of how the different subpopulations used the tracking tool.

Privacy.

Good privacy policies include making participants aware of the risks of the study: that any system can be hacked, that this data can be used to preference some groups over others, that there is information they might prefer not to know, and so forth. It is also important to ensure that data is collected at the population level and that your data is anonymized and aggregated. One must also clearly define the use of the data (such as for program management) and, if possible, provide a benefit to the participants in the form of an analysis of their network. The benefits to the participant may then begin to outweigh the risks, making participation and use more attractive.

Proposed Additional Network Measures

Unique to this approach to network measures is the perspective that they are being used to plan and measure social programs—that is, that they are active measures designed to record what is happening while, or shortly after, it happens. Thus, traditional network measures may not be as useful in achieving this goal as new measures that are built specifically for this application.

As noted in Chapter 3, network measures have been classified as node-level (e.g., centrality, structural holes), dyad-level (e.g., tie strength, multiplexity), or network-level measures (e.g., density, size). For the purposes of calibrating a social program design and measurement tool, we need to look at how to measure all three anew, with particular attention to network-level measures that will be used to evaluate the program in network terms.

An extension of the techniques used in Chapter 5 would include additional metrics that would be helpful in evaluating social and economic development programs. Some suggestions for what these metrics might include are listed in Table 16.

Table 16

Some Proposed Measures for Program Evaluation

Type	Measurement	Description	Detail
Cluster-based	Cluster interconnection rate	To what degree predefined clusters connect with each other	Predefine groups (e.g., Chilean vs. non-Chilean) and measure how quickly and to what extent these clusters interconnect
Cluster-based	Rate of connections by node type	To what degree different types of nodes connect to each other	Measure to what degree entrepreneurs connect to each other versus investors, mentors, prospective employees, etc.
Time-based	Network growth rate	Rate of growth of the size of the network over time	How quickly is the overall network growing? How quickly are the clusters of interest growing during the incubation period?
Time-based	Overall density growth rate	Rate of increase of network density as members of the network meet each other	At what rate does the network grow denser? Does this compare to expectations?

Conclusion

One of the goals of this thesis is to unify the efforts of what Bogenschneider and Corbett (2010) term the *knowledge producers* (researchers) and *knowledge consumers* (policymakers). By applying techniques from computational social science to policy evaluation and design, we can create better social programs and spend wisely on policies that work. Use of these techniques will make measurement less costly and more timely, rendering program evaluation easier to integrate into social programs. We look forward to more research in this area, with the goal of improving the efficacy of social and economic programs through more accurate, granular, and timely metrics.

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Appendix A – LinkedIn Fields

Table 17 and Table 18 list the LinkedIn fields that are accessible through the API. LinkedIn allows developers to pull information about the company, education, and language of each participant. LinkedIn limits API access to these descriptive fields and to social ties and does not allow access to messages, posts, or other types of communication.

Table 17

Selected LinkedIn API Fields

Field	Parent node	Description	Notes
id	person	a unique identifier token for this member	This field might return a value of private for users other than the currently logged-in user depending on the member's privacy settings
first-name	person	the member's first name	This field might be omitted from some results depending on the member's privacy settings
last-name	person	the member's last name	This field might be omitted from some results or return a value of private, depending on the member's privacy settings
location:(name)	person	Generic name of the location of the LinkedIn member, (ex: "San Francisco Bay Area")	
location: (country:(code))	person	country code for the LinkedIn member	Lower case values as defined by ISO 3166-1 alpha-2 standard.

(continued)

Table 17 (continued)

Field	Parent node	Description	Notes
industry	person	the industry the LinkedIn member has indicated their profile belongs to (Industry Codes)	
num-connections	person	the # of connections the member has, as defined by those who have chosen to "connect" on LinkedIn	
num-connections-capped	person	true if the value of num-connections has been capped at 500. false otherwise.	Allows you to distinguish whether num-connections = 500 because the member has exactly 500 connections or actually 500+ because we're hiding the true value.
email-address	person	primary email address of user	
languages	person	A collection of languages and the level of the member's proficiency for each	See Languages Fields below
education	person	A collection of education institutions a member has attended, the total indicated by a total attribute	See Educations Fields below
date-of-birth	person	member's birth date	May return only month and day, but not year, or all three, depending on information provided.

Note. Data retrieved from LinkedIn website on March 21, 2015.

Table 18

Company, Education, and Language Fields

Field	Parent node	Description	Notes
id	position	a unique identifier for this member's position	
title	position	the job title held at the position, as indicated by the member	
start-date	position	a structured object with month and year fiel ds indicating when the position began	
end-date	position	a structured object with month and year fiel ds indicating when the position ended	Blank when the position is current
is-current	position	a "true" or "false" value, depending on whether it is marked current	
company	position	the company the member works for	
id	education	a unique identifier for this member's education entry in the database	
school-name	education	the name of the school attended , as indicated by the member	
field-of-study	education	the field of study at the school, as indicated by the member	
start-date	education	a structured object a year field indicating when the education began	
end-date	education	a structured object with a year field indicating when the education ended	Blank when the education is current

(continued)

Table 18 (continued)

Field	Parent node	Description	Notes
degree	education	a string describing the degree, if any, received at this institution	
id	language	A unique identifier for a single language in the list of languages	
language: (name)	language	A structured object specifying the language name	May be localized in the future
proficiency: (name)	language	A structured object specifying the user's fluency by name. ▪ Elementary proficiency ▪ Limited working proficiency ▪ Professional working proficiency ▪ Full professional proficiency	

Note. Data retrieved from LinkedIn website on March 21, 2015.

Appendix B – Interview Questions

Story of experience at Start-Up Chile

- How did your company come to be?
- How did you come to join Start-Up Chile?
- How did Start-Up Chile affect your company?
- Is the focus of the company Chile, Latin America, the Spanish-speaking world, global, home country, other?
- Generation at Start-Up Chile
- Current status of company
- Current status of employment with company

If non-Chilean: Integration into Chilean ecosystem

- Chilean employees, partners, investors, friends?
- How long did you stay in Chile? Did they settle permanently?

If Chilean: Integration into Start-Up Chile

- Non-Chilean employees, partners, investors, friends?
- Did you move to another country from Chile?

How did Start-Up Chile help your company? How did it help you integrate into the Chilean ecosystem (or the global ecosystem)?

Probe for involvement and evaluation of:

- Tribes
- Godfathers ("Padrinos")
- Multi-generational pairing

What improvements to Start-Up Chile or future similar programs do you recommend?

Appendix C – Selected Survey Questions

Generation at Start-Up Chile (or when you joined Start-Up Chile): *

Company name while you were at Start-Up Chile: *

Age:

Gender:

Educational attainment:

Network Goals
Is building an international network a key objective for you? *
- Extremely important
- Moderately important
- Somewhat important
- Neutral
- Not important
- Other:

Which is your top objective for your time in Start-Up Chile? *
- Building an international network
- Making a billion dollars
- Traveling and exploring Latin America
- Maximum social impact
- Other:[3]

How have you built your international network before Start-Up Chile? *
(Choose all that apply.)
- MBA program
- International youth network (e.g., Sandbox)
- Attend conferences
- Other accelerators/incubators
- Travel
- Couchsurfing/other social networks
- I don't have an international network
- Other:

What is the target market for your startup? *
(If the categories overlap, please select more than one.)
- Chile
- Latin America (excluding Chile)
- The Spanish speaking world

[3] Many participants filled in that they were building a prototype, setting up a business, or launching their first product, or similar. These were all grouped together and formed the second largest category of respondents to this question.

- India
- Europe
- China
- North America
- The English speaking world
- Your home country
- The world
- Other:

Social Network Usage

How often do you use LinkedIn? *

- Multiple times per day
- Daily
- Several times a week
- Weekly
- A few times a month
- Monthly
- Every once in a while
- Extremely rarely
- Never
- Other:

What do you use LinkedIn for? *

- Keeping track of professional contacts
- Keeping track of personal contacts
- Recruiting
- Business development
- Investors
- Press contacts
- I don't use LinkedIn
- Other:

How often do you use Facebook? *

- Multiple times per day
- Daily
- Several times a week
- Weekly
- A few times a month
- Monthly
- Every once in a while
- Extremely rarely
- Never
- Other:

What do you use Facebook for? *

- Keeping track of professional contacts
- Keeping track of personal contacts

- Recruiting
- Business development
- Investors
- Press contacts
- I don’t use Facebook
- Other:

Initial Network Properties
What is your nationality? *
(If you identify with more than one country, please check the box for all of the ones that apply)

- United States
- Canada
- Australia
- United Kingdom
- Chile
- India
- An African country
- Other Latin American country
- Spain
- Other Asian country
- Other European country
- China
- Brazil
- Russia
- Other:

Language Acquisition
What is your level of English proficiency? *
(If this is different for speaking/writing/listening, choose the one that is your lowest level of skill)

- Native
- Fluent
- Advanced
- Conversational
- Basic

What is your level of Spanish fluency? *
(If this is different for speaking/writing/listening, choose the one that is your lowest level of skill)

- Native
- Fluent
- Advanced
- Conversational
- Basic
- None

Start-Up Chile Involvement

How many Chilean employees did you hire?

How many Chilean contractors did you hire?

How many Chilean partners (businesses you worked with) did you hire?

How many Chilean investors did you formally pitch?

Did you ever incorporate in Chile?

- Yes
- No

Did you use any of the following features of Start-Up Chile? *

- Tribes
- Godfathers and godmothers (padrinos and madrinas)
- Investors
- Mentors

Follow-up

What are you up to these days? Are you still working on the company? *

Is the company still in existence? In what form? *