

SCALING UP FIRMS IN ENTREPRENEURIAL ECOSYSTEMS: FINTECH AND LAWTECH ECOSYSTEMS COMPARED

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15 January 2020

Acknowledgements

This research forms part of the research programme *Unlocking the Potential of AI in English Law* (<https://www.law.ox.ac.uk/unlocking-potential-artificial-intelligence-english-law>) and is funded by UKRI pursuant to the Next Generation Services Industrial Strategy Challenge Fund. We are grateful to Professor John Armour for early comments to shape the direction of this research, and to Agata Kapturkiewicz, and Tzvetan Moev, and Yi Tan for research assistance. The authors are solely responsible for all remaining errors.

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ABSTRACT

What factors drive the scaling up of firms in entrepreneurial ecosystems? We address this question by investigating whether startup founders' within-ecosystem social ties explain firms' relative success. We develop a novel database of startup companies and their founders in two markets (fintech and lawtech) and three locations (London, New York City, and San Francisco Bay Area), resulting in six ecosystems. We find that ecosystems with denser social ties experience faster growth and earlier timing for external funding. Within each ecosystem, startup founders with denser social ties achieve faster growth and earlier external funding. Thus, social ties are key metrics indicative of social capital, that can be captured at the ecosystem and individual levels. We suggest different ways in which these metrics can be computed and may be applied in a robust manner to all startups and ecosystems, with utility for entrepreneurs, investors, and policy makers.

KEYWORDS: Entrepreneurial ecosystem, social ties, network analysis, Fintech, Lawtech, Crunchbase, LinkedIn, Burning Glass.

JEL CODES: J24, L14, L16, L26, L84, L86, M13, O33

1. INTRODUCTION

Why do some startup companies scale up faster than others? Scholars, practitioners, and policy makers are paying greater attention to entrepreneurial ecosystems to address this question. Growing interest in ecosystems stems from a realization that the success or failure of entrepreneurial activities depends not just on entrepreneurs themselves but also on the infrastructure and other stakeholders in local communities. Regarding an entrepreneur, not as a solitary Schumpeterian “economic superman”, but as an agent embedded in a broader context, however, raises the question of how to capture this context. Some focus on specific components, such as the availability of funding for scaling up (Duruflé et al. 2017; Hellmann and Thiele 2019; MIT 2015). Others have conceptualized the whole context as an industrial district (Harrison 2007; Markusen 1996; Piore and Sabel 1984), a cluster (Feldman et al. 2005; Martin and Sunley 2003; Pitelis 2012; Porter 2000), and more recently an ecosystem (Autio et al. 2018; Donegan et al. 2019; Feld 2012; Spigel and Harrison 2018), with the last gaining traction not

least because of the attractiveness of the metaphor of an ecosystem as a self-organizing and self-sustaining habitat (Isenberg 2016; Sako 2018).

While a prominent place is given to entrepreneurs themselves to create an entrepreneurial ecosystem, extant literature tends to have a top-down focus to examine authoritative action by government or other powerful actors, for example to facilitate links with universities (Bell-Masterson and Stangler 2015; Feld 2012; Mack and Mayer 2016; Mason and Brown 2014).¹ This highlights the paucity of research that links entrepreneurs' action to the bottom-up characteristics of the ecosystems. What ecosystem characteristics do individual entrepreneurs then bring with them to shape ecosystems? And in what ways do such ecosystem characteristics explain why some startup companies scale up faster than others? We address these theoretical and policy-relevant questions by designing and developing a data-driven approach to comparing entrepreneurial ecosystems of digital technology startups, with metrics which are novel to this field of research.

Digital technology startups have the option to access remotely deployed resources (e.g. cloud computing) and distant customer markets. As a result, entrepreneurs potentially have more degrees of freedom in choosing the location of their new ventures. However, this seeming downgrading of the importance of location-specific resources is countered by other important resources specific to a local ecosystem, in particular social ties within the ecosystem. In this study, we propose startup founders' social ties within an ecosystem as metrics of ecosystem characteristics that entrepreneurs bring with them when they choose to establish a company in a specific location. We study relatively nascent ecosystems of startups that apply artificial intelligence (AI) to products and services in two professional service areas, namely financial and legal services, which we call fintech and lawtech respectively. We link three data sources

¹ Mason & Brown (2014) suggests combining a top-down and a bottom-up approach to promoting entrepreneurial ecosystems.

– Crunchbase, LinkedIn, and Burning Glass – to sample these startups and their founders in three locations, namely London, New York City, and San Francisco Bay Area. We find that founders’ social ties have positive impacts on company growth as measured by job vacancies and the timing of first external funding. We also find some evidence that the positive impacts are stronger in ecosystems with denser social ties.

Our study contributes to a data-driven approach to comparing entrepreneurial ecosystems in two ways. First, we identify social ties, as measured by past education and employment ties between founders, as a key determinant of start-up success. Furthermore, when aggregating social ties to the ecosystem level they represent measures that allows the comparison of different geographically bounded ecosystems with one another. In this way, we contribute to refining the theoretical foundation and concrete measures for a bottom-up evolutionary perspective on entrepreneurial ecosystems. Second, our approach paves the way for future work that includes the dynamic analysis of ecosystem development across time. With appropriate data access and collection, it will allow real-time analysis of the development of ecosystems. It will also provide insights into the most opportune types of ties and the optimal moment of tie creation. Such insights are invaluable for both policy and practice to stimulate vibrant and successful startup ecosystems.

The rest of the paper is structured as follows. In Section 2, we review the extant literature on entrepreneurial ecosystems with a view to developing our hypotheses. Section 3 explains the data and methods used, and Section 4 presents key findings. Section 5 discusses avenues for extensions of the current analysis with implications for theory and public policy, before Section 5 concludes.

2. ENTREPRENEURIAL ECOSYSTEMS: THEORY AND METRICS

Work on regional agglomerations such as industrial districts and clusters goes back to Alfred Marshall who stressed the benefits of co-location such as labor (and resource) pooling and knowledge spillover (Marshall 1920). Recent interest in entrepreneurial ecosystems builds on Marshall's insight on these co-location advantages in the context of the entrepreneurial opportunities afforded by digital transformation (Autio et al. 2018; Nambisan et al. 2019).

Because entrepreneurial ecosystems are defined with geographic boundaries, studying startups that exploit digital technology enables us to shed light on the relative importance of location-specific and location-agnostic factors. Digitalization, especially with the most recent wave of artificial intelligence fuelled by exponential growth in processing power and data availability (Brynjolfsson and McAfee 2014), provides new opportunities for entrepreneurship generally (Nambisan et al. 2019; Yoo et al. 2009) and for business model experimentation in particular (Armour and Sako 2020 forthcoming; Autio et al. 2018). Autio et al. (2018) focus on entrepreneurial ecosystems as systems for the discovery and pursuit of entrepreneurial opportunities. They go as far as stating that the main ecosystem benefit from digitalization lies in business model innovation, which implies being location-agnostic.

Digital technology startups have the option to access remotely deployed resources (e.g. cloud computing) and distant customer markets. As a result, entrepreneurs potentially have more degrees of freedom in choosing the location of their new ventures. In other words, digitalization affects the balance between what Autio et al (2018) call 'digital affordance' and 'spatial affordance' in entrepreneurial ecosystems.² However, this seeming downgrading of the importance of location-specific resources is countered by other important resources specific to a local ecosystem, in particular social ties within the ecosystem – the focus of this study.

² An affordance is defined as opportunities for action offered by an object (either digital technology or location) in a specific use context, i.e. what entrepreneurs can do with the digital technology or space (Nambisan et al. 2019).

This section reviews this literature on entrepreneurial ecosystems, defined as systems of entrepreneurial opportunity discovery and pursuit (Acs et al. 2014; Autio et al. 2018), with a view to developing hypotheses on the importance of social ties within digitally focused ecosystems.

2.1 Entrepreneurial ecosystem characteristics: the extant literature

It is fair to state that the notion of an entrepreneurial ecosystem has arisen, not from academic discourse, but initially in policy-making circles (Isenberg 2010). This conceptual origin accounts in part for the primary causal direction of interest, from ecosystem characteristics to entrepreneurial action. For instance, governments may create incubator or accelerator facilities and university programs to accelerate startup births and scale-up in a locality. Measures to characterize the entrepreneurial ecosystem abound, for example, by Babson Entrepreneurial Ecosystem Project (Isenberg 2011; Isenberg 2010), Kaufman Foundation (Bell-Masterson and Stangler 2015) and World Economic Forum (WEF 2013). Such exercises in developing ecosystem measures, unfortunately, end up with a rather long list,³ without much attention to how each measure may interact with another. At the end of the day, every component or characteristic becomes a moving part within a system. For example, Mason and Brown advocated combining top-down and bottom-up approaches to promoting an entrepreneurial ecosystem, defining it as *“a set of interconnected entrepreneurial actors...institutions... and entrepreneurial processes which formally and informally coalesce*

³ The Babson Project lists 12 key components or domains of a healthy entrepreneurial ecosystem, namely financial capital, success stories, social norms, non-government institutions, support professions, infrastructure, educational institutions, labor, networks, early customers, leadership, and government. Kaufman Foundation proposes three measures each for density, fluidity, connectivity, and diversity as indicators of entrepreneurial ecosystem vibrancy. World Economic Forum identifies, via a survey of entrepreneurs who are Stanford University alumni, eight components of accessible markets, human capital, and funding & finance, support system, regulatory framework and infrastructure, education and training, major universities as catalysts, and cultural support as both important for the success of start-up companies and for explaining differences across ecosystems around the world.

to connect, mediate, and govern the performance within the local entrepreneurial environment” (Mason and Brown 2014).

The extant academic literature on entrepreneurship has grappled with multiple levels of analysis, ranging from studies about individual entrepreneurs’ personality traits (Rauch and Frese 2007), to organization-level research about founding teams and the impact of external funding (Hellmann and Puri 2002; Hellmann et al. 2019; Van de Ven et al. 1984). Ecosystem-level studies are an extension in this spectrum of analytical levels, in order to respond to a greater awareness of the need for a broader perspective that recognizes the role of social, cultural, and economic forces in the entrepreneurial process (Spigel and Harrison 2018). Recent research about entrepreneurial ecosystems draws on a variety of theoretical traditions in economic geography (Storper and Scott 1995), studies of innovation systems (Lundvall et al. 2002), and technology strategy (Jacobides et al. 2018; Teece 2017).

2.2 Entrepreneurs’ social capital and social ties

In order to develop a theoretical foundation and metrics that link ecosystem characteristics to individual startup firms and their founders, we focus on what Stam and Spigel (2016) call “systemic conditions” such as network characteristics of talent, finance, and support services, which arise from individual entrepreneurs’ activities. They are in contrast to the “framework conditions” of physical infrastructure which are independent of entrepreneurs. In particular, these “systemic conditions” may be conceptualized using the lens of social capital (Adler and Kwon 2002; Burt 1997; Nahapiet and Ghoshal 1998). Social capital is the “goodwill available to individuals...(whose) source lies in the structure and content of the actor’s social relations” (Adler and Kwon 2002:18). Individuals may develop external ties that generate “bridging” forms of social capital to facilitate exchange. They may also develop social capital via “bonding” ties within the firm. The relational dimension of social capital is based on trust and norms of reciprocity that create “expectations that bind” (Nahapiet and Ghoshal 1998).

This allows individuals to gain access to resources and information through networks (Adler and Kwon 2002; Leana and Pil 2006).

In the context of entrepreneurial ecosystems, past and current network ties that entrepreneurs bring into and retain within an ecosystem are indicative of the amount of social capital that they possess. Social capital facilitates access to talent and finance, by lowering search cost for identifying sources of talent, finance, and other essential resources such as mentoring and professional support services (e.g. accounting and law services to register and grow the business). At the cutting edge, social capital facilitates access to dealmakers, namely individuals with valuable social capital, who have deep fiduciary ties within the ecosystem and mediate relationships, make connections, and facilitate new firm formation (Feldman and Zoller 2012; Kemeny et al. 2015). Social capital also enables informal know-how trading (Von Hippel 1989), leading to knowledge spillovers (Breschi and Lissoni 2001; Jaffe et al. 1993). Shared knowledge includes knowledge about how to pursue and scale-up entrepreneurial opportunities (Autio et al. 2018). These features of social capital lead to accelerating the growth of firms within ecosystems.

Education and employment ties are good proxies for social capital within an entrepreneurial ecosystem. Research to date has focused on how educational background or prior employment experiences influence the orientation of entrepreneurs (Boeker 1988; Cumming et al. 2016; Donegan et al. 2019; Kato et al. 2015; Rider et al. 2019; Sarada and Tocoian 2019). But network ties based on education or employment are relatively novel constructs for entrepreneurship and entrepreneurial ecosystems. In particular, if a startup founder has other founders in the same ecosystem who attended the same educational institution, she could rely on either direct past contact or alumni networks to seek referrals. Similarly, if a startup founder has other founders in the same ecosystem who had worked for the same company at the same time, she could use her social capital for referrals of various

sorts. Both education and employment ties are useful for access to talent and funding, and to knowledge about the entrepreneurial process (such as opportunity identification and pitching for investment)(Spigel and Harrison 2018). Employment ties are additionally useful for accessing potential clients for a startup; an ex-employer, be it a bank or a law firm, might become an important first client for the startup.⁴ In short, social capital, as proxied by education and employment ties within an ecosystem, leads to faster firm growth as a result of better access to relevant resources and lower transaction costs. Moreover, we expect startups whose founders have denser social ties to have better mechanisms for signalling the quality of their company, thus leading to faster identification of potential investors. Once funded, investors also provide a valuable signalling function, soliciting inputs from other growth-facilitating professional service providers such as lawyers, recruiters, and consultants.

The above discussion leads to our first set of hypotheses:

H1: Startup founders who have more dense social ties within the ecosystem achieve faster company growth.

H2: Startup founders who have more dense social ties within the ecosystem receive their first external funding earlier.

2.3 Social ties at the ecosystem-level

We now move from considering social ties at the individual level to the ecosystem-wide network structure and its evolutionary nature. The aim is to examine the impact of the entire local entrepreneurial ecosystem, over and above the simple aggregation of individuals' social ties. The 'bottom-up' focus in studying entrepreneurial ecosystem adopted in this study highlights the importance of remembering that some ecosystem characteristics are endogenous, rather than exogenously given, created by entrepreneurs themselves. This is especially the case

⁴ Arguably, two startup founders with employment ties may compete, rather than cooperate. The tension between competition and cooperation has been noted in earlier literature on clusters and industrial districts. But startups in digitally mediated entrepreneurial ecosystems face global competition which may be more important than competition from local peers.

in early stages of ecosystem evolution, as ecosystem infrastructure and characteristics may be under-developed or non-existent. Entrepreneurial ecosystems evolve over time through endogenous, bottom-up, and time-patterned processes (Thompson et al. 2018), because ecosystem evolution involves a process through which entrepreneurs acquire resources, knowledge, and support in order to establish themselves and scale up (Spigel and Harrison 2018). As a consequence, especially when approaching ecosystems through social ties, ecosystems will differ in nature at certain points in time and levels of maturity.

To date, attempts to develop a typology for the evolution of ecosystems have been “top down”, identifying the phases of emergence, growth, and decline (Mack and Mayer 2016), or the rise and fall of heterogeneity among firms through lifecycle stages (Menzel and Fornahl 2009). Autio et al. (2018) explicitly recognize the structural and process differences as ecosystems evolve from “stand-up” to “start-up” to “scale-up” stages. However, scholars generally acknowledge that we know very little about the lifecycle and evolution of entrepreneurial ecosystems and clusters (Autio et al. 2018; Braunerhjelm and Feldman 2007). One line of enquiry is not to trace the entire ecosystem lifecycle from emergence and growth to decline, but to distinguish between nascent and more mature ecosystems. In nascent ecosystems, firms co-create ecosystems and markets. The more nascent an ecosystem is, the less established the pre-existing ecosystem characteristics, and the more we need to focus on startups themselves as party to creating the ecosystem characteristics. Moreover, in nascent markets, when markets are “thin” or “nonexistent”, firms co-create markets and ecosystems (Pitelis 2012). In other words, particularly in nascent ecosystems and nascent markets, entrepreneurs pursue value creation and appropriation by contributing to the co-evolution of firms, markets, and ecosystems. For pioneering entrepreneurs, there are little pre-existing ecosystem advantages to exploit. By contrast, startups in more mature ecosystems can leverage and take advantage of pre-existing ecosystem characteristics including its social ties. Therefore,

as a nascent ecosystem evolves over time, with more members and more social ties, the salience of network ties within the ecosystem increases. This leads to our second set of hypotheses:

H3: The positive impact of startup founders' social ties on company growth is stronger in more densely networked ecosystems.

H4: The positive impact of startup founders' social ties on the timing of first external funding is stronger in more densely networked ecosystems.

3. DATA AND METHODS

This section justifies the choice of our empirical setting and presents our data sources, variables, and econometric specifications.

3.1 Empirical setting: why Fintech and Lawtech, and why the three locations?

We take a pragmatic approach in choosing our empirical setting and available metrics. We chose to study fintech and lawtech startups as companies with at most a history of just over a decade. They exploit opportunities created by digital technologies to adopting new business models to serve clients in pre-existing markets. Fintech and lawtech refer to digital innovations and technology-enabled business model innovations in the financial sector and the legal sector respectively. Such innovations facilitate disintermediation, revolutionize how existing firms create and deliver products and services, and provide new gateways for entrepreneurship. Examples of innovation in fintech include the use of cryptocurrencies, new digital advisory and trading systems, peer-to-peer lending, equity crowdfunding and mobile payment systems (Gomber et al. 2018; Lee and Shin 2018; Philippon 2016). Examples of innovation in lawtech include smart contracts using blockchain-based technologies; predictive coding in litigation support, legal research and contract analytics that make use of machine learning, and prediction of court decisions (Armour and Sako 2020 forthcoming; Becerra 2018; Katz et al. 2017; LegalGeek and ThomsonReuters 2019). It is clear that startups in fintech and lawtech leverage

the potential of similar digital technologies and artificial intelligence specifically to create new products, services, and platforms to service corporate and individual clients.

In terms of location, both London and New York City are large global cities with a concentration of professional services, classified as “alpha world cities” in a study of leading cities in professional services including finance and law (Beaverstock et al. 1999). They both have labor and financial capital pools, and proximate clients within the ecosystem in the form of financial institutions in the case of fintech startups, and law firms and corporate legal departments in the case of lawtech startups. The same study classified San Francisco as a “beta world city”, but of course the Bay Area is well known for its talent and funding pools for high tech ventures, with some headquarters for prominent corporate clients with financial and legal services needs.

3.2 Data and variables

Our empirical study is based on linking three datasets: first, names of startup companies and their founders from Crunchbase; second, the educational and employment backgrounds of founders from LinkedIn; and third, online job vacancy postings from the internet, tracked by Burning Glass Technologies (henceforth Burning Glass).

Crunchbase is a “leading platform for professionals to discover innovative companies, connect with the people behind them, and pursue new opportunities”. We used ‘Fintech AND AI’ as search terms in each of the three locations (London, New York City, and San Francisco Bay Area); similarly, we used ‘Legaltech’ (but without ‘AI’ as a search term to increase the number of companies identified) in the three locations as well. On 6 November 2019, when Crunchbase was accessed, we identified 199 fintech firms and 137 lawtech firms. These firms formed the basis of our study cohort. Further interrogations of Crunchbase revealed that these cohort companies had a total of 609 founders and / or co-founders, of whom 401 were founders / cofounders of our fintech cohort and 208 were founders of our lawtech cohort. As both the

fintech and lawtech ecosystems are nascent, only a small number of firms had an exit. We have 12 firms which have been acquired and 5 firms which have been closed.

LinkedIn is a well-known “social network that focuses on professional networking and career development.” Although its usage varies from location to location, many users are professionals who use the site to link to other professionals for the purpose of advancing their career and identifying work and business opportunities. Therefore, LinkedIn profiles generally feature past education and work experiences, as well as skill sets. For these reasons, LinkedIn is ideal for identifying the educational profile and the employment career profile of individual start-up founders. For the fintech and lawtech (co-)founders identified in Crunchbase, we developed a database of the universities attended, and names of employers for whom each founder had worked prior to establishing their startups.

Burning Glass Technologies, an analytics software company, scrapes job postings from the internet. Every day, the firm checks a corpus of more than 40,000 online job boards and company webpages to find new job vacancies. Burning Glass then parses and deduplicates the job vacancies into a machine-readable form. This process extracts up to 70 standardised fields from vacancies, including occupation, geography, skill requirement, firm identifier and salaries. The broad coverage of the database represents a significant improvement over single source databases, such as Reed.co.uk or the Labour Force Survey. But a notable shortcoming is the exclusion of non-online vacancies, and the share of jobs advertised online changes over time, with the corpus of job boards and company webpages that the firm collects data from also varying over time. Notwithstanding such shortcomings, we are able to count the number of online job vacancies advertised since 2010 in the United States and since 2012 in the United Kingdom for the fintech and lawtech startups identified in Crunchbase.

Our final sample consists of 531 founders, after dropping those founders who were misclassified or without LinkedIn profiles.

Dependent variables

We use two scale up measures for startup ventures. First, the average annual number of job vacancies posted by a startup and, second, the time it takes each startup to get funded. We count the total number of job vacancies that each firm posted online, as captured by Burning Glass, from January 2010 to November 2019 in the US and from January 2012 to November 2019 in the UK. The variable “scale up” (*scaleup*) is a dummy that equals one if the firm features in the top 20 percent of jobs posted per year within the location-specific ecosystem and zero otherwise. The *scaleup* threshold varies substantially between ecosystems: they range from fintech firms in San Francisco with a threshold of 6.20 jobs, to lawtech firms in London with a threshold as low as 0.2 jobs.

Our second measure for startup success is composed out of the variable *funded*, which is a dummy indicating whether the startup has received external funding, and if it did, the timing of its first external funding. The latter variable acts as the duration variable in a cox regression model. From a founder’s perspective, it is desirable to win external funding, ideally shortly after the firm is founded, in order to hire more staff and to further scale the firm. We use Crunchbase to identify the date the firm was founded and the date on which the first external funding was announced. The duration variable “years until first external funding” (*yearsToFunding*) measures how many years founders await their first funding. The median start-up gets funded after 338 days. Fintech firms get funded earlier, after 288 days, compared to the overall median value of 348 days for all firms to win initial external funding. If a start-up firm does not get funded until November 2019, the duration variable is equal to the number of days between the date the firm was founded and the 30st of November 2019, the cut-off date for the data collection of our study. We pre-filter the data to remove all records where “years until first funding” are smaller than 7 days or larger than 10 years.

Social ties and social network ties

Our main variables of interest are social ties and social network ties of founders within our six ecosystems. We define three measures of direct social ties, namely “educational ties” (*eduTies*), “employment ties” (*empTies*) and “co-founder ties” (*coTies*), and two measures that further take into account the structure of the social network, namely “educational network ties” (*eduNetTies*) and “employment network ties” (*empNetTies*). All network ties stem directly from the LinkedIn profiles of startup founders within each ecosystem, specifically their past education and employment histories.

Educational ties are created by two or more founders of an ecosystem attending the same university, although not necessarily at the same time.⁵ Since highly ranked universities, which founders usually attend, have well developed alumni organisations that host regular meetings in global hubs, such as New York, San Francisco and London, the past membership at the same university is usually associated with regular interactions with other alumni. The universities sending the highest proportion of students to the fintech ecosystem are Stanford (25 people), Harvard (18 people), Columbia (12 people), Massachusetts Institute of Technology (12 people); similarly, the feeder universities for the lawtech ecosystem are Stanford (21 people), Berkeley (7 people), Harvard (7 people) and Oxford (7 people). Our *eduTies* variable is a dummy variable which is coded one, if the number of educational ties is larger than two. The list of most frequent universities suggests that founders disproportionately recruit from highly selective universities. By formulating the education tie variable *eduTie* as a dummy, we construct a social tie which is less correlated with the reputation of a university, alleviating concerns regarding omitted variable bias related a founder’s abilities driving the relationship between educational ties and scaling up.

⁵ LinkedIn data on the years in which founders have attended university are sparse, which around half of the educational history missing a timestamp. Therefore, we do not require founders to have attended university at the same time for educational ties.

The “employment ties” are formed when two or more founders of an ecosystem have worked for the same company and at the same time before they launched their startup. For the fintech ecosystem, founders have worked most frequently at Google (26 people), Morgan Stanley (14 people) and Microsoft (12 people). In contrast, lawtech past employers are more diverse, with Stanford University (13 people), Google (4 people) and Thomson Reuters (4 people) the most frequent mentions. In total we have 878 distinct past employers for lawtech founders and 1942 different past employers in fintech. The *co-founder* ties reflect current employment at a start-up firm and thus is a special case of an employment tie.

Our three direct social tie measures are further complemented with two additional measures which take the social network structure of the ecosystems into account more broadly: the *eduNetTies* and *empNetTies*. These variables are similarly constructed as the direct social ties, but instead of evaluating the total number of ties a founder might have we evaluate the total size of the greater cluster a founder is connected to. Motivation to include this metric is that it accounts for higher degree connections to the network, and not just one’s direct connections. To further illustrate this, consider the hypothetical case where two founders are solely connected to one other. In our main specification, both these founders would have the same connectivity measure (of one) as a third founder who is also directly connected to only one other founder, but through this founder is connected to many others. Figure A.1 illustrates this situation. In such a case, it might be argued that the latter is more embedded into the broader network than the former. We evaluate this second measure for both education and employment by using the size of the total cluster one is part of as the independent variable.⁶

INSERT FIGURE 1 ABOUT HERE

⁶ We also choose to combine co-founder ties and employment ties, because the former naturally has limited variability.

Finally, to evaluate the hypotheses H1 to H4, we aggregate our five network measures *eduTie*, *empTie*, *coTie*, *eduNetTies* and *empNetTies* into a single measure for social ties. We use principal component analysis to combine the five variables into *socialPCA* which is a linear combination of our disaggregated social tie measures that best preserve the covariance structure among them. The *socialPCA* variable is our composite and preferred measure to reflect the overall importance of social ties.

Further control variables

We include ecosystem level, firm level and individual level characteristics as additional control variables. As ecosystem level variables, we include location-specific ecosystem dummy variables. They pick up location-specific characteristics, including the regional culture in fostering innovation and entrepreneurship, that influences the development trajectory of local ecosystems (Saxenian 1996; Storper and Scott 1995). We include one location dummy variable per ecosystem.

Firm level control variables include “age of firm” (*age*) and “years until first external funding”. We use the latter variable as a dependent variable also. As a control variable, it determines the optimal timing for external funding for startup firms. Furthermore, we can estimate the effect of not obtaining funding within the first years on subsequent scale up probabilities. The “age of firm” variable counts the number of years since the startup has been founded.

Individual level control variables are i) an indicator for serial entrepreneurs called “prior startups” (*prior*) and ii) skills in legal, finance and coding (*skillLegal*, *skillFinance*, *skillCoding*). The “prior startups” variable is a dummy which is coded one if the founder had set up startups prior to this firm. We construct this variable from the job title of previous employments as extracted from the LinkedIn profile of the founder and counting the previous

job titles which contain the keyword ‘founder’. We define a serial entrepreneur as a person who has founded more than three organisations previously.

The “skill” variables are constructed from LinkedIn skill endorsements. Over 82 percent of founders have listed skills on LinkedIn and we use these skills to identify founders who are highly endorsed in legal, financial and programming skills. We define the “skill” variable as a dummy, which is coded one if more than three of the top 10 skillsets of an individual relate to the respective categorisation.⁷ Endorsement ties also measure social ties, yet for our sample, most endorsement ties were generated from co-founders and the remaining ones were too sparse to form meaningful social ties.

Table 1 contains the variable descriptions, and Table 2 presents the correlation matrix, and Table 3 descriptive statistics.

INSERT TABLES 1, 2 AND 3 ABOUT HERE

3.3 Econometric specifications

We test the hypothesis H1 using a logit model with the binary variable *scale up* as the dependent variable (McFadden 1974). We choose to work at an individual level, to increase our sample size. The logit model predicts the probability of scale up, based on our measures of social ties, the control variables and the location-specific ecosystem dummies. The model is specified as:

⁷ Keywords for legal skillsets are: law, legal, litigation, intellectual property, due diligence, mediation, international tax, chapter 11, procurement, prosecution, trials, contract, trademark, patent, liability, fraud, mediation. Keywords for finance skills are: finance, sales, commerce, financial, portfolio, economics, capital, payments, trading, account management, credit, investments, risk management, equities, structured products, mergers, equities, auditing, accounting, investment, insurance, hedge funds, fixed income, equity, market research, commodity, valuation, corporate governance, M&A, securities, acquisitions. Keywords for coding skills are: software, web, development, java, python, machine learning, cloud computing, R, computer science, CSS, jquery, artificial intelligence, ruby, analytics, data, signal processing, algorithms, distributed systems, linux, unix, bash, programming, enterprise architecture, programming, natural language processing, MATLAB, node, C++, C#, computer vision, semantic technologies, express, SQL, .NET, C, SAS, blockchain, ethereum, perl, bitcoin, git, HTML, hadoop, PHP, objective C, business intelligence, IOT, apache, androind, mongodb, HTML5, open source, eclipse, saas, data science, amazon web services, CSS3, Django, oracle, image processing, iOS development, rabbitmq, java enterprise, elasticsearch, predictive modelling, forecasting, apache, database design, data warehousing, cryptocurrency, high performance computing, pattern recognition, deep learning, ajax, angularjs.

$$\text{Logit}(\text{scaleup}_{ie}) = \mu_e + \beta_1 \text{socialPCA}_{ie} + \gamma \text{controls}_{ie} + \epsilon_{ie} \quad (1)$$

where the index i refers to the individual founder and the index e refers to the location-specific ecosystem. We cluster the standard errors of the coefficient estimates at the firm level. The temporal order of the formation of *employment* and *educational ties* before the decision to launch the venture alleviates concerns on endogeneity of our variable of interest. We can thus rule out that a successful scale up in turn resulted in better developed ties. Also note that *co-founder ties* are coterminous with the formation of new ventures but predate scaleup. Given the regression equation, the null hypothesis for H1 can be written as $H_{0,1}: \beta_1 = 0$. The alternative hypothesis is $H_{a,1}: \beta_1 \neq 0$.

Next, we evaluate whether social ties influence the venture's timing of obtaining external funding, which is formalised in hypothesis H2. We use the Cox proportional hazard regression, which uses *yearsToFunding* as its duration variable and *funded* as the dummy variable indicating survival. Cox proportional hazard regressions are used in the literature on start-up ventures to evaluate the exit options of venture capital firms (Giot and Schwienbacher 2007) and to study the hazard of obtaining outside funding (Cockburn and MacGarvie 2009). The Cox regressions are tailored to model durations that end with binary exits: the venture is either funded or unfunded. Unfunded firms introduce right censoring which occurs when a firm leaves our study before it obtained funding. While OLS regression models of *yearsToFunding* drop right censored data, in Cox regressions, these observations contribute to the time at risk until the final sampling date.

Our Cox proportional hazards regression model can be written as:

$$h(t) = h_0(t) \exp(\mu_e + \delta_1 \text{socialPCA}_{ie} + \gamma \text{controls}_{ie}) \quad (2)$$

where $h(t)$ is the expected hazard of obtaining external funding at time t , $h_0(t)$ is the baseline hazard and represents the hazard when all of the predictors are equal to zero. Given the

regression equation, the null hypothesis for H2 can be written as $H_{0,2}: \delta_1 = 0$. Our alternative hypothesis is $H_{a,2}: \delta_1 \neq 0$.

To assess the hypothesis H3 and H4, which posit a bigger impact of social ties on scale up and the time to obtain external funding in better developed ecosystems, we introduce interaction terms of social ties with the ecosystem dummy variables for fintech and lawtech. Founders in fintech ecosystems in San Francisco, New York and London exhibit more social ties than in their respective lawtech ecosystems. We therefore test if the regression coefficients for social ties in fintech is larger than their counterpart in lawtech.⁸ The regression specification is therefore:

$$\text{Logit}(\text{scaleup}_{ie}) = \mu_e + \phi_1 \text{socialPCA}_{ie} 1_{fintech} + \phi_2 \text{socialPCA}_{ie} 1_{lawtech} + \gamma \text{controls}_{ie} + \epsilon_{ie} \quad (3)$$

where $1_{lawtech}$ is a dummy variable which is one if the individual is part of the lawtech ecosystem. The null hypothesis for H3 can be written as $H_{0,3}: \phi_1 = \phi_2$. The alternative hypothesis is then $H_{a,3}: \phi_1 \neq \phi_2$. The null hypothesis for H4 follows correspondingly.

4. ANALYSES AND FINDINGS

Before presenting regression results, some descriptive statistics of our variables are provided, as well as network graphs of the various ecosystems.

4.1 Descriptive statistics

As Figure 2 demonstrates, both fintech and lawtech startups are nascent, originating only in the last decade and a half. Comparing the two tech sectors, the fintech ecosystem “took off” around 2015, accelerating in the number of startups being founded at a more rapid rate than lawtech startups.

⁸ Ideally, we would wish to test whether changes in the social tie density over time in an ecosystem affects the coefficients. See Section 4 for further elaboration.

As a first test of our general research focus, Figure 3 contains a comparison of how social ties are related to the number of job vacancies across the six ecosystems. As shown, at a first glance, the ecosystems with denser social ties are associated with both higher proportions of firms that scaled⁹, and larger overall numbers of job vacancies in the ecosystem.

Figure 4 gives the Kaplan-Meier survival curves estimated from the outcome variable *funded* and the explanatory duration variable *yearsToFunding*. The data is grouped by ecosystem and location. Here, “survival” means failure to attract external funding, and the survival functions plot the fraction of firms that have yet to receive funding as a function of time elapsed since they were founded. As can be seen from the figure, fintech firms receive funding earlier than lawtech firms. Furthermore, San Francisco firms receive funding earlier than London firms. New York firms, in most cases, receive funding the latest. The proportion of unfunded firms is only at around 20 percent five years after the ventures were launched, probably due to some form of pre-selection of startup firms by Crunchbase.

INSERT FIGURES 2, 3, AND 4 ABOUT HERE

4.2 Network graphs and statistics

Figure 5 presents the network graphs for each of the ecosystems and are meant to give a first insight into the overall shape of the network of social ties per ecosystem. In each graph, individual founders are represented by nodes. Vertices between nodes indicate a social tie between two founders, driven by shared education and/or employment between the two. The size of each node is governed by our continuous dependent variable of interest – the number of job vacancies – with larger nodes indicating a higher number of vacancies. Node sizes thus provide an indication of the location of successful founders within each network.¹⁰

⁹ Scale-up in Figure 3 is defined as the firm hiring on average more than one person per year.

¹⁰ Network graphs have been produced using Gephi 0.9.2 (Bastian, M., S. Heymann, M. Jacomy. 2009. Gephi: an open source software for exploring and manipulating networks *Third international AAAI conference on weblogs and social media.*) and visualizations are driven by the Force Atlas 2 algorithm (Jacomy, M., T. Venturini, S. Heymann, M. Bastian. 2014. ForceAtlas2, a continuous graph layout algorithm for handy

As can be seen from each ecosystem's network graph, the overall connectedness is largest in the San Francisco ecosystems and least so in the London ecosystems. This difference can be formalized by a number of network statistics presented in Table 4. The *average degree* statistic represents the average number of social ties per founder, with fintech ecosystems generally having higher average degree values and San Francisco having higher values overall. The *graph density* statistic provides a measure of the overall connectedness of the network. Formally it is calculated as the percentage of all actual connections in the network relative to the total of all possible connections (if every node was connected to one another). Again, the San Francisco ecosystems have the highest network density, whereas there is no clear dominance in density between lawtech and fintech networks. Finally, the *modularity* statistic provides an indication of the division of the network in separate partitions of cluster of well-connected nodes. A positive value of the modularity statistic indicates that there is more groupings present in the network than would be expected by chance, given the number of nodes and ties in the network. The higher the value of the modularity, the stronger these clusters are connected with each other relative to other clusters in the network. As can be seen, there is clear clustering present throughout the ecosystems, but substantially more in the case of the London and New York ecosystems.¹¹

INSERT FIGURE 5 AND TABLE 4 ABOUT HERE

With respect to our research interest, a consistent pattern arises regarding the location of successful founders within each network. Isolated founders are rarely among the more successful founders in the ecosystem. Nonetheless, there are numerous examples of (as of yet) unsuccessful founders being quite central in each network. Especially the San Francisco fintech

network visualization designed for the Gephi software. *PloS one* 9(6) e98679.) for varying parameter settings to generate each individual graph.

¹¹ Louvain modularity is used in calculating the modularity values (Blondel, V.D., J.-L. Guillaume, R. Lambiotte, E. Lefebvre. 2008. Fast unfolding of communities in large networks. *Journal of statistical mechanics: theory and experiment* 2008(10) P10008.).

ecosystem shows some extremely well-connected individuals in prominent positions within the network. This could be a result of the networks as visualised here making no distinction between different types of ties, with any social tie being plotted. Regression results will have to point out whether some tie types are more important determinants of success than others.¹² Finally, it is interesting to note that the relative maturity of the fintech ecosystem relative to the lawtech ecosystem seems not to determine the general shape of the networks. Instead, location seems to be a much stronger determinant of the overall connectedness and shape of the various ecosystems, especially with both fintech and lawtech ecosystems in San Francisco Bay Area being surprisingly well-connected. Note that similar network graphs are presented in the Appendix where only education (A.1) and only employment (A.2) ties are considered.

4.3 Regression results

Table 5 summarizes the results of estimating equation (1). The estimated effect of *socialPCA* on the probability of scaleup is positive and significant. This indicates that entrepreneurs are significantly more likely to scale their venture, if their tie-density within the ecosystem is high. This result supports hypothesis H1.

We decompose social ties into its five constituent components and run a regression for each of the tie measures. The average marginal effect of having more than 2 education ties on scale up probabilities is 10 percent. Having graduated from a university from which other founders within the ecosystem have graduated helps with the scale up of the venture. The effect of doubling the number of employment ties is an eight percent increase in the scale up probability. Having worked at large organisations, that have a history of nurturing up and coming entrepreneurs can increase the odds to scale. Doubling co-founder ties increases scale up probability by 15 percent. Being able to rely on co-founders and to benefit from their

¹² Figures A.1 and A.2 in Appendix show network graphs for each ecosystem based on education and employment separately, which form the basis for our network measures (our eduNetTies and empNetTies variables).

network and relationships help a firm scale. The effect of educational networks is positive but insignificant, which is possibly due to the very extensive nature of educational networks (again, see Appendix Figures A.1 and A.2 for network graphs for employment and education separately). Doubling the size of employment network ties increases the chances for scale up by 4 percent. The magnitude of the effect of employment network ties is less than the employment ties, suggesting that direct social ties are more beneficial to scaleup than indirect ties.

In Table 5, the coefficients on our controls emphasize the following four points. First, the age of the firm has a positive probability on scaleup. A firm twice the age has on average a 25 percent higher probability to scale. This age effect could be driven by an exponential growth in employment at startup firms after a certain time threshold is surpassed. Second, the average marginal effect of being a serial entrepreneur is negative and significant. Founders with more than four job titles containing the keyword ‘founder’, have on average a 14 percent lower probability to scale a firm.¹³ The result may change, if we consider the type of exit from the previous venture. Founders which had a successful exit may well have a higher probability to scale another venture. Third, the effect of skill sets on scale up probabilities reveal a surprisingly significant negative effect of legal skillsets. Founders who are highly endorsed for their legal skillsets have a 19 percent lower probability to scale a firm. For coding and finance skills the effect is positive, yet insignificant. Fourth, we use a quadratic term to study the effect of the timing of first external funding on scale up success. We find that the best time to win external funding is exactly one year after the formation of the firm. The results suggest that there are costs associated with winning funding too early in the lifecycle of a startup. Firms

¹³ An explanation for the negative relationship could be the tendency of a small subset of founders to exaggerate their past experience on their LinkedIn profile, by listing themselves as founders of many organisations, which, however, usually are small and obscure organisations.

that win external funding one year after their inception have a 20 percent higher probability of scaling up.

Table 6 summarizes the results of estimating equation (2). The results in the first column suggest that social ties are not only important for the scale up of firms, but they also significantly affect the moment in which startups obtain external funding. Founders with better developed social ties on average win funding earlier.

Decomposing the drivers within social ties, we find that two measures are significant. First, co-founder ties and second, employment network ties. Moving from one to two co-founders increases the hazard to obtain funding by 18 percent. Similarly, increasing the employment network from ten to twenty people increases the funding hazard by another 15 percent. While well-developed social ties help founders to attract external funding earlier, getting funding too early can also hurt subsequent scaleup, with the optimal timing for external funding being one year after the inception of the firm. Overall, the regression results from Table 6 support our hypothesis H2, which posited that startup founders who have more dense social ties within the ecosystem receive their first external funding earlier.

From our set of five control variables, only the age of the firm is significant. For every year that passes, the probability of a firm to get funding decreases substantially by 50 percent. This result suggests that founders who were unsuccessful in attracting funding within the first few years of their venture, should consider a reboot of their career.

To sum up, our estimates support our expectation that the role of social networks is important to scale startup ventures and for winning external funding. Founders who have attended educational institutions and who worked for firms where other ecosystem members hail from before deciding to start their firm have, on average, a substantially higher chance to scale their firm with external capital. It takes the right social connections to build a company from scratch. Furthermore, among the strongest type of social tie is a co-founder tie. A co-

founder does not only bring into the firm complementary skill-sets and experiences, but also contributes his own social network, which can vastly expand the number of indirect ties available to the founder.

INSERT TABLES 5-7 ABOUT HERE

Moving on to evaluate hypothesis H3 and H4, we use the interaction term from equation (3). For each of the three locations, London, New York and San Francisco, we find that the fintech ecosystem has denser social ties than the corresponding lawtech ecosystem. Table 4 showcases the different network characteristics per ecosystem. We thus compare whether there is a different effect of social ties on scale up in the densely connected fintech ecosystems as compared to the more loosely connected lawtech ecosystems.

Table 7 displays the results. We find support for hypothesis H3. First, we establish that the social ties are significant to explain scale up in fintech ecosystems. Second, we note that the effect of social ties on scale up is significantly lower in lawtech than it is in fintech. The results suggest that the positive association between social ties and the likelihood of scaleup varies based on the density of ties within the ecosystem as a whole. One explanation is the positive externalities of social ties, where the usefulness of ties grows exponentially with the aggregate number of connections within the ecosystem. As social ties can be an important source for new ideas for innovation and information of opportunities, the spread of ideas and information is faster in networks that exhibit in the aggregate higher levels of connectiveness. We cannot reject the null hypothesis for H4. While there is a negative coefficient on the interaction term, indicating a weaker relationship between social ties and the time to get external funding, the coefficient is not significant. We conclude that our two dependent variables, *scaleup* and *yearToFunding*, while both related to social ties, nevertheless exhibit idiosyncrasies in their determinants.

4.4 Robustness checks

Education ties and employment ties may proxy for the founders' human capital (having attended good universities or worked at top-tier firms) as well as their social capital. While it is difficult to pin down which skill-sets are the most useful to founders (we only established that legal skills are especially helpful), it is even more difficult to gauge whether the human capital accumulated at highly ranked universities is of a type of knowledge that helps firms scale.¹⁴ By contrast, human capital accumulated at previous employers may be more directly relevant for startup founders. We therefore test for the separate effects of human capital and social capital by running regressions that drop the top five previous employers of fintech and lawtech entrepreneurs.

Table 8 showcases the results of our robustness checks. We find that social ties retain their significance in both the Logit model and the Cox regressions. We conclude that our results are not driven by the human capital that accumulates at the most popular employers for the entrepreneurs in our ecosystems.

There are two further checks that we could make but which we have not carried out for this study. One is to consider co-founder heterogeneity. Instead of a simple variable *coTies* (the number of co-founders per firm) that we employ, we could develop a measure of co-founder skill heterogeneity (for example, by looking at the skills endorsed) to see if startup founding teams with diverse and complementary skills perform better (see Section 5.2 below for further research on this). This would contribute to further separating out the human capital of co-founders from their social capital.

¹⁴ A prominent proponent of the idea that entrepreneurs should avoid university altogether is Peter Tiehl, a successful entrepreneur from the San Francisco ecosystem. He established the Thiel Fellowship to encourage young students to drop out of college prematurely, or even avoid university education all together to become more successful innovators and entrepreneurs. Former Harvard President Larry Summers disagrees and said that using philanthropic dollars to tempt people to drop out of college is a very dangerous idea.

Last and not least, our study evaluates the ecosystems at the end of 2019 for all firms, so that we do not account for connectivity measured at different stages of development of startup firms. A good robustness check may involve interacting the variables of interest – social ties or social network ties – with the age of the firm, and recalculating social tie variables in, say, five-year intervals and run the regressions for all firms active per each five-year interval.

INSERT TABLE 8 ABOUT HERE

5. FURTHER ANALYSIS AND FUTURE RESEARCH

In this paper, we develop a framework for analyzing and comparing entrepreneurial ecosystems using startup founders' social ties as metrics proxying for social capital. We demonstrate empirically that founders' social ties, measured in a variety of ways, explain the success of their new ventures in terms of employment growth and early timing of first external funding. A focus on within-ecosystem social ties is consistent with the process-based view that ecosystems are endogenously created from the fabric of social interaction and purposeful action within the system (Autio and Thomas 2016; Spigel and Harrison 2018; Thompson et al. 2018). We have furthered the empirical possibilities by collecting data and producing metrics that allow researchers to directly evaluate the importance of membership to an existing ecosystem in determining startup success. Our current study should be seen as a first attempt at collecting and combining relevant data sources in ways that allow the quantification of the importance of social ties. With clear signals in our results pointing at the relevance of social ties in explaining both external funding and the number of vacancies put out by a firm, there is clear merit in further building on this initial effort.

Given the exploratory nature of this study, there are some clear limitations to our current research setup. For example, there are potent ways of proxying for connectedness beyond our current social ties metrics. There are also other ways in which our measures could

be finetuned to provide ever more detailed insights to policymakers and practitioners on how ecosystem and start-up growth could be nurtured. We discuss below in two parts, specific ways in which our measures, methods and data could be developed further in future work: first, refining our current analysis to address additional questions with further data collection efforts; and second, related avenues of research to answer different, yet closely related questions.

5.1 Further unpacking social ties

The measures we propose evaluate the connections of a founder to others in an ecosystem based on shared employment and/or education. There are three ways in which we envisage building on this initial measure: i) by improving our proxy for connectivity and including a taxonomy of connection types, ii) by collecting connectivity measures across time to allow temporal analyses, and iii) by increasing the scope of connectivity to include multiple ecosystems per founder.

First, we based our current measures of connectivity on the publicly accessible LinkedIn profiles of individuals. Although shared employment and education episodes are logical proxies for a connection between individuals, full access to LinkedIn's database would allow ties between individuals to be determined more precisely. Having worked at the same firm at the same time and/or studying at the same university might not be sufficiently indicative for all cases of an actual tie between two individuals. Using explicit profile-to-profile connections would address this issue. Full access to LinkedIn's database (or by enriching our current data with other online data, e.g. Twitter) would allow messaging information between individuals to further determine the intensity of contact between individuals. We can then weigh ties and distinguish those founders who actively reach out to their peers from passive ecosystem members. We might also identify a general taxonomy of ties as a potent avenue of future research. For example, using the self-listed skills for which founders are endorsed, we

can classify ties by skill types, for example to analyze whether a coder-to-coder or coder-to-lawyer connection might have greater impact on start-up success.

Second, our current measures have been collected at a single point in time. But collecting the measure at different points in time would open up the possibility to evaluate at what stage a connection was made. This would allow an analysis of the importance of existing connections to an ecosystem prior to entry vis-à-vis generating new connections to an ecosystem after entry. A temporal analysis could also provide insights into the most important moment when having connections to the ecosystem is relevant. For example, it could be found that ecosystem connectivity is essential within the first 12 months of the start of a company, providing invaluable insights for founders and investors. Such time-sensitive insights would assist policy makers in targeting and sequencing their policy instruments, adding concreteness to what is already known, that entrepreneurial ecosystems evolve with different components, characteristics, and outcomes becoming important at different stages (Feld 2012; Mack and Mayer 2016; Pitelis 2012; Thompson et al. 2018).

Third, our current scope has been limited to the fintech and lawtech ecosystems. Already comparing these two ecosystems, we have seen differences in the nature of connections and importance of ties across these ecosystems. Clearly, this raises questions about the nature and relevance of social ties in ecosystems outside of fintech and lawtech and we identify similar analyses for other ecosystems as a logical follow-up. Further to this point, however, our current analysis has been focused on the relevance of connections to the ecosystem one is entering, i.e. connections to individuals *within* one's own ecosystem. Another important extension could be to include measures of connectivity *outside* one's own ecosystem. Within the context of start-ups, connections to ecosystems of venture capitalists or financiers immediately springs to mind as a logical 'outside' ecosystem where additional measures of connectivity might be fruitful for start-up success.

5.2 Related avenues of research

Beyond social ties being an important predictor of startup growth, there are a number of promising avenues of research that further build on the data we collected and are in line with our overall research goal of generating insights into the determinants of start-up success. We identify three such avenues of research: i) aggregating our analysis to the firm level, ii) switching focus to the conditions under which individuals decide to become a founder of a start-up, and iii) changing the outcome variable of interest to include different moments along a start-up's developmental trajectory.

First, individual founders have been our main level of analysis, but of course some of these founders join forces as co-founders when establishing ventures. Aggregating to the firm level is a logical extension of our work, because individual founders may specialize and thus founder ties may be differentially important dependent on one's role in a founding team and the networks of other co-founders. Characteristics of the founding team – the degree of heterogeneity in skills among co-founders for example – have already been found to affect the trajectory of startups (Ensley et al. 2006; Hellmann et al. 2019)^[10]. We might study the impact of joint social ties of a co-founding team, including to one another, on firm-level success. We might also interact social ties and specific co-founder traits (such as skills endorsed), to determine, for example, if larger networks may be of limited added value for co-founders with certain content-focused skills like coding.

Second, we have been interested so far in identifying the importance of social ties for startup success. To proxy for social ties, we have collected extensive information on founders' past work experiences and education. A logical and relevant question to ask is which types of individuals are more likely to become a founder in the first place. Such an analysis would require a valid control group of individuals who have (as of yet) decided *not* to become a founder, which could be generated relatively easily by sampling from similar educational

institutions or firms which the founders in our database have attended. Further investigating this tendency to become a founder along the different locations and ecosystems could provide insights into the varying conditions under which individuals may or may not be tempted to become a founder, providing invaluable information for policy makers in generating startup friendly environments.

Third, our analysis has focused on employment growth and early timing of first external funding as measures of the success of start-ups. As we found throughout our analyses, there were subtle differences between these dependent variables and there might be a number of other outcomes of interest along the developmental trajectory which would provide important nuances to our findings. For example, alternative outcomes could include actual employment growth (rather than vacancy growth), the total amount of funding received (rather than the timing of first funding), performance indicators (like cash flow, profitability, customer base, international expansion), and successful exits.

6. CONCLUSION

Entrepreneurial ecosystems provide a forum for theorizing and analyzing about the importance of social capital that accrue to individual founders. This study focused on within-ecosystem social ties of startup founders as a key metric to explain the relative success of their ventures, thus contributing to a ‘bottom-up’ process-based theory of entrepreneurial ecosystems. Our approach involved collecting and combining relevant data sources in ways that allow the quantification of social ties, measured in different ways. Our study is very much a first attempt, but our initial results and the mapping out of a number of avenues for further analysis and research has given us much confidence that there is great value in developing our social tie measures further and using them as the source of valuable insights. This data-driven approach will undoubtedly provide essential information for policymakers in shaping entrepreneurial ecosystems, as well as for founders in making their startup succeed further.

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Table 1: Variable description and data sources

	Variable	Variable description	Data source
1	scaled	Dummy variable which is one if the firm has hired more than 1 person per year on average.	Burning Glass
2	yearsToFunding	The number of years between the date the first external funding was announced and the date the firm was founded. This variable is capped at 800 days, when the variable is used as a regressor.	Burning Glass
3	funded	Dummy variable which is one if the firm has received external funding.	Crunchbase
4	eduTies	Dummy variable which is one if the founder went to the same university as at least three other founders in the same ecosystem.	Crunchbase
5	empTies	The number of other founders of the same ecosystem, who worked at the same firm as the founder in overlapping time periods prior to forming the startup.	LinkedIn
6	coTies	The number of co-founders within the startup.	LinkedIn
7	eduNetTies	The number of other founders within the same ecosystem, that the founder is connected to via direct and indirect educational ties. In this context, an educational tie is formed if two founders have attended the same university. Indirect ties include the ties of arbitrary number of intermediate founders.	Crunchbase
8	empNetTies	The number of other founders within the same ecosystem, that the founder is connected to via direct and indirect employment ties. In this context, an employment tie is formed if two founders have worked for the same firm at overlapping time periods before launching their start-up. Indirect ties include the ties of an arbitrary number of intermediate founders.	LinkedIn
9	age	The number of years since the startup has been founded.	LinkedIn
10	prior	Dummy variable which is one if the founder has had more than four job titles containing 'founder' before launching his in-sample startup.	Crunchbase
11	skillLegal	Dummy variable which is one if the founder has more than three legal skill endorsements within his top 10 skill sets.	LinkedIn
12	skillCoder	Dummy variable which is one if the founder has more than three coding skill endorsements within his top 10 skill sets.	LinkedIn
13	skillFinance	Dummy variable which is one if founder has more than three financial skill endorsements within his top 10 skill sets.	LinkedIn

Table 2: Correlation matrix (N = 531)

	1	2	3	4	5	6	7	8	9	10	11	12	13
1	1.00	0.07	0.28	0.13	0.14	0.23	0.09	0.17	0.29	-0.01	-0.08	0.09	0.08
2	0.07	1.00	0.13	-0.04	0.06	0.14	-0.02	0.08	-0.20	0.03	-0.07	0.04	0.05
3	0.28	0.13	1.00	0.09	0.08	0.17	0.09	0.16	0.05	0.00	-0.09	0.07	0.03
4	0.13	-0.04	0.09	1.00	0.19	-0.04	0.62	0.10	0.10	0.03	0.15	0.03	0.06
5	0.14	0.06	0.08	0.19	1.00	0.09	0.18	0.44	-0.01	-0.01	0.02	0.16	-0.03
6	0.23	0.14	0.17	-0.04	0.09	1.00	0.09	0.38	-0.17	0.09	-0.05	0.08	0.04
7	0.09	-0.02	0.09	0.62	0.18	0.09	1.00	0.17	0.02	0.06	0.05	0.06	0.00
8	0.17	0.08	0.16	0.10	0.44	0.38	0.17	1.00	-0.07	0.06	-0.20	0.20	-0.01
9	0.29	-0.20	0.05	0.10	-0.01	-0.17	0.02	-0.07	1.00	-0.07	0.05	0.01	0.00
10	-0.01	0.03	0.00	0.03	-0.01	0.09	0.06	0.06	-0.07	1.00	-0.03	-0.09	-0.04
11	-0.08	-0.07	-0.09	0.15	0.02	-0.05	0.05	-0.20	0.05	-0.03	1.00	-0.18	-0.09
12	0.09	0.04	0.07	0.03	0.16	0.08	0.06	0.20	0.01	-0.09	-0.18	1.00	-0.23
13	0.08	0.05	0.03	0.06	-0.03	0.04	0.00	-0.01	0.00	-0.04	-0.09	-0.23	1.00

Table 3: Descriptive statistics

		mean	std	min	max
1	scaled	0.24	0.43	0	1
2	yearsToFunding	215.54	253.42	0	775
3	funded	0.69	0.46	0	1
4	eduTies	0.34	0.47	0	1
5	empTies	1.15	2.27	0	16
6	coTies	1.42	1.29	0	9
7	eduNetTies	18.18	22.79	1	62
8	empNetTies	29.18	35.08	1	93
9	age	4.59	2.62	0.26	11.98
10	prior	0.36	0.48	0	1
11	skillLegal	0.10	0.29	0	1
12	skillCoder	0.23	0.42	0	1
13	skillFinance	0.15	0.36	0	1

Table 4: Network statistics

		Average degree	Graph Density	Modularity
San Francisco	Lawtech	6.28	0.09	0.39
	Fintech	8.64	0.06	0.47
New York	Lawtech	2.83	0.03	0.64
	Fintech	4.44	0.04	0.63
London	Lawtech	2.50	0.05	0.72
	Fintech	3.74	0.03	0.64

Table 5: Logit model on the probability of scale up

	Logit model: probability of scale-up					
	(1)	(2)	(3)	(4)	(5)	(6)
Social ties						
socialPCA (log)	0.33** (0.16)					
Social ties decomposition						
eduTies		0.68** (0.29)				
empTies (log)			0.56** (0.26)			
coTies (log)				1.23*** (0.46)		
eduNetTies (log)					0.10 (0.12)	
empNetTies (log)						0.35** (0.15)
Control Variables						
Age (log)	2.00*** (0.63)	1.99*** (0.64)	2.06*** (0.61)	2.22*** (0.63)	2.02*** (0.64)	2.04*** (0.62)
prior	-24.54*** (0.43)	-19.20*** (0.44)	-19.61*** (0.43)	-20.05*** (0.52)	-25.36*** (0.43)	-21.90*** (0.42)
yearToFunding	2.85*** (0.99)	2.80*** (1.00)	2.82*** (0.98)	2.44** (1.04)	2.82*** (1.00)	2.60** (1.03)
yearToFunding ^2	-1.45*** (0.53)	-1.41*** (0.53)	-1.45*** (0.53)	-1.24** (0.55)	-1.43*** (0.53)	-1.31** (0.54)
skillLawyer	-1.93** (0.82)	-1.99** (0.81)	-1.85** (0.80)	-1.86** (0.84)	-1.83** (0.82)	-1.79** (0.81)
skillCoder	0.41 (0.33)	0.41 (0.33)	0.33 (0.32)	0.33 (0.34)	0.43 (0.31)	0.32 (0.34)
skillFinance	0.47 (0.38)	0.46 (0.39)	0.42 (0.43)	0.48 (0.37)	0.5 (0.39)	0.48 (0.40)
Location-specific ecosystem intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	531	531	531	531	531	531
R2	0.18	0.18	0.19	0.21	0.17	0.19

Notes: Standard errors are clustered at a firm level and are displayed in parentheses: * p<.1, ** p<.05, ***p<.01. For Logistic Regression, the R2 measure uses McFadden (1974)'s pseudo-R2.

Table 6: Cox regression models on the duration of startup to get external funding

	Cox model: years to funding					
	(1)	(2)	(3)	(4)	(5)	(6)
Social ties						
socialPCA (log)	0.39*** (0.13)					
Social ties decomposition						
eduTies		0.16 (0.12)				
empTies (log)			0.16* (0.09)			
coTies (log)				0.18*** (0.05)		
eduNetTies (log)					0.10 (0.13)	
empNetTies (log)						0.15** (0.06)
Control Variables						
age (log)	-0.51*** (0.19)	-0.55*** (0.18)	-0.52*** (0.18)	-0.45** (0.18)	-0.54*** (0.18)	-0.51*** (0.19)
prior	-0.07 (0.36)	-0.21 (0.38)	-0.18 (0.38)	-0.48 (0.31)	-0.22 (0.38)	-0.09 (0.34)
skillLegal	0.03 (0.27)	0.06 (0.27)	0.08 (0.27)	0.05 (0.26)	0.09 (0.27)	0.1 (0.26)
skillCoder	0.14 (0.13)	0.19 (0.13)	0.17 (0.13)	0.18 (0.13)	0.2 (0.13)	0.13 (0.14)
skillFinance	0.22 (0.17)	0.21 (0.18)	0.22 (0.18)	0.21 (0.17)	0.22 (0.18)	0.22 (0.17)
Location-specific ecosystem intercepts	Yes	Yes	Yes	Yes	Yes	Yes
Sample size	531	531	531	531	531	531

Notes: Standard errors are clustered at a firm level and are displayed in parentheses: * p<.1, ** p<.05, ***p<.01.

Table 7: Logit and Cox regressions on the probability of scale up and the years to first funding with interaction terms on social ties

	Logit model: probability of scale up	Cox model: years to funding
	(1)	(2)
Social ties		
socialPCA (log)	0.07** (0.03)	0.45*** (0.14)
socialPCA (log) * lawtech	-0.10** (0.05)	-0.36 (0.31)
Control Variables		
age (log)	0.25*** (0.06)	-0.49*** (0.19)
prior	-0.13*** (0.05)	-0.07 (0.35)
yearToFunding	0.40*** (0.15)	
yearsToFunding^2	-0.20** (0.08)	
skillLegal	-0.16*** (0.06)	0.1 (0.30)
skillCoder	0.1 (0.05)	0.1 (0.14)
skillFinance	0.07 (0.07)	0.05 (0.21)
Location-specific ecosystem intercepts	Yes	Yes
Sample size	531	531
R2	0.17	

Notes: Standard errors are clustered at a firm level and are displayed in parentheses: * p<.1, ** p<.05, ***p<.01. For Logistic Regression, the R2 measure uses McFadden (1974)'s pseudo-R2.

Table 8: Robustness check: Logit and Cox regressions on the probability of scale up and the years to first funding without the top 5 feeder organisations for employment ties

	Logit model: probability of scale up	Cox model: years to funding
	(1)	(2)
Social ties		
socialPCA (log)	0.50*** (0.19)	0.71*** (0.21)
Control Variables		
age (log)	2.65*** (0.66)	-0.51** (0.21)
prior	-22.45*** (0.57)	0.01 (0.30)
yearsToFunding	3.58*** (0.98)	
yearsToFunding^2	-1.71*** (0.53)	
skillLegal	-1.90** (0.93)	0.1 (0.28)
skillCoder	0.3 (0.39)	0.2 (0.15)
skillFinance	0.42 (0.44)	0.15 (0.17)
Location-specific ecosystem intercepts	Yes	Yes
Sample size	421	421
R2	0.24	

Notes: Standard errors are clustered at a firm level and are displayed in parentheses: * p<.1, ** p<.05, ***p<.01. For Logistic Regression, the R2 measure uses McFadden (1974)'s pseudo-R2.

Figure 1: Social ties and social network ties, illustrated

Note: For the two dark green nodes, the former variable has the value 1 for both, whereas the for the latter variable, all node in the left-hand cluster have the value 17 and all nodes in the right-hand cluster have the value 2.

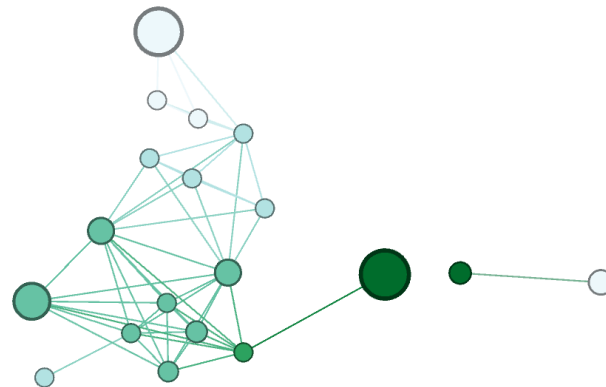


Figure 2: Cumulated number of fintech and lawtech startups in our sample

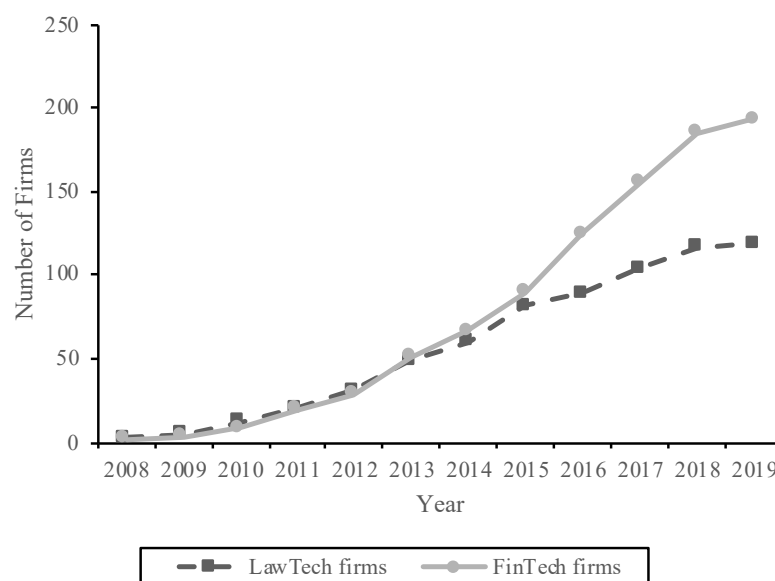
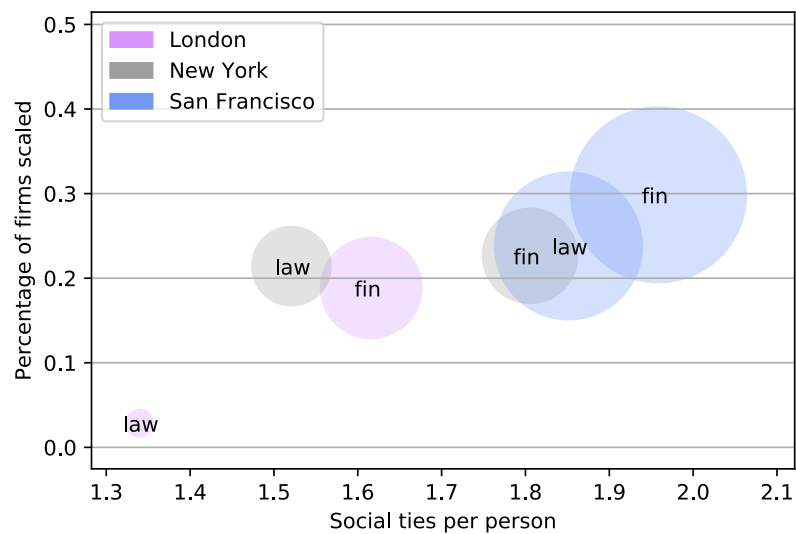


Figure 3: Bubble plot of the relationship between social tie density and job vacancy growth for the six ecosystems



Note: the size of the circle is proportionate to the total number of online job vacancies generated by a location-specific ecosystem. In this chart, a firm scaled, if it has on average posted more than one vacancy per year.

Figure 4: Survival functions for the hazard of obtaining external funding

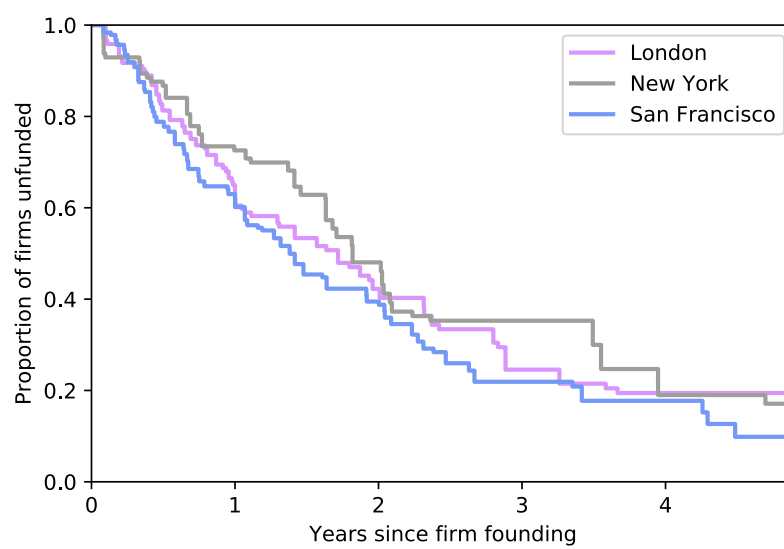
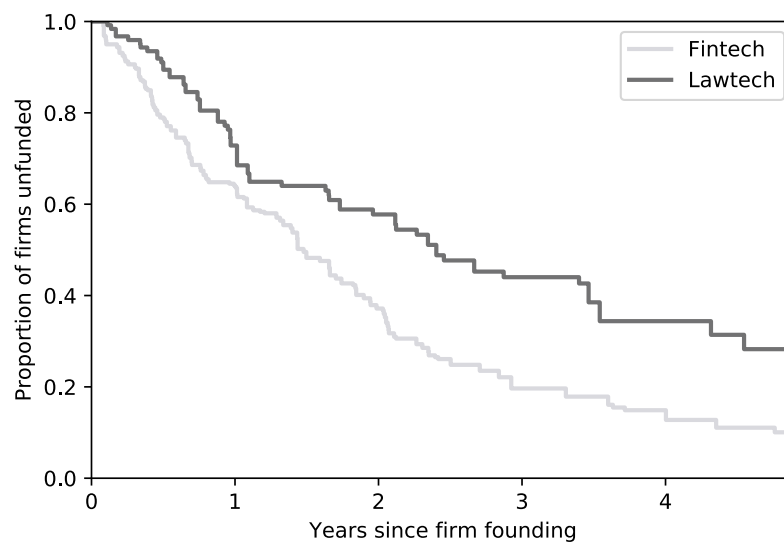


Figure 5. Network Graphs

Note: the size of the balls indicates the number of vacancies that a firm has posted. The sizes are normalised by ecosystem and should not be compared between ecosystems.

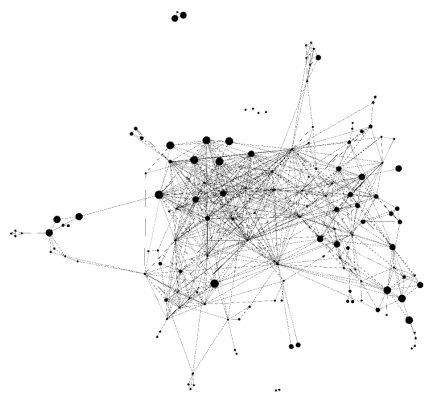


Fig 5a. San Francisco fintech

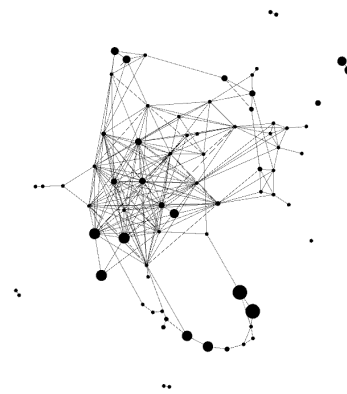


Fig 5b. San Francisco lawtech

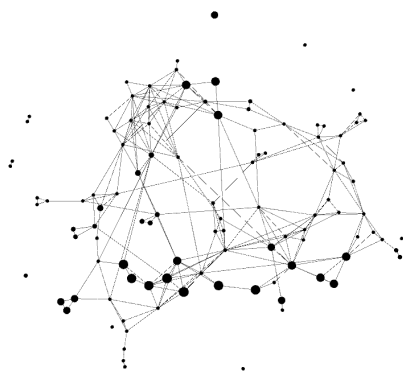


Fig 5c. New York fintech

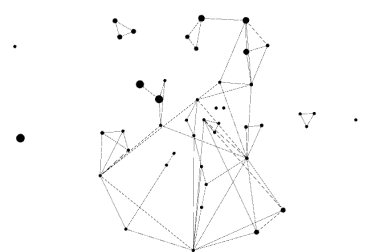


Fig 5d. New York lawtech

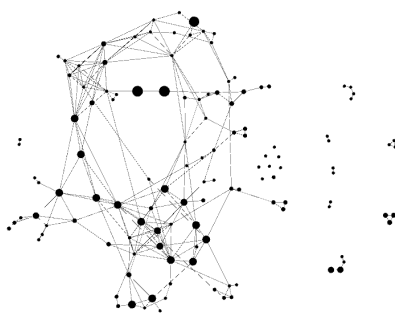


Fig 5e. London fintech

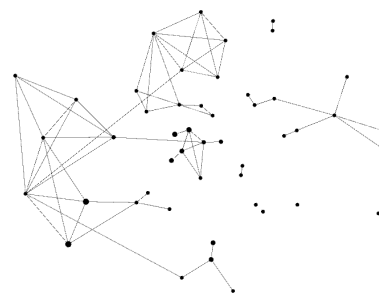


Fig 5f. London lawtech

Appendix

Figure A.1. Network Graphs by Education Ties

Note: the size of the balls indicates the number of vacancies that a firm has posted. The sizes are normalised by ecosystem and should not be compared between ecosystems.

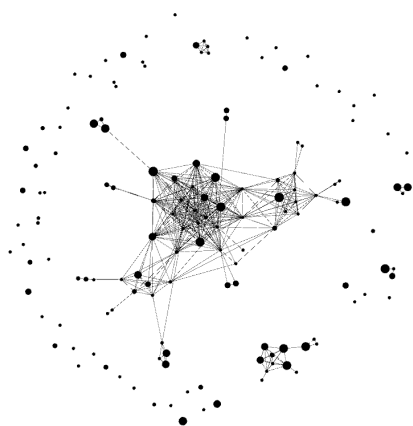


Fig A.1a. San Francisco, fintech

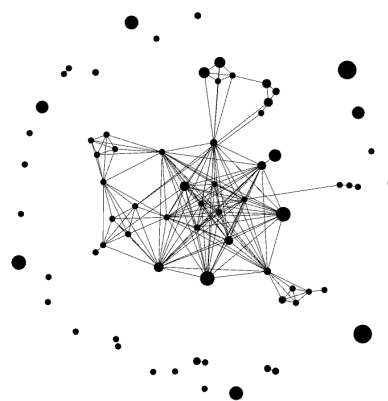


Fig A.1b. San Francisco, lawtech

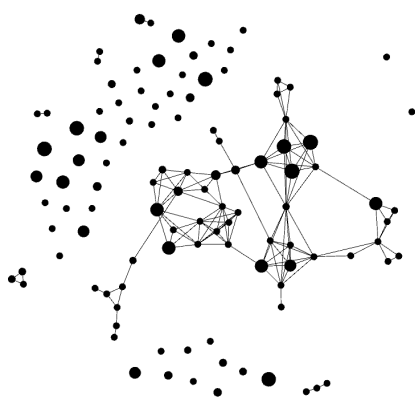


Fig A.1c. New York, fintech

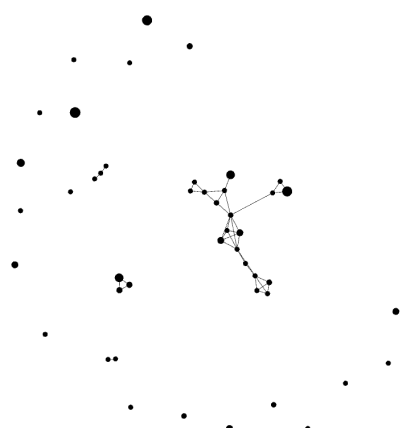


Fig A.1d. New York, lawtech

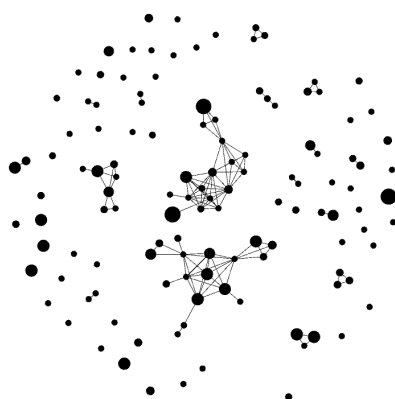


Fig A.1e. London, fintech

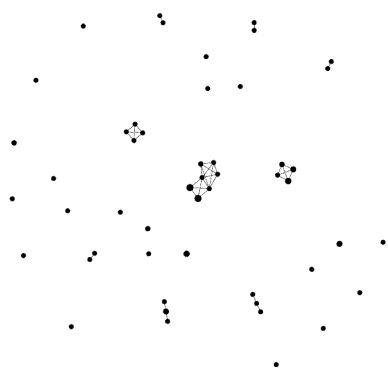


Fig A.1f. London, lawtech

Figure A.2. Network Graphs by Employment Ties

Note: the size of the balls indicates the number of vacancies that a firm has posted. The sizes are normalised by ecosystem and should not be compared between ecosystems.

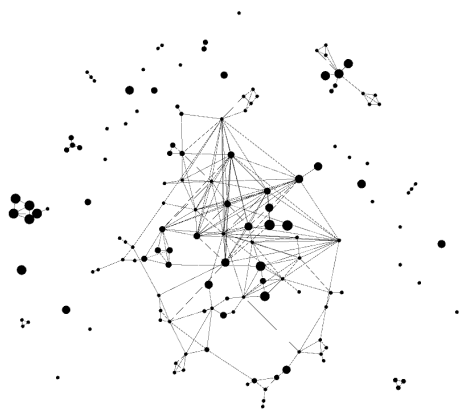


Fig A.2a. San Francisco, fintech

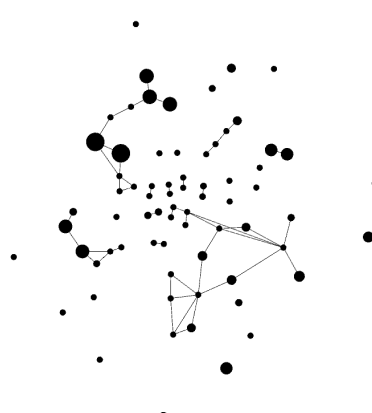


Fig A.2b. San Francisco, lawtech

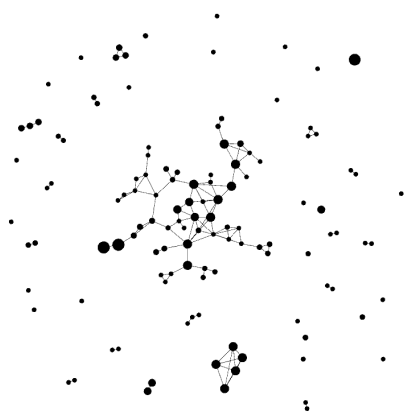


Fig A.2c. New York, fintech

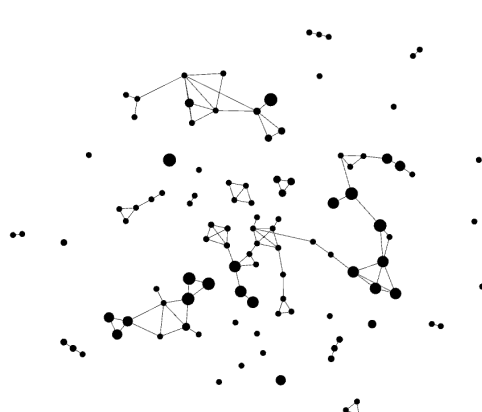


Fig A.2d. New York, lawtech

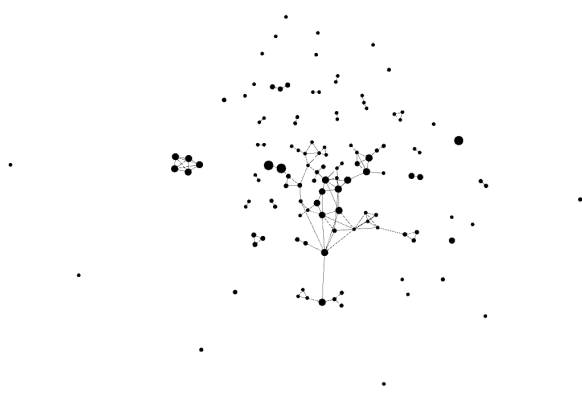


Fig A.2e. London, fintech



Fig A.2f. London, lawtech