The London School of Economics and Political Science

Social networks and the geography of innovation

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Declaration

I certify that the thesis I have presented for examination for the PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not infringe on the rights of any third party.

I declare that my thesis consists of 56,015 words.

Statement of conjoint work

I confirm that chapter 1 was jointly co-authored with Neil Lee and Michael Storper (LSE, Geography & Environment) and I contributed 70% of this work.

Augustin Boey

Abstract

This thesis examines the relationship between city-regional networks and the geography of innovation in the UK. Social and economic networks are vital to the economic vitality and creative dynamism of cities. They are the social infrastructure connecting individuals, ideas, and places--bringing them together in novel and more productive ways—and generating opportunities to advance the technological frontier. The complex patterns linking individuals and communities also affect performance by unevenly structuring access to economic opportunities. Network diversity at the city-regional scale likewise contributes to divergent local development by constraining prospects for cluster growth and technological upgrading.

Social networks are broadly acknowledged as the locus of high-technology innovation. Unfortunately, insight into the causes and mechanisms underpinning the social gains of city-regional networks remains thin: networks with open structure are pervasively thought to underpin high-tech cluster success, yet this critical assumption has remained unexamined; the roles and contributions of networked individuals on regional innovation has yet to be systematically studied; and the question of how new high-tech industries at the cutting-edge emerge vis-à-vis networks in related industries has not received sustained examination. Moreover, the empirical literature has focused on a relatively limited set of prominent agglomerations—partly due to a lack of appropriate relational data to construct city-regional networks—leaving open questions of generalizability beyond these settings.

This thesis makes five substantive contributions towards remedying these research gaps. First, it integrates emerging large-scale data sources and develops novel datasets to build and analyse UK city-regional networks. Second, it examines the impacts of highly connected individuals – ‘dealmakers’ – on local performance, finding a causal effect of regional dealmakers on innovativeness productivity. Third, it evaluates their asymmetric roles relative to other actors in importing externally sourced knowledge

into city-regions. Fourth, it systematically revisits foundational claims about the importance of open networks in sustaining highly innovative places. It develops a new measure of network openness by synthesizing complex multidisciplinary debates. It finds a causal effect of open networks on subsequent high-tech growth – the findings also suggest limits to open network effectiveness. Fifth, it provides a first empirical examination of emerging frontier industries focusing on fintech, exploring how much of its development has been shaped by antecedent capabilities and the social organization of regional finance and digital economy industries. The findings suggest that open network structures in the disrupting antecedent industry drive new industry growth.

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Introduction

1. Preface

Innovation is seen as an important motor of long-run economic development. Yet it is highly geographically concentrated. Some cities can be highly innovative ‘social reactors’ – complex interconnected networks that concentrate the critical mass of human capital, information, resources, and diverse opportunities for interpersonal interaction required for creativity and knowledge-intensive innovation processes (Bettencourt, 2021; Storper & Venables, 2004). In an era of unprecedented urbanization and global interdependence, urban innovativeness is key to sustainable human development and prosperity for billions worldwide (Acs et al., 2002; Asheim & Meric, 2005; United Nations, 2015; Feldman & Storper, 2018). However, the question of how metropolitan economies can become highly innovative and sustain high levels of innovation remains unsettled.

Urban economists and economic geographers often attribute city-regional innovative capacity to broad structural determinants and antecedent technological trajectories (Feldman & Florida, 1994; Glaeser, 1998; Kenney, 2000; Boschma & Frenken, 2012). Yet, scholars studying the organization of social systems emphasize the importance of connectivity between heterogenous agents interacting on social and economic networks as the wellspring of innovative capacity (Saxenian, 1994; Powell et al., 1996; Eagle et al., 2010). By bringing a diversity of individuals, ideas, and places together, urban social networks provide a dynamic relational context for collective learning and knowledge creating processes, and institutionalized differences in their intensity and structure shape the innovativeness of local economies (Bathelt et al., 2004; Spigel, 2017; Granovetter, 2017; Storper, 2018). A growing multidisciplinary body of work thus recognizes the importance of both city-regional colocation and place-based socioeconomic networks for the success of high-tech and highly innovative agglomerations.

Place-based social networks are seen as highly important for the geography of innovation. Influential analyses have drawn largely on the US technology sector, and on the concentration of digital technology industries around Silicon Valley in particular. Although the focus on leading US high-technology clusters does not necessarily generalize to other urban systems, this has nonetheless contributed to a 'pervasive folklore' about the economic benefits of place-based social networks (Kemeny et al., 2016) that persists partly due to the lack of appropriate relational data sources to construct city-regional networks. The lack of systematic studies on role of socioeconomic networks in the entrepreneurial and technological dynamism of cities outside the usual empirical settings thus remains an obstacle to rigorous understanding and effective policy. While the importance of effective place-based social networks for the entrepreneurial and technological dynamism of cities is now widely acknowledged, many fundamental questions about what 'effectiveness' entails and implies remain little understood.

This thesis makes several substantive contributions to the literature on networks and the geography of innovation. It addresses the pervasive lack of available network data by developing a novel dataset that integrates emerging large-scale data sources with comprehensive administrative data on the universe of all companies in the UK. This newly constructed data allows me to build a comprehensive city-regional network at the scale of an entire major advanced economy beyond the US, thereby giving me a highly-detailed lens into the regional role of localized social networks in both established and emerging high-tech industries. I train this lens on functional UK regions in all four of the papers in this thesis, as we are interested primarily in the system-wide regional impacts to innovation rather than the average impact for individual firms, as the latter does not necessarily aggregate to the former due to the potential social gains of networking (Fleming et al., 2007). My approach is interdisciplinary, bringing together complex multidisciplinary debates while also developing a novel empirical approach that integrates causal inference with social network analysis. Overall, the unique combination of these elements enables me to systematically assess—for the first time, to the best of my knowledge—influential claims about the role of regional social networks that has become foundational to ongoing scholarly and policymaking debates. I likewise make novel contributions to unpacking the differential impacts of highly connected individuals on regional innovation dynamics. I also make a first empirical and analytical cut into the uneven local impact of the disruptive technological innovation from the so-called 'Fourth Industrial Revolution' by exploring the emerging geography of the nascent financial technology ('fintech') industry in the UK

2. Overview of the PhD

3.1 Paper 1 – Dealmakers, networks, and local innovation

Who are the critical actors in the innovativeness of local economies? What are their impacts on city-regional innovation performance relative to those from ordinary actors? Answering these questions is becoming increasingly salient as policymakers and practitioners turn towards explicitly ecosystemic and network-oriented approaches to innovation and strategic industrial development policy (Casper, 2012; Tech Nation, 2019; Audretsch et al., 2019; BEIS, 2021).

In the first substantive chapter in this thesis my co-authors, Neil Lee and Michael Storper, and I accordingly investigate the emerging debate on the regional role of so-called 'dealmakers' – highly-influential individuals deeply embedded within local economies (Feldman & Zoller, 2012; Kemeny et al., 2016; Pittz et al., 2021). The dealmakers literature focuses on corporate affiliation networks in leading US regions, and find that dealmakers, whom they define as individuals who are exceptionally well-connected in each cluster, play a disproportionately large role on regional- and firm-level the growth and innovativeness of high-tech firms compared to less well-connected actors.

However, there is a virtually complete lack of empirical evidence that these highly-influential actors play similarly economically significant roles in other, non-US, high-tech ecosystems. We develop a unique dataset using scraped public data on the universe of company board appointments in the UK and provide the first systematic analysis, and the first non-US assessment, of the relationship between dealmakers and regional patenting productivity in the life sciences and information technology, two widely-studied innovation sectors. Our findings are consistent with the intuitive idea that highly-connected individuals play important roles in the innovation performance of high-tech clusters. The instrumental variable analysis indicates that regions with more interconnected actors are more innovative, and that the number of inter-connections matters.

3.2 Paper 2 – Innovation in the pipelines: Dealmakers, non-local knowledge, and regional innovation

What are the relative roles and impacts of internal and external connectivity on local knowledge dynamics and innovation performance? And what are the relationships between these two different forms of social connectivity? Such questions animate longstanding debates in economic geography and the geography of innovation on the relative importance of localised linkages ('buzz') compared to wider linkages ('pipelines') (Bathelt, 2007; Bathelt et al., 2004, 2017; Bathelt & Glückler, 2011; Fitjar & Huber, 2015; Fitjar & Rodríguez-Pose, 2014; Li & Bathelt, 2018; Maskell, 2014; Maskell et al., 2006; Moodysson, 2008; Morrison et al., 2013; Tödtling et al., 2006; Trippl et al., 2009). Many uncertainties remain on how socially interacting individuals matter in buzz and pipeline dynamics, despite the manifest importance of interpersonal interaction in the transmission and diffusion of knowledge through region-spanning pipeline channels. Data availability limitations have thus far hindered efforts to systematically unpack how the effects of pipelines on knowledge creation are mediated by the network positions of the actors at the ends of pipelines.

To address this gap, I integrate the dealmakers and pipelines literatures and evaluate the extent to which innovation is due to external ‘pipeline’ connections from dealmakers to non-local networks compared to pipelines intermediated by ordinary actors, while controlling for the ‘buzz’ generated through locally clustered connections. Putting the previously separate dealmakers and buzz and pipelines literatures in contact is especially productive as it allows us to answer important but underexplored questions in both simultaneously. Whereas the first substantive chapter focused on the local impacts of highly-networked individuals versus ordinary individuals on innovation performance, the second chapter considers how dealmaking interacts with the effects on buzz and pipelines on regional patenting performance. More cogently, while the regional roles of regional dealmakers have been theorized (Feldman & Zoller, 2012; Storper, 2013; Kemeny et al., 2016), there has yet been sustained attention directed towards investigating potential mechanisms for dealmaker effects.

Using the novel dataset developed in Paper 1 allows me to construct localized social networks to systematically investigate how regional life science patenting performance is influenced by the structure of the connections between and across UK regions. The results suggest that the effects of pipelines on regional innovation depend on the network positions of the individuals they connect to. The overall results generally accord with the existing buzz and pipelines research and affirm the importance of external connectivity for cluster performance. The findings indicate that pipelines that are intermediated by dealmakers have an asymmetric enabling and catalysing effect on those that are connected to less influential individuals. I therefore conclude the chapter by discussing the policy implications of these asymmetric roles in importing externally sourced knowledge into city-region and highlight where my findings suggest substantive deviations from the recommendations put forth by the existing pipelines literature.

3.3 Paper 3 – Do open social networks foster high-tech growth?

How does social network structure impact local performance? How do geographical variations in social macrostructure shape the uneven geography of high-technology cluster growth? Scholars and policymakers worldwide have long been keen to understand the sustained innovation-led growth and dynamism of globally leading innovation clusters – most notably the Silicon Valley's high-tech industry (Piore & Sabel, 1984; Saxenian, 1994; Glaeser, 1998; Kenney & von Burg, 1999; Brown & Duguid, 2001; Acs et al., 2002; Storper et al., 2015; Ferrary & Granovetter, 2017). Emerging from this widespread interest is a central explanation that distinctively links open and flat socioeconomic networks and city-regional institutions to sustained gains to local innovation cluster performance (Boschma, 2005; Breschi & Malerba, 2005; Casper, 2007; Saxenian & Sabel, 2008; Chesbrough et al., 2014; Crescenzi et al., 2016; Huggins & Thompson, 2021). The idea that flatter and more open social networks in metropolitan regions underpin the technological and entrepreneurial dynamism of high-tech and knowledge-intensive industries has also become commonplace in innovation and local development policy worldwide (Nesta, 2019; BEIS, 2021).

This deep and widespread interest belies the fact that many uncertainties about open networks have not been systematically addressed despite the idea's growing global influence for over three decades. We still know little about the most fundamental questions – whether place-based open networks really matter for local high-tech performance and, if they do, when their benefits are likely to be economically significant. Moreover, the 'open networks' concept is fuzzily defined, and the lack of metrics that meaningfully quantify the key terms in this complex debate remains an obstacle to rigorous understanding and effective policy.

This paper therefore systematically examines the relationship between local network openness on high-tech growth. I inductively synthesize the conceptual kernel of open networks from the multidisciplinary literature and propose a formal definition that rigorously encapsulates the essential characteristics of open networks. In doing so, I lay the conceptual groundwork for further analyses by addressing the conceptual fuzziness and imprecision that has impeded further understanding of its effects and implications. I provide the first country-wide empirical analysis of the systemic impact of open networks on regional high-tech performance in a major advanced economy and show the wider impact of open social structure beyond the usual empirical setting in leading U.S high-tech clusters. The findings indicate that initial network openness in 2010 has a statistically and economically significant positive effect on employment growth in high-tech industries over the subsequent decade. Likewise, I also find similarly positive associations for digital tech — the subset of high-tech specifically focused on the digital economy. To test the idea that open networks have a causal effect on high-tech cluster growth, I instrument the measure of open networks using a novel measure of institutional openness and find a persistent causal link between open network structure and high-tech employment growth. This paper provides new evidence that suggest substantive limits to the importance of open networks, even when only science- and technology-oriented industries are considered, contradicting expectations based on the motivating literature.

3.4 Paper 4 – Open networks drive new industry success: antecedent industries and the emergence of UK fintech

How do new industries develop in local economies? A primary concern of economic geographers and urban economists has been to identify the sources of sustained city-urban development. This has motivated a burgeoning literature that has deeply enriched our understanding of the key role of urban environments with a diverse mix of economic activities and dense concentrations of highly-skilled workers for the growth of localized industries. However, considerably less attention has been accorded to investigating the emergence and development of entirely new industries. We have limited empirical understanding of budding industries at the technological frontier, and the broad structural factors that are widely seen to explain the growth of established industries leave much unexplained about the innovation infrastructure that support the emergence and development of new high-technology industries in local economies.

As such, I study the growth of financial technology (fintech), a major new industry, in the UK from 2010 to 2019. Fintech refers to financial services innovation through digital technological integration. Fintech entrepreneurs are frequently finance industry 'outsiders' that attempt to disruptively compete with incumbents in the financial services sector by transforming how financial services are used and provided (Goldstein, Wei & Karolyi, 2019). While fintech has been in the public spotlight, it remains an open question as to how it has developed, and how much its development has been driven by antecedent regional capabilities in finance and digital technology.

I provide a first empirical exploration of these questions by first developing a dataset that integrates big data sources and administrative data on the universe of UK firms and top employees. My results show that open networks in fintech's primary antecedent related industries in the finance and digital economy industries encourage regional fintech firm growth. The moderating effect of digital economy network openness on finance openness in fostering regional fintech entrepreneurship is robust to controls for specialization and absolute diversity. The evidence suggests that the growth of disruptive frontier industries might be biased towards regions that are already comparatively advantaged with open entrepreneurial networks in more technologically sophisticated antecedent industries.

3. Conclusion

Networks are seen as highly important to innovation. Many of the classic studies of Silicon Valley and other highly-innovative local economies focus on the role of networks (Storper et al., 2015). Yet this literature has developed largely on the basis of qualitative work and case studies of successful places. It has, to date, been hard to use quantitative data to investigate these issues. By developing a new dataset which integrates web-scraped data from emerging data sources with 'big data'-like characteristics and comprehensive administrative data on the universe of UK company directors, I have hoped to contribute to this literature. The results support, in general, the literature's emphasis on the importance of networks to innovation in local economies. However, they provide additional nuance to this view – by focusing on the openness of networks and the role of networks in the creation of entirely new sectors.

The consistent setting of all four papers on the social gains from place-based social networks at the city-regional level in the UK helps to address the pervasive tendency in the empirical literature to focus on leading high-tech clusters in the US. As such, these papers presented here thus also contribute to addressing concerns, about whether the systemic gains from place-based social networks might simply be idiosyncratic to the fairly limited set of leading high-tech clusters that are the typically in the literature, particularly through the quasi-experimental analyses in Papers 1 and 3. More importantly, Paper 3 also provides an important first step in dispelling the pervasive conceptual fuzziness and imprecision surrounding the idea of open networks that has only steadily accreted since Saxenian's (1994) seminal analyses. The novel findings in Paper 2 gained by putting the previously distinct dealmakers and pipelines and buzz literature into tension provide a fresh perspective on the role of distant connection for local innovativeness that also imply substantive differences that deviate from those established by the seminal studies. While the non-causal approach taken in Paper 2 mean that these findings must be seen as only indicative – and thus emphasize the need for further investigation – the integrative approach in Paper 2 nonetheless points to the potential gains to understanding that might be realized with a more sustained conversation between the dealmakers and pipelines literatures.

Cities are engines of innovation and unlocking their potential is key to sustained prosperity and human flourishing in an increasingly urbanized and interdependent world. The thesis opens up some new avenues for future research. While my dataset is novel and provides data on all UK directors, it only represents a partial view of networks. They will ignore other networks which are not included in Companies House and which may play an important role in innovation, such as networks of inventors (van der Wouden & Rigby, 2021). There is further work to do in investigating the formation of these networks, for example how some develop more open than others. Moreover, my research has not, so far, considered the role of policy in driving network formation. Future work may want to consider how government attempts to sponsor network creation affect structure and so innovation.

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Paper 1 – Dealmakers, networks and local innovation: evidence from the UK

Augustin Boey, Neil Lee, Michael Storper

Abstract

Networks are considered vital for processes of innovation and economic development. Recent research has focused on the particular role played by highly-connected corporate board members – sometimes called "dealmakers" – in the growth and innovativeness of high-tech firms in the US. Yet there is no empirical evidence on the importance of these influential actors in other high-tech ecosystems. This paper builds a unique dataset of highly-connected individuals in the UK by using scraped public data on the entire universe of company board of director appointments. In doing so, it provides the first analysis of the relationship between dealmakers and regional patenting productivity in the life sciences and information technology, two widely-studied and leading high-tech sectors, outside of the US. Our results are consistent with the idea that highly-connected individuals play an important role in innovation processes in these sectors. Instrumental variable analysis shows that regions with more interconnected actors are more innovative, and that the number of inter-connections matters.

1. Introduction

Networks have long been seen as important for innovation and economic development. They provide access to knowledge, capital, credibility, information, and reduce the transaction costs of doing business (Granovetter, 2005), all benefits which are particularly acute for innovation-intensive sectors which are reliant on technological novelty (Breznitz, 2013; Huggins & Thompson, 2015; Ascani et al., 2020). As a result, many of the classic studies of innovative places have emphasised the importance of networks. For example, Marshall (1920) highlighted the role of networks in sharing ideas in the industrial districts of northern England. In their classic work on the Third Italy, Piore and Sabel (1986) considered the growth of clusters of highly-networked groups of smaller firms, and the benefits of flexibility and adaptability that allowed. And more recent work has highlighted the importance of a thickness of social networks in the Bay Area in ensuring the growth of the high-tech economy (Storper et al., 2015).

However, while networks are generally seen as important some fundamental questions remain (Acs et al., 2017; Alvedalen & Boschma, 2017; Spigel et al., 2017). Empirical studies differ widely in what exactly they mean by 'networks', and often focus on explanatory variables that are not clearly substantively appropriate for discerning the effects of localized social structure. There is therefore little robust evidence for whether and how place-based networks matter for local economic success (Gordon & McCann, 2000).

One promising avenue of research here has been to focus on highly influential and widespread actors, often termed "dealmakers", that link companies to one another and to other kinds of actors such as in R&D and finance (Feldman & Zoller, 2012; Kemeny et al., 2016). In their conceptualization, dealmakers are highly influential individuals that leverage their connections and positional advantages in local social networks to "make things happen" (Senor & Singer, 2011). Quasi-experimental research using this definition has provided robust causal estimates of dealmaker effects on the fortunes of individual firms in high-tech sectors in the US (Kemeny et al., 2016), giving support to the overarching contention that "the anatomy of social networks matters significantly in determining the vibrancy of local entrepreneurial economies" (Feldman & Zoller, 2012).

The strength of this nascent literature is that it empirically reflects the common sense observation that certain individuals play disproportionate roles in networks. This agent-centred view of social networks then helps reflect this and, in doing so, makes the notion of networks more concrete (Fuhse, 2015; Lin, 2002; White, 2002). The distinctive ways in which these inter-agential relations are embedded within social networks constitute the institutional underpinnings of regional innovation systems, and are a persistent source of regional advantage in high-tech innovation (Powell et al., 1996; Storper, 2018). However, this literature relies on proprietary data for a relatively small number of US regions. There remains no further research to determine whether dealmakers possess a similarly important role outside of the US; thus, we have little knowledge about whether this is a general phenomenon or an American specificity. This is thus one of our primary motivations for seeing whether the positive results for dealmaking reproduce in the UK. Moreover, while social networks are seen as vital for innovation in innovation intensive industries, there has been no work relating the localised presence of highly connected individuals specifically to innovation, as opposed to other local economic outcomes.

This paper addresses this gap in the UK setting, taking up the charge given in the concluding suggestions of Feldman and Zoller (2012) and Kemeny et al. (2016) to examine the role of "structured social capital" and dealmakers in regional entrepreneurial ecosystems. We do this through a novel big data approach using scraped open data from Companies House, the UK's company registration agency, on the entire universe of company board of directorship appointments in the UK, focusing on the period between 2011 and 2016. With this data, we use social network analysis methods to construct indicators using the bipartite network connecting company officers to firms in particular travel-to-work areas (TTWAs). The empirical research finds a significant and positive association between regions with more inter-connected actors, dealmakers in particular, and patenting. An instrument based on gender differences in entrepreneurship suggest that this is a causal relationship. Our results are consistent with the interpretation that networks matter and that the benefits of highly-connected individuals are felt locally.

We focus on the UK, a country with significant regional disparities in innovation performance (McCann, 2016). We consider two sectors - life sciences and information technology – which are well-cited examples of knowledge-intensive industries that have received significant attention from social network studies of the geography of innovation (Audretsch & Stephan, 1996; Powell et al., 1996; Owen-Smith & Powell, 2004; Ferrary & Granovetter, 2009; Whittington et al., 2009; Breznitz, 2013; Lee & Clarke, 2019). Our choice is partly pragmatic because of comparability to the existing dealmakers literature (Kemeny et al., 2016; Feldman & Zoller, 2012). But it is also theoretically motivated: biotechnology and information technology are hallmark examples demonstrating the importance of localized and networked interactions in high-tech innovation, making them ideal for analysing the effects of local social networks on innovation (Audretsch & Feldman, 1996; Saxenian, 1996; Storper, 2018). Both industries are innovative and, theory suggests, network-intensive.

Our paper makes a number of contributions to the literature. First, we provide the first analysis, as far as we are aware, directly relating the concentration of highly connected individuals to regional innovation outcomes. In doing so, we provide new evidence which links the general literature on the role of networks in innovation with the more specific literature on dealmakers. Second, we show the wider impact of highly connected individuals outside of leading high-tech clusters in the United States. Third, we do so by constructing a new dataset and making the data open for other researchers to use.

The rest of the article is organized as follows. The next section reviews the literature on social networks and regional innovation, before discussing the conceptual framework. The following section describes the data and presents basic descriptive statistics. The penultimate section presents an empirical model of regional innovation and the estimation results. The final section concludes.

2. Networks and localised innovation

Multiple studies have highlighted the importance of social networks as the "locus of innovation" in leading high-tech biotechnology and information technology clusters (Audretsch & Stephan, 1996; Powell et al., 1996; Saxenian, 1996; Owen-Smith & Powell, 2004; Whittington et al., 2009; Huggins & Thompson, 2015; Storper et al., 2015). For these highly competitive research-intensive sectors at the technological frontier, geographically collocated social networks provide critical institutional structures enabling and constraining localized knowledge spillovers. Social networks provide interpersonal conduits for the face-to-face diffusion of tacit knowledge; provide channels that facilitate matching and access to human capital; and structure the opportunities and incentives for strategic alliances and collaborations by fostering the emergence of trust and reputation effects (Jaffe et al., 1993; Almeida & Kogut, 1999; Breschi & Lissoni, 2005; Singh, 2005; Sonn & Storper, 2008; Feldman et al., 2016; Acs et al., 2017). Regional innovation is thus characterized in economic sociology and organizational research as being socially "embedded" within social relationships, in the sense that economic outcomes are powerfully shaped by the cultural norms, beliefs, and non-market interactions of the broader social and institutional context (Gordon & McCann, 2000; Granovetter, 1985; Uzzi, 1997; Zukin & DiMaggio, 1990).

The performance and capabilities of high-tech clusters is also commonly cited as being embedded in regional innovation networks (Ahuja et al., 2011; Bathelt et al., 2004; Glückler, 2007; Storper, 2018). Innovation capacities and performance is seen as being shaped by evolving webs of interconnection within social networks (Burt, 2000). Antecedent patterns of association influence knowledge diffusion and recombination processes by shaping the organization and dynamics of such interactions in the present: who individual agents get to interact with, how they interact, and the outcomes of their interactions. Networks are, in this sense, the regional context for innovation, and it can be thought that such contexts can differ in intensity and structure, and contribute to differences in regional innovation performance. On the other hand, if we find that certain basics of networks are reproduced in different places for similar industries, then perhaps causality runs from industry to network structure as well as from network to industry structure and performance.

Scholars have generally focused on studying localized networks. This local emphasis is consistent with empirical observations that collaborations, spin-offs, and knowledge spillovers tend to be highly localized in knowledge-intensive agglomerations despite globalization (Storper, 2013). Note, however, that this does not preclude relational interactions with extra-regional and transnational sources from contributing to knowledge creation and local learning processes, though the importance of such cross-border network connections has been comparatively less studied (Saxenian, 1996; Bathelt et al., 2004; Whittington et al., 2009; Meyer et al., 2011; Balland & Rigby, 2017). Nonetheless, while our dataset technically allows us to simultaneously consider localized and region-spanning network interlinkages, we focus on local social interactions here, following the empirical conventions set out in prior dealmakers research to facilitate comparative interpretation.

The idea of social capital is useful here. The resource-based view of social capital suggests that interfirm ties represent “network resources” or “network capital” – thus individual and group position within social structures are productive assets in their own right that can be accumulated and used to augment economic performance (Bourdieu, 1986; Burt, 2000; Gulati, 1999; Huggins & Johnston, 2010). Stated another way, accumulated relationships, underpinned by trust and reputation effects that come from multiple rounds of inter-relating, could become something like a relational asset base of the region. It is also possible to read this perspective broadly as suggesting an argument about the merits of scale, albeit operationalized via social rather than spatial proximity. More specifically, a growth in the number of locally connected actors within a region might plausibly augment innovation by enlarging the pool of potential collaborators, while also enabling the diffusion of new knowledge to reach a larger and more diverse set of actors. The resulting growth in the scale of knowledge spillovers in turn would potentially increase opportunities to derive economic benefits through novel applications and recombination. The foregoing suggests the following hypothesis:

> Hypothesis 1: Greater concentration of locally connected individuals → higher levels of local patenting

2.1 Socially embedded actors and regional innovation

We anticipate that aggregate membership in local social networks in high-tech industries will indeed be positively associated with regional innovation in the UK. However, both the social capital and social networks literatures both amply demonstrate that network structure confers unique effects on economic outcomes net of aggregate network membership (in a variety of other contexts). How different actors are linked up within local social networks structures opportunities and incentives for individuals and groups to make new and reinforce existing connections, interact productively, and receive useful information, and thus constrains the innovativeness of local social networks (Granovetter, 1985; Casper, 2007; Jackson, 2010). It therefore seems reasonable to expect that network structure will likewise substantively matter for the current study. However, Hypothesis 1 is too abstract from notions of network roles and position to be more informative on this intuition.

We adapt the approach used in the emerging dealmaker literature to address this (Feldman & Zoller, 2012; Kemeny et al., 2016; Pittz et al., 2019). The dealmakers literature has developed insights into the roles of specific actors and the benefits they derive from being deeply embedded and advantageously positioned on local social networks net of network membership. They attempt to avoid many of the widely-cited problems of studying regional social capital in the aggregate (Glaeser et al., 2002) by developing a distinctive approach that focuses on the structural roles of individual actors within local networks, and their influence on regional outcomes.

Feldman and Zoller (2012) showed that the presence of individuals with highly central positions within local social networks – dealmakers – is more strongly positively associated with the growth of regional entrepreneurial ecosystems than the aggregate measures of network membership commonly used in the empirical literature. They found that dealmakers have a disproportionately large influence on regional innovative performance compared to other, less well connected, individuals, theorizing that dealmakers are afforded unique opportunities and advantages, by virtue of their central network positions, in leveraging and organizing local social networks to extract pecuniary benefit. Feldman & Zoller (2012) also found that more vibrant regional economies tend to have exponentially more dealmakers than lagging regions. They argue that this uneven distribution contributes to regional differences in regional performance, as the social networks within more successful regions tend to accrue more social capital due to the positive effects of dealmakers on network cohesion. Kemeny et al. (2016) provided more rigorous support for dealmaker effects, by using a quasi-experimental research design to demonstrate a causal link from dealmakers to firm employment and sales. However, both of these papers focused on the director interlock networks located within top information technology and life sciences firms in high-tech entrepreneurial regions in the USA, leaving the question of whether the importance of dealmakers generalize to other empirical settings.

Moreover, it is uncertain the extent to which the non-linear differences in dealmaker distribution Feldman & Zoller (2012) observed between leading and lagging high-tech regions is specific to the US setting, and likewise, whether this distribution is actually necessary for positive dealmaker effects to obtain at the regional level. Kemeny et al.'s (2016) unit of observation is the firm, arguing that regional innovation performance is expected to vary as a function of region- and industry-specific characteristics, conceptualizing the collective effect of dealmakers on regional performance as a function of the complex network interactions between dealmakers and other agents. They interpret their finding as lending support to the hypothesis that dealmakers lower the costs of making connections and enhance exposure to novel ideas, thereby enhancing economic performance for their affiliated firms. This corresponds accordingly with the argument posited for the regional scale in Feldman & Zoller (2012) – that dealmakers perform roles that lowers the costs of innovative activity, while creating network connections that that encourage localized knowledge spillovers. Dealmakers are thus integral parts of the local enabling environment within highly innovative regional agglomerations.

Dealmakers are thought to augment the performance and growth of affiliated firms by mobilizing place-bound personal networks. Kemeny et al. (2016) conceptualize dealmakers in terms of their fiduciary and statutory obligations for the success of their affiliated companies. There are some differences with this, and the more expansive set of network roles theorized for dealmakers in Feldman & Zoller at the regional scale (2012). The main features common to both are: 1) centrality: dealmakers are exceptionally well-connected directors on regional interlock networks; 2) brokerage: they act as network brokers who mediate access to external sources of knowledge, investment, and human capital for performance gains; 3) proactive: they leverage their network positions to "make things happen" (Senor & Singer, 2011); 4) regional stewardship: they have an observable commitment to participating and investing within their localities; and 5) experienced: they tend to be highly experienced and accomplished. As Feldman & Zoller (2012) state, these are meant to describe general traits, and are not intended to be definitive for any individual dealmaker. The first two of these apply network mechanisms canonical in social network theory that explain how unevenness in network structure can provide competitive advantage and performance benefits. Network actors that are appropriately positioned to bridge otherwise separated, or poorly interconnected, groups are able to exploit indirect ties by "brokering" the transmission of non-redundant information between otherwise poorly connected communities (Burt, 2004). Mediating between indirectly connected actors puts the intermediary in an advantageous position to gatekeep the flow of influence and resources, while also potentially conveying the ability to gain economic rents (Jackson, 2010). Novel information and ideas moreover tends to flow more efficiently from acquaintances, rather than close associates, particularly within scientific fields, because social networks of a given individual, and those of their close associates, are much likely to have greater overlap, than those between that individual and one of their acquaintances (Granovetter, 1973).

Being centrally located within cohesive interfirm networks has been shown to enhance patenting and revenues, though the realized benefits can be contingent on having the right balance between direct and indirect ties (Ahuja, 2000; Gilsing et al., 2008; Stuart, 2000). In this vein, Feldman & Zoller (2012) find denser and more cohesive dealmaker interlock networks, relative to the aggregate regional networks, in each of their studied US city-regions. This is also thought to facilitate the ability of dealmakers to act as regional stewards, providing crucial networked leadership and steering their regions towards greater vibrancy and innovation capacity. There has been preliminary qualitative evidence supporting the idea that dealmakers mediate and shape regional institutions consciously and proactively in leading high-tech clusters in the USA (Storper, 2018). Nonetheless, the reorganization of local network structure to facilitate "robust" collective action need not result from conscious agency or partisanship on the part of leading network actors, but could also emerge unintentionally from their efforts to activate and organize social relationships for personal gain (Padgett & Ansell, 1993). For instance, dealmakers leveraging their positional advantages on local networks to strategically broker access to finance and non-redundant information (e.g. by brokering opportunities for cross-boundary inter-organizational interaction and intermediating tie formation between start-ups and venture capitalists) could thus still unintentionally lead to enduring spillover benefits to regional innovation. Such interactions potentially lead to new connections being formed, thereby increasing social network proximity. The cognate organizational and management research appears to be nearly unequivocal that innovativeness will increase with decreased social network distance, since this opens up a greater larger and more diverse range of sources to the reach of networked individuals, and in turn potentially hastening knowledge transmission and the exposure to novel information and cross-disciplinary perspectives (Fleming et al., 2007; Schilling & Phelps, 2007; Uzzi et al., 2007). Dealmakers can thus be seen as a kind of "robust actor" that provide distinctive contributions to regional innovativeness by augmenting both the quantity and quality of local interactions (Storper, 2013).

Given the findings in the prior dealmakers literature, it seems reasonable to suppose that dealmakers will likewise exert a positive effect on regional innovation in the UK. Thus, we hypothesize that:

> Hypothesis 2: Greater concentration of highly connected individuals → higher levels of local patenting

3. Data

3.1 Building company-director interlock networks

As set out above, networks have long been seen as important for innovation – and attention has increasingly focused on the highly networked individuals at the centre of these networks. Yet it has been hard to test the economic importance of local networks. There are few large-scale relational datasets suitable for constructing the requisite social networks necessary to identify dealmakers. To the best of our knowledge, only sampled data is available for select regions in the United States. We solve this problem by making novel use of UK open government data with census-like characteristics to construct the universe of company-director interlocks in the UK.

Our data comes from Companies House, an executive agency of the United Kingdom's Department for Business Innovation and Skills, that has acted as the national registrar of companies since 1844. By law, private limited companies in the UK must have at least one director; public limited companies must have at least two directors. The Companies Act requires all companies in the United Kingdom to publicly register, and keep up-to-date, a comprehensive set of profiling information with Companies House. Company profile data includes all board appointments, modification, and resignations, and biographical data on board members. It is the most extensive source of company profile and board of directors information available for the UK. It provides a historical census of the universe of UK companies and their affiliated officers, with coverage stretching back from at least a century from the latest daily updates. This information is made publicly available as open data via the Companies House Application Programming Interface (API), a web service to digitally access this data online. As of this paper's writing, this is a new web service that is currently in the beta software development stage. To the best of our knowledge, this is the first analysis to make use the relational structure of this open data source to study the link between social networks and innovation. We construct company-director interlock networks for the life sciences and information technology sectors (see Appendix B for more details).

Companies house data provides a unique dataset to explore the geography of dealmakers, providing a census of those in important positions in the UK's business base. However, some limitations need to be borne in mind. As we discussed above, company directors are expected to play important roles in leveraging social networks for innovation performance. However, our use of company-director interlocks also makes a number of limitations noted in the previous research relevant here as well (Kemeny et al., 2016; Feldman & Zoller, 2012). We are neither able to capture informal links between directors, nor connections between non-elite employees. This restriction appears to be unavoidable in practice, and we are aware of no alternative data sources that can be reasonably used to define networks with comparable coverage and relevance.

We define sectoral boundaries using the Standard International Classification of economic activities (SIC) industry code information contained within individual company records using the Science and Technology (S&T) SIC classifications published by the Office of National Statistics (Office for National Statistics, 2015)

We use the 5-digit SIC codes categorized under the S&T topics relating to biotechnology, pharmaceuticals, and medical equipment activities. These were all originally grouped under the broader "Life Sciences & Healthcare" S&T category, though we excluded "Healthcare"-related services from consideration here to avoid complications related to the UK's National Health Service (NHS). Life-sciences includes manufacturing of pharmaceuticals, medical equipment, and biotechnology R&D activities.

For information technology, we use the SIC codes selected for the "Digital Tech" sector in the latest Tech Nation report (Tech Nation, 2018) instead of the ones in the corresponding S&T "Digital Technologies" category in the ONS report, as the former provides a more current set of officially-endorsed SIC codes that capture the breadth and depth of the rapidly evolving UK information technology industry. This set of SIC codes encompasses computer hardware manufacturing, software development and publishing, data hosting and other web services, IT consulting, and other related activities. IT is the larger sector, including computer manufacturing, software and programming, telecommunications activities, data processing, web portals, and computer repair. See Table S1 in the appendix for the list of SIC codes used.

We are concerned that there may be differences in innovation processes between life sciences and information technology, so consider the two sectors separately. While the companies in these two highly innovative sectors are expected to face similar environmental pressures, separately considering each is useful in the case that there are substantive differences in the underlying networks in the two sectors.

With these considerations in mind, our implementation of the network building algorithm described above is fully populated at around 2.6 million observations. We consider connections between approximately 24,000 directors on the boards of life sciences firms, and around 1.4 million indirectly connected directors in firms outside of the life sciences via company-director interlocks. Put differently, these other directors are within the same network component as at least one director affiliated with the life sciences. We discuss how we proceed with constructing regional social network indicators below.

3.2 Constructing social network indicators

Table 1. Social capital indicators

Social capital indicator	Definition	Regional operationalization
Actors	All relevant company directors in a local social network	the total number of individuals in the study industry within each regional interlock network
Dealmakers	Actors who are unusually well connected within a local network	the total number of actors with at least four concurrent ties to local firms via board interlocks
Investors	Non-dealmaker actors who are affiliated with finance-related firms	the total number of non-dealmaker actors who have a concurrent tie with a finance-related firm
Entrepreneurs	All local actors that are neither dealmakers nor investors	the total number of non-dealmaker actors, who are also not investors

Note: The definitions here are operationalized following Feldman & Zoller (2012) and Kemeny et al. (2016).

We construct social network indicators from this data, following the empirical conventions set out in the past literature on highly-networked individuals. The overarching idea is that director interlock connections indicate the degree to which individual directors are interconnected within the regional level through their board positions. More highly connected individuals are assumed to be more influential within local social networks for the reasons discussed in this paper's literature view. To ease comparability, we operationalize our social network indicator definitions following the conventions used in Feldman and Zoller (2012) and Kemeny et al. (2016) [see Table 1]. Accordingly, we define dealmakers as an individual with at least four concurrent ties to local firms via board interlocks.

In more detail, starting with the two aggregate networks from the previous section (i.e. the life sciences and information technology director interlock networks), we proceed by first systematically excluding irrelevant network vertices from consideration. Non-natural persons (i.e., companies, public bodies, and other legal entities) are removed as they would clearly have qualitative behavioural differences in director engagement. Their omission is not expected to have a material impact on our results, as broad inspections of the data suggest that these non-human directorships are much less prevalent in our chosen study sectors than on the aggregate network. We leave the answering of why this might be the case, and evaluations of relative importance, for future research. For consistency, we match data coverage with our measure of regional innovation, and restrict consideration to directors with active appointments from 2011 to 2016.

We then use the postcode information contained within the company profile data to partition the aggregate director interlock networks into regional networks separated at the Travel to Work Area (TTWA) level. TTWAs have been officially used to define local labour market areas since the 1960s. They are in standard use in econometric analyses to approximate city-regions, as they represent functional economic regions rather than administrative units (Lee, 2014). We use the latest TTWA boundaries defined by commuting flow data from the 2011 national census. Company and director nodes are allocated into 210 regions based on their individual postcode sectors, to provide relatively fine-grained boundaries for the TTWAs.

The above steps yield TTWA-based regional networks defined by the board interlocks between individual directors with active appointments during 2011-2016. Considering each of these regional networks separately, we measure the number of connections held by each individual director to local firms, singling out directors with 4 or more connections - in line with Feldman and Zoller (2012), we term these "dealmakers". We then calculate the total number of dealmakers per TTWA, considering only those directors who have board positions within companies in the study industry.

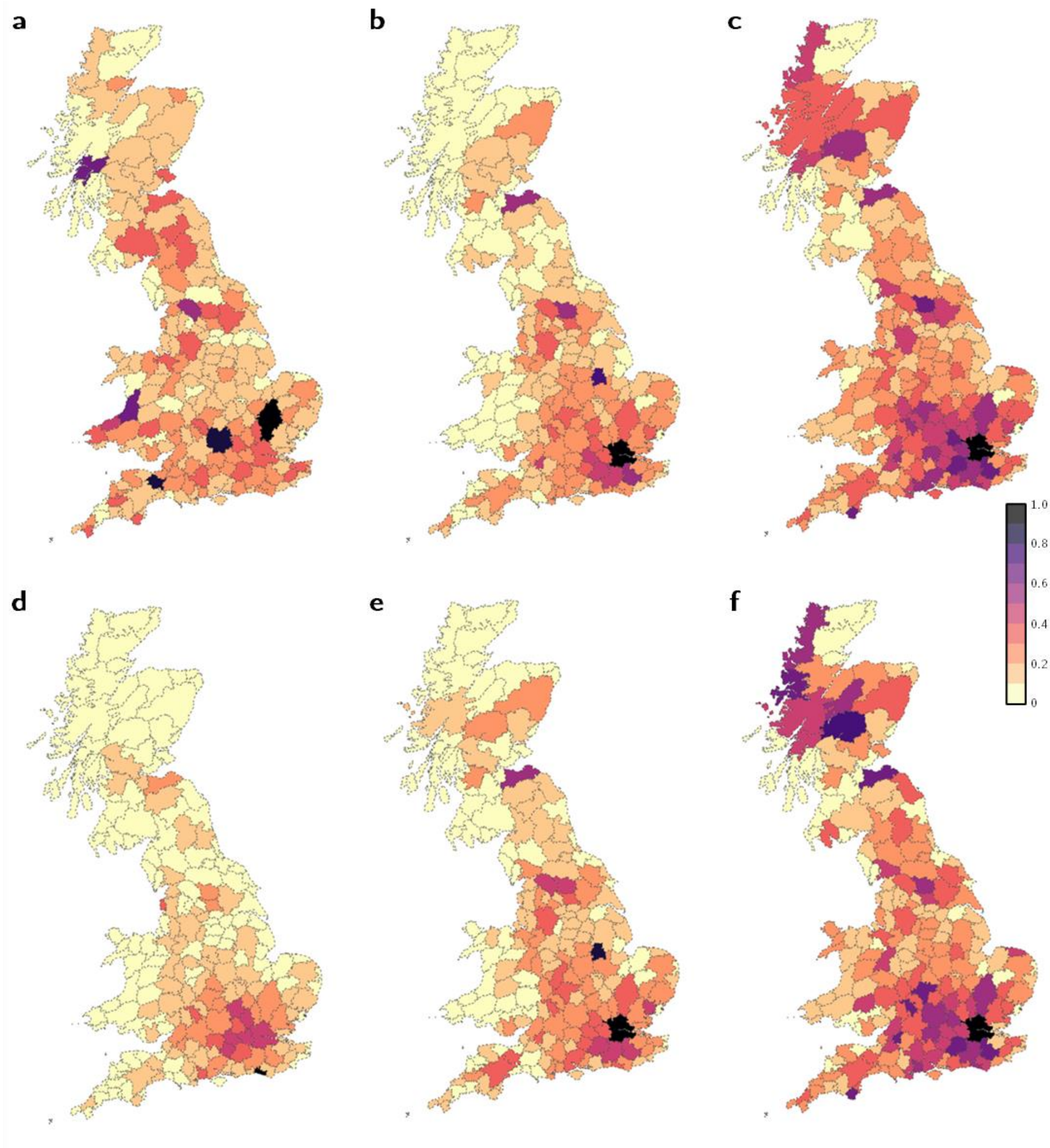

Figure 1 The distribution of local social network indicators in the UK. a-c Show the indicators at the TTWA level for the life sciences for entrepreneurs, investors, and dealmakers, respectively. d-f Show the corresponding indicators for the information technology sector. All indicators are working population normalized to facilitate comparability. Higher regional values are mapped to darker colours, as shown in the colour bar.

The spatial distribution of dealmakers in the UK is presented in Figure 1. There tend to be more dealmakers in absolute terms in TTWAs with larger networks, though there is inter-regional variation, and the relationship is not strictly monotonic. As Table 2 shows, the number of dealmakers comprise a minority of directors. The vast majority of individuals in every region are only affiliated with a single firm. Around 7% of the individual directors in the life sciences are dealmakers, for instance, while around 76% of them have one local affiliation. Across the TTWAs, the vast majority of directors to be connected to a single firm in their locality, with the proportion of individuals falling precipitously with every degree increase in local connections.

A similar pattern can be observed for the information technology sector, though the proportion of single-tie actors tends to be somewhat larger, while tending to be smaller for dealmakers, in comparison to the life sciences. The progressive drop-off in the degree of interconnectedness observed within local social networks found here is generally less pronounced than in the USA settings studied in the prior dealmakers research. Kemeny et al. (2016) found that around 90% of agents in the combined local director interlock networks have a single local tie, while only around 1% of them have enough ties to be considered regional dealmakers. These divergences might be plausibly explained by the relative completeness of our relational data. They might also plausibly reflect fundamental institutional differences between the USA and UK high-tech economies. Alternatively, these inter-country differences might possibly be largely an artefact of the aggregation of the life sciences and information technology interlock networks in the prior research. We leave further investigation into this matter for future work. Nonetheless, the general relationship presented here for the UK is broadly consistent with the one found for dealmakers affiliated with the life sciences and information technology firms in the USA city-regions studied by Feldman and Zoller (2012) and Kemeny et al. (2016). The fact that substantially less than 10% of individuals have more than four local network connections also mitigates worries about the arbitrariness of the discrete threshold used to define dealmakers.

Table 2. Regional distribution of actors and their local interconnections

	Life Sciences					*Information Technology*				
		Number of local affiliations (%)					Number of local affiliations (%)			
Region	Total actors	One	Two	Three	Four+	Total actors	One	Two	Three	Four+
Birmingham	425	0.79	0.10	0.05	0.06	8,945	0.82	0.11	0.04	0.03
Bristol	348	0.75	0.13	0.05	0.08	6,868	0.83	0.11	0.03	0.03
Cambridge	1,304	0.78	0.12	0.05	0.07	6,747	0.81	0.13	0.03	0.03
Crawley	315	0.75	0.13	0.08	0.09	6,373	0.81	0.13	0.03	0.03
Edinburgh	420	0.78	0.13	0.04	0.07	5,496	0.84	0.11	0.02	0.02
Glasgow	283	0.75	0.16	0.04	0.05	5,554	0.84	0.11	0.03	0.03
Guildford and Aldershot	369	0.75	0.16	0.01	0.04	8,380	0.80	0.13	0.03	0.04
Leeds	284	0.73	0.12	0.06	0.10	6,071	0.84	0.10	0.03	0.03
Leicester	238	0.68	0.16	0.04	0.08	4,981	0.82	0.11	0.03	0.03
London	4,706	0.78	0.12	0.05	0.07	136,368	0.83	0.11	0.03	0.03
Luton	395	0.81	0.08	0.03	0.05	10,684	0.88	0.08	0.02	0.02
Manchester	1,459	0.77	0.15	0.03	0.05	16,765	0.81	0.12	0.03	0.04
Oxford	883	0.75	0.14	0.05	0.07	4,864	0.79	0.14	0.04	0.03
Reading	253	0.78	0.11	0.03	0.05	9,097	0.83	0.11	0.03	0.02
Slough and Heathrow	683	0.74	0.14	0.04	0.07	22,129	0.85	0.10	0.02	0.02
All study regions	24,217	0.76	0.13	0.04	0.07	456,217	0.83	0.11	0.03	0.03

Note: Dealmakers are individuals with four or more local affiliations. Actors are identified through their positions within regional director interlock networks, following the empirical conventions set out in the dealmakers literature (Feldman & Zoller, 2012; Kemeny et al. 2016). The values reported under the two table subheadings are only for actors affiliated with companies in these two study industries. Aside from the final row, for which values are measured over all studied regions, the subset of study regions shown here correspond broadly to the TTWA regions with the largest clusters of life sciences and information technology firms in the UK within the period 2011 to 2016.

This finding shows that directors with at least four connections are indeed unusually highly connected within their localities. This suggests that, at the least, the minimum dealmaker degree threshold is sufficiently high, and we need not be overly concerned about false positives. Indeed, we might instead worry that the threshold is too strict given the degree distribution, and we might potentially fail to detect real dealmaker influences on innovation outcomes.

The relatively small proportion of highly-connected individuals, in both the current study and the USA context focused on in the existing literature, suggests that the networks are relatively sparsely connected, yet certain individuals are disproportionately important in terms of their network centrality. Calculating the network density, the fraction of edges in the network that actually exist, confirms this intuition. The lowness of the network density is not a very surprising finding, since real-world networks are generally sparse (Newman, 2018). Yet interconnection is the rule rather than the exception in the interlock networks. Despite the observed sparseness, most companies (and by extension their affiliated directors) that have more than one connection belong to the most cohesive and highly-connected networks within their regions. This is consistent with Feldman & Zoller's (2012) findings in the USA context, and their argument that this in turn implies a hierarchy underlying the structure of social capital of each study regions' entrepreneurial ecosystems.

The apparent contradiction between these two observations suggests that regional network interconnectedness is not primarily a network density effect. It also lends credence to our hypothesis that dealmakers are important regional hubs, providing the network channels that link individuals that would otherwise be distantly connected.

3.3 Measuring innovation

Our measure of innovation is the log of total patent counts in either biotech or IT. Patent counts are robust indicators of invention and technological progress with well-understood properties. They are measures of inventiveness by definition, and are relatively objective measures of innovation across firms and industries (Griliches, 1990). The breadth of information provided by patent data sources has also made it commonly used among scholars studying the geography of innovation (Acs et al., 2002; Lee & Rodríguez-Pose, 2013; Sonn & Storper, 2008; Wouden & Rigby, 2019; Esposito, 2020). Patent data are subject to number of widely noted limitations (Hall et al., 2013). They do not measure economic value directly. Patents also do not capture innovation in novel organizational processes and arrangements, or in non-patentable services innovation. The limitations above are not expected to be very important here, given our emphasis on knowledge production rather than on direct economic impacts (Sonn & Storper, 2008). One other potential limitation is that patent importance varies in terms of their impacts. We do not account for this here and focus on aggregate innovative productivity. Thus, patent data are expected to provide reasonable robust indicators for the creation of new technological knowledge (Acs et al., 2002), particularly within the intensely competitive innovation milieus associated with the information technology and the life science industries.

Profile data for patents filed in the UK from 1978 is made publicly available under an open government license by the Intellectual Property Office (IPO). The patent dataset contains information about the basic details of the patents, their associated inventors and assignees, as well as their respective addresses and countries of origin. The lifecycle of a patent filed in the UK is defined by stages: from their initial application; to their publication; and thence possibly being granted, and put in force contingent on meeting the patent office’s inventiveness criteria. It takes time for a patent to progress through these stages. Moving from the application to publication stage, for instance, typically takes 18 months. We use the patent application date to measure outcomes as it is the closest among these to capturing when the research was completed (Jaffe & Trajtenberg, 2002; Whittington et al., 2009). To avoid erratic results from yet-to-be-reported changes to patent status, we use total patent application data for the five-year period from 2011-2016, following Lee (2017). Each patent is linked to a TTWA region by the postcode sector of their applicants. The data lists the technology areas associated with each patent at the subclass level according to the International Patent Classification (IPC) System. We construct separate indicators for the life sciences and the digital technology sectors, using the IPC-based industry classifications published by the OECD and Tech Nation, respectively.

4. Model

The model used here applies a modified regional knowledge production function framework, where regional innovativeness is assumed to be a function of locality-specific factors. (Griliches, 1979; Ó hUallacháin & Leslie, 2007; Lee, 2017; Rodriguez-Pose & Wilkie, 2019) We therefore estimate the following empirical model for each TTWA ‘i’ –

$$log(\,Innovation_i) = \alpha + \beta_1\, log(\,NETWORKS_i) + \beta_2\, log(\,CONTROLS) + \epsilon_i.$$

Here, the dependent variable Innovation is the (log) number of patent applications lodged in the period 2011-2016. The variables of interest are given by NETWORKS, a vector of social network indicators, as defined in Table 1 above. CTRLS are either vectors of observed regional characteristics as controls, or region dummies for location fixed effects to mitigate the role of unobservable characteristics across regions. The constant is α and the error term is ϵ.

All control variables for regional observables are calculated using official statistics for the study period from the UK Office of National Statistics (ONS). We include a variable for the size of the TTWA, which is the log of the total working population. This controls for the expectation that larger TTWAs should generally (but not unequivocally) be more innovative due to positive urban density effects on knowledge spillovers and labour market matching, particularly in high-skill industries (Duranton & Puga, 2004; Lee & Rodriguez-Pose, 2013).

We control for human capital, as proxied through education, using the share of the local population with National Vocational Qualification (NVQ) level 4 and above. As an indicator of high skills, this is expected to be positively associated with innovation. Both of these controls use data from the Annual Population Survey.

The collocation of firms in knowledge intensive industries is also expected to be positively associated with innovation via positive agglomeration externalities. Accordingly, we use data from the Business Register and Employment Survey (BRES) to control for both the absolute size and the share of relevant employment in either IT or life sciences (Kemeny & Storper, 2015).

We also include controls for first-order network connectivity, as measured from the constructed networks: the log regional count of within-region local linkages, and the log regional count of between-region external linkages. As the correlation matrices show (Tables S2 and S3 for the life sciences and information technology sectors, respectively), the social network indicators and controls are positively associated with patenting, with stronger associations for the former set of variables than the latter.

5. Results

5.1 Basic results

We report basic OLS results for the life sciences in Table 3, and in Table 4 for information technology. Columns 1-6 consider the regional social network variables without controls. These variables are expected to be positively associated with innovation. From the prior findings on USA dealmakers, the dealmakers variables, in particular, are expected to have a stronger relationship than actors, as the latter are a simple regional counts that do not take network structure into account (Kemeny et al., 2016; Feldman & Zoller, 2012). More specifically, actors represent the total number of individuals in the study industry within each regional social network. Entrepreneurs represent the total number of directors per region in the study industry who have less than four local ties, and who are also not investors. Based on the theoretical literature, we expect the association for dealmakers to be stronger than for entrepreneurs, since the latter are less embedded within their locality's social networks by construction. Investors represent the total number of non-dealmaker individuals in the study industry who have a concurrent tie with a finance-related firm. To explore this trend in greater detail, we include an additional variable, dealmakers (3+), which is defined similarly to dealmakers, except that the local social network tie threshold is relaxed from a minimum of four to a minimum of three. As such, the coefficients for the regional social network variables are expected to become progressively higher, such that actors < entrepreneurs < dealmakers (3+) < dealmakers.

All of these variables are statistically significant at the 0.01 level in the base estimation results for both the life sciences and information technology sectors. In the case of the life sciences, when the regional social network variables are included (Column 6), the dealmaker variable remains the most important. It is plausible that these basic findings can be explained by other factors such as the size of regional agglomerations or education levels. However, the observed trends are maintained even after including controls and regional fixed effects (Columns 7-12); the estimated coefficients for all regional social network variables have similar magnitudes and remain highly significant at the 0.01 level. Similar results are also seen for the information technology sector. One important exception is that the dealmaker variable no longer remains statistically significant when the other social network indicators are included in Columns 6 and 12, though this is likely due to methodological rather than substantive reasons (more on this below).

Table 3. Regression Results (Ordinary Least Squares): Lodged life sciences patents, mean 2011-2016 (ln)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Actors	0.336 ***						0.127 *					
	(0.018)						(0.049)					
Entrepreneurs		0.339 ***				0.155 ***		0.123 *				0.070
		(0.018)				(0.029)		(0.048)				(0.043)
Investors			0.684 ***			0.209 **			0.245 ***			0.135 *
			(0.096)			(0.064)			(0.068)			(0.060)
Dealmakers (3+)				0.391 ***						0.320 ***		
				(0.020)						(0.056)		
Dealmakers (4+)					0.430 ***	0.243 ***					0.433 ***	0.394 ***
					(0.022)	(0.036)					(0.049)	(0.051)
Working population							0.277 ***	0.279 ***	0.372 ***	0.160 *	0.234 ***	0.161 *
							(0.082)	(0.082)	(0.066)	(0.076)	(0.060)	(0.072)
NVQ 4+ %							0.514 ***	0.518 ***	0.595 ***	0.345 *	0.390 ***	0.299 *
							(0.141)	(0.140)	(0.130)	(0.135)	(0.116)	(0.124)
Sector size							-0.041	-0.041	-0.048	0.011	-0.018	-0.013
							(0.050)	(0.050)	(0.050)	(0.049)	(0.043)	(0.043)
Relevant employment %							0.056	0.057	0.105	-0.024	0.024	0.018
							(0.083)	(0.084)	(0.082)	(0.081)	(0.071)	(0.072)
Local linkages							-0.003	-0.002	0.002	-0.027 *	-0.044 ***	-0.040 ***
							(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)
External linkages							0.011	0.011	0.011	0.003	-0.010	-0.011
							(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Constant	-0.572 ***	-0.566 ***	0.622 ***	0.032	0.164 ***	-0.198 *	-4.269 ***	-4.274 ***	-4.901 ***	-3.177 ***	-3.815 ***	-2.929 ***
	(0.072)	(0.072)	(0.039)	(0.041)	(0.036)	(0.079)	(0.811)	(0.814)	(0.683)	(0.751)	(0.603)	(0.738)
Observations	210	210	210	210	210	210	210	210	210	210	210	210
Region FE							Y	Y	Y	Y	Y	Y
R2	0.617	0.614	0.195	0.654	0.653	0.708	0.690	0.689	0.695	0.723	0.770	0.776

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 4. Regression Results (Ordinary Least Squares): Lodged information technology patents, mean 2011-2016 (ln)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Actors	0.401 ***						0.195					
	(0.024)						(0.131)					
Entrepreneurs		0.402 ***				0.137		0.182				-0.042
		(0.024)				(0.077)		(0.130)				(0.125)
Investors			0.555 ***			0.337 ***			0.305 ***			0.255 ***
			(0.031)			(0.052)			(0.051)			(0.055)
Dealmakers (3+)				0.400 ***						0.278 **		
				(0.024)						(0.100)		
Dealmakers (4+)					0.408 ***	0.063					0.391 ***	0.231 *
					(0.025)	(0.079)					(0.089)	(0.096)
Working population							0.081	0.088	0.056	0.066	-0.033	-0.029
							(0.355)	(0.354)	(0.322)	(0.346)	(0.337)	(0.325)
NVQ 4+ %							0.683 **	0.693 **	0.536 *	0.629 **	0.555 *	0.454 *
							(0.242)	(0.241)	(0.210)	(0.230)	(0.221)	(0.224)
Sector size							0.139	0.143	0.137	0.103	0.138	0.117
							(0.335)	(0.335)	(0.303)	(0.327)	(0.315)	(0.306)
Relevant employment %							0.112	0.111	0.145	0.134	0.077	0.127
							(0.381)	(0.381)	(0.351)	(0.375)	(0.364)	(0.348)
Local linkages							-0.031	-0.030	-0.022	-0.043 *	-0.059 **	-0.040 *
							(0.020)	(0.020)	(0.018)	(0.020)	(0.020)	(0.019)
External linkages							-0.014	-0.013	-0.008	-0.014	-0.019	-0.012
							(0.018)	(0.018)	(0.016)	(0.017)	(0.017)	(0.016)
Constant	-1.742 ***	-1.735 ***	0.191 ***	-0.636 ***	-0.364 ***	-0.612 *	-4.315 **	-4.393 **	-2.463	-3.389 *	-2.518	-1.436
	(0.157)	(0.156)	(0.050)	(0.096)	(0.080)	(0.290)	(1.599)	(1.597)	(1.345)	(1.546)	(1.468)	(1.539)
Observations	210	210	210	210	210	210	210	210	210	210	210	210
Region FE							Y	Y	Y	Y	Y	Y
R2	0.576	0.577	0.612	0.567	0.570	0.656	0.660	0.659	0.710	0.669	0.687	0.719

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

The basic results suggest that highly connected individuals have substantively important roles in regional innovation in both life sciences and IT. The estimated effect sizes for dealmakers in the life sciences, to illustrate, should be considered in relation to the average annual patenting rate in life science firms, which is much lower at around 0.035 patents/firm. The average rate of life sciences patenting for all relevant dealmaker effects are not a simple function of firm size. It is also worth considering this in conjunction with the estimates for the controls. The population variable, which represents regional scale, is positively associated with innovation. These differences are nonetheless not obviously stark enough for us to reasonably surmise that this implies that the former is only of minor substantive importance relative to "pure" urban agglomeration effects in their contributions to explaining the observed geography of regional innovation. We might indeed speculate to the contrary. The fact that board sizes are generally small on average suggest that a given firm would obtain a more immediate and relevant pecuniary benefit to having a dealmaker on board, than they might from the more diffuse spatial externalities that might obtain from a marginal increase in their locality's density. Moreover, while we might worry that the control variables might also plausibly measure the size and density of regional social networks, variables like population size are likely too general, in the first instance, to be reliably used for this purpose (Gordon & McCann, 2000), particularly given how highly specialized the study industries are.

The findings here generally validate the base of existing literature. We find that the expected ordinal relationship between the regional social network variables obtains in the UK context as in the life sciences and information technology firms in the previously studied USA city-regions. Dealmakers appear to have a stronger effect on economic performance than having less embedded board members (Kemeny et al., 2016; Feldman & Zoller, 2012). The consistently lower magnitude of the actor variable compared to the social network variables is also consistent with the dealmaker literature's existing findings in the USA empirical context. These results are in alignment with the argument that proxy indicators for social capital that ignore place-specific network structure, or only account for it in a highly aggregate sense, are more likely to result in biased estimates that are further from the ground truth effects of local social interaction.

However, the investors estimates (Columns 3 & 10) appear to contradict the relatively weaker associations found between investors, compared to dealmakers, with regional performance in US context (Feldman & Zoller, 2012). This might indicate real differences in economic and institutional fundamentals between high-tech industries in the USA and the UK. It is plausible, for instance, that opportunities to acquire seed financing and private equity are scarcer and thus more valuable in the UK than the USA, perhaps due to comparatively thicker institutions and structural cohesiveness in the latter’s start-up ecosystems. A more mundane possibility there is a misalignment between the way we theorize about dealmakers, and how it is technically defined. The conceptualization of dealmakers in the literature appears to imply that the set of dealmakers is a superset of investors, and that dealmakers also take on the characteristics of investors to some extent. However, the technical definition only stipulates that dealmakers are those directors with at least four concurrent local ties. The connection between dealmakers and investors is thus entirely contingent on the idiosyncrasies of the measured regional networks. It is also plausible that dealmakers in the UK are less likely to also be investors than in the US context.

Nonetheless, the model estimates in Columns 7 and 12 imply a radically different situation from Columns 3 and 10, as the investors estimates are sharply diminished in absolute magnitude, and moreover have opposite signs, when estimated together with entrepreneurs and dealmakers. Note that actors and dealmakers (3+) are not included to avoid collinearity. To facilitate interpretation, Figure S1 graphically presents the estimates for Column 12, where the regression inputs have been standardized as per Gelman (2008) to place the predictors on a common scale, such that we may directly compare the coefficients. The standardized dealmaker estimates are the largest by a substantial margin, and are nearly twice as large as those for investors. While not shown here, a similar picture obtains in the corresponding ICT standardized estimates.

This suggests that the apparent importance of investors could simply be driven by outliers. The attached map shows that investors are not only relatively uncommon but are also generally concentrated in London and the South East (Figure 1). Note however, that we should be cautious of over-interpreting the results from Columns 7 and 12. Given their inherently relational definitions, the entrepreneurs, investors, and dealmakers variables are all likely endogenous to an overlapping range of underlying network characteristics and formation processes. These variables are almost surely mutually codetermined given how we use them here, since they could only be expected to be reasonably independent in the improbable situation where there is minimal interconnection between individual directors in the study industries. Future comparative research might aim to provide more insight into the driving forces behind these differences.

5.2 Robustness checks

We discuss the results of using alternate specifications as a sensitivity test, focusing chiefly on concern that scale effects might bias our findings. While our preferred specification attends to this issue by controlling for local labour market size, big cities obviously produce more patents than small ones, and the present worry is that our focus on the relationship between local patenting productivity and highly locally networked agents that might not be robust and, in the worst case, inadvertently cause our results to simply reflect the impact of regional scale.

To investigate this possibility, we re-run our preferred OLS specification (i.e., Column 10 of Tables 3 and 4) with scaled dependent variables; we also try using dealmakers/capita as the explanatory variable. The results are presented in Table S4. Column 1a repeats our baseline specification, while Column 1b replaces the explanatory variable with dealmakers/capita. This pattern repeats for the next three pairs of columns. ‘Baseline’ models use the default patenting dependent variable; ‘Patenting/Capita’ accounts for the size of local labour markets by dividing local patenting by the working population; ‘Patenting Growth’ is the growth in patenting productivity over the study

Table 5. Lodged life sciences patents: Standardized OLS estimates for baseline and alternate specifications

Dependent variables:	Baseline	Baseline	Patenting / Capita	Patenting / Capita	Patenting Growth	Patenting Growth
Per capita dealmakers variable:		Y		Y		Y
Model:	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Dealmakers	8.413** [7.15]	2.156* [2.22]	0.08* [7.15]	0.054* [2.22]	0.26* [6.14]	0.143* [2.31]
	(3.007)	(0.923)	(0.033)	(0.027)	(0.116)	(0.059)
Working population	1.633* [6.62]	5.438* [5.84]	-0.098 [6.62]	-0.052 [5.84]	-0.031 [5.86]	0.064 [5.85]
	(0.683)	(2.13)	(0.059)	(0.048)	(0.082)	(0.08)
NVQ 4+%	0.713* [1.52]	1.092* [1.54]	0.039** [1.52]	0.036** [1.54]	0.015 [1.47]	0 [1.54]
	(0.333)	(0.531)	(0.013)	(0.011)	(0.055)	(0.056)
Sector size	-0.481 [6.4]	-0.974 [6.37]	0.023 [6.4]	0.023 [6.37]	-0.023 [6.34]	0 [6.37]
	(0.287)	(0.509)	(0.045)	(0.039)	(0.045)	(0.046)
Relevant employment %	-0.591 [2.78]	-0.537 [2.9]	-0.016 [2.78]	-0.025 [2.9]	0.015 [2.74]	-0.024 [2.9]
	(0.831)	(0.836)	(0.03)	(0.028)	(0.056)	(0.057)
Local linkages	-4.708* [4.99]	-2.302* [4.46]	0.01 [4.99]	0.012 [4.46]	-0.155 [7.19]	-0.048 [4.52]
	(1.839)	(1.015)	(0.027)	(0.022)	(0.143)	(0.11)
External linkages	-0.779 [3.15]	0.673 [2.89]	-0.034 [3.15]	-0.024 [2.89]	0.012 [2.9]	-0.025 [2.9]
	(0.753)	(0.438)	(0.018)	(0.019)	(0.082)	(0.077)
Constant	1.288**	1.097*	0.061***	0.056***	0.206*	0.199*
	(0.458)	(0.451)	(0.012)	(0.013)	(0.086)	(0.092)
Observations	210	210	210	210	210	210
Region FE	Y	Y	Y	Y	Y	Y
R2	0.524	0.390	0.161	0.172	0.107	0.102

*Hereoskedacity-robust standard-errors in parentheses. *p<0.05, **p< 0.01, ***p<0.001* period, $ln\left(\frac{\text{Patenting}_{i,2011}}{\text{Patenting}_{i,2016}}\right)$, measured for each TTWA *i*. Both 'Patenting/Capita' and 'Patenting Growth' are essentially uncorrelated with regional scale. All columns report robust standard errors and prints variance inflation factors (VIFs) next to each corresponding coefficient's standardized estimates. While not discussed further for brevity, we note that comparable standardized estimates and VIFs are obtained when the exercise is repeated for the ICT sector. The results also remain largely unchanged when the control for regional working population is dropped.

The standardized estimates for the variables of interest are substantively similar across all baseline and alternative models. The dealmakers variable is positive, statistically significant, and has the largest standardized estimates in all columns. This consistency despite the varying specifications might reassure us our findings thus far are not likely a straightforward artefact of regional scaling effects.

Variable inflation factors are widely used to diagnose potential multicollinearity issues. However, opinions divide on how VIFs might be properly interpreted. A commonly encountered rule-of-thumb is to regard VIFs above 10 as a moderate cause for concern; yet some practitioners lower this VIF benchmark to 5; while others reportedly disregard VIFs entirely. Nonetheless, following commonly used heuristics, the VIFs in Table S2 suggest that collinearity is not a pressing concern for the dealmakers variable.

Table S4 also shows that the VIFs are consistently lower whenever dealmakers/capita are substituted in place of the default dealmakers variable. However, this alone does not warrant modifying our preferred specification. Substantively, our main empirical concern here – the social gains to local innovativeness from highly networked local agents, conditional on regional scale and the other controls – is conceptually distinct from the effect of having a higher proportion of highly connected agents in local economies. Moreover, since the proportion of highly connected vertices within a given place-based network is not necessarily bound to relative regional size, using dealmakers/capita as the explanatory variable risks the inverse concern to the present one, such that small regions might have an outsized influence on the estimates.

5.3 Instrumental variable results

The OLS results presented show a positively association between highly connected individuals and regional innovation. They are consistent with the idea that highly connected individuals are substantively more important than less connected actors. However, there is a simultaneity problem: it may be that the presence of dealmakers directly promotes innovation; simultaneously, more innovative regions may simply attract or produce more highly connected individuals. Alternatively, it may also be that the presence of highly connected individuals and regional innovation are spuriously correlated and are instead both driven by an omitted variable. We use an Instrumental Variable (IV) method here with two instruments to address these issues. A good instrument needs to meet three assumptions: relevance - having a causal effect on the number of highly connected individuals; independence - lacking common confounders, and the exclusion restriction, that it affects innovation only through its impact on highly connected individuals. These are difficult to meet, but we identify two instruments which fulfil these criteria.

Our first instrument is an indicator of gender disparity: the ratio of female to male company directors in each TTWA prior to the study period in 2010. Measuring gender disparity prior to the beginning of the study period mitigates simultaneity concerns, since present innovative productiveness cannot causally influence gender imbalances in the past. More importantly, the gender of any given director will not have any significant direct impact on innovative productivity. Rather, as elite employees working in firms operating in highly competitive business environments, we should expect that individual directors for any given industrial sector are likely exposed to similar performance and selection pressures, and are therefore likely to have, on average, broadly comparable incentives, skills, qualifications and any other relevant human capital attribute relevant to their competence—unless robust evidence proves

Table 6. Instrumental Variable Results (2SLS): Lodged patents in the life sciences, mean 2011-2016 (ln)

IV used:	Gender disparity		Connecting channels		*Both instruments*	
	(1)	(2)	(3)	(4)	(5)	(6)
Dealmakers (4+)	0.460 ***	1.002 ***	0.544 ***	0.993 ***	0.464 ***	0.624 ***
	(0.045)	(0.256)	(0.042)	(0.213)	(0.031)	(0.161)
Working population		0.035		-0.015		0.127 *
		(0.085)		(0.107)		(0.062)
NVQ 4+ %		0.017		0.032		0.225
		(0.197)		(0.221)		(0.150)
Relevant employment %		-0.028		-0.049		-0.028
		(0.058)		(0.068)		(0.051)
Local linkages		-0.103 ***		-0.091 **		-0.061 **
		(0.029)		(0.027)		(0.019)
External linkages		-0.040 *		-0.043 **		-0.016
		(0.017)		(0.015)		(0.013)
Constant	0.127 **	-1.478	-0.026	-0.987	0.087 *	-2.689 **
	(0.048)	(1.088)	(0.072)	(1.504)	(0.041)	(0.845)
Observations	210	210	210	210	210	210
Region FE		Y		Y		Y
R2	0.617	0.650	0.592	0.599	0.711	0.719
Weak instruments *F* statistic	9.69 **	9.19 **	242.21 ***	11.71 ***	316.94 ***	13.39 ***
Sargan's *J* statistic					0.131	1.583

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

otherwise—in general. In short, there is no reason to believe that female directors are, on average, any less capable or performant than male ones. The correlation matrices are consistent with this supposition: the pre-existing level of pre-existing gender disparity does not appear to measure local qualifications in the study industries as it has no statistically significant relationship with population qualified to NVQ4+ (Tables S2 and S3).

Given pervasive gender differences in UK society, male directors nonetheless substantially outnumber female ones in both the life sciences and ICT sectors. The gender gap appears to measure local dealmaker presence, as past gender disparity and regional dealmaker concentration is negatively and highly statistically significantly correlated. Moreover, the overall gender ratio is heavily imbalanced in favour of male directors (see Appendix Figure S2: the median female director share is indicated by the dashed line). While there is notable variation in the gender balance across the study regions, as indicated by the box plots, the gender imbalance becomes increasingly wide as directors become more highly connected within regional social networks, as the proportion of female directors tends to fall rapidly below the overall proportion across the study regions.

The negative relationship between the gender ratio and local dealmaker concentration thus appears to be generated through deep-seated mechanisms that are likely some combination of self-selection and sorting processes, and because of the pernicious impact of gender discrimination. The latter might plausibly obtain if male directors have a preference to connect to other members of predominantly male old boys' networks (the mixing patterns in the study networks provide some indicative evidence for this, as male directors have a clear bias towards forming ties with other males over females, while the converse is true for female directors). More focused empirical investigation is necessary to uncover why such pervasive and stark gender disparities exist. Nonetheless, for our present purposes, it seems reasonable to suppose that this gender disparity makes it less likely for a given female director, than a male one, to

Table 7. Instrumental Variable Results (2SLS): Lodged patents in information tech, mean 2011-2016 (ln)

IV used:	Gender disparity		Connecting channels		*Both instruments*	
	(1)	(2)	(3)	(4)	(5)	(6)
Dealmakers (4+)	0.307 ***	0.688 ***	0.450 ***	0.502 ***	0.407 ***	0.449 **
	(0.036)	(0.197)	(0.038)	(0.137)	(0.036)	(0.140)
Working population		-0.133		0.009		0.059
		(0.157)		(0.100)		(0.106)
NVQ 4+ %		0.373		0.518 **		0.543 **
		(0.242)		(0.194)		(0.198)
Relevant employment %		0.145		0.201		0.205 *
		(0.105)		(0.102)		(0.102)
Local linkages		-0.079 ***		-0.058 ***		-0.061 ***
		(0.020)		(0.015)		(0.015)
External linkages		-0.023		-0.023		-0.020
		(0.013)		(0.013)		(0.012)
Constant	-0.080	-0.296	-0.51 ***	-1.739	-0.392 ***	-2.285
	(0.089)	(1.881)	(0.095)	(1.343)	(0.092)	(1.383)
Observations	210	210	210	210	210	210
Region FE		Y		Y		Y
R2	0.533	0.667	0.578	0.683	0.569	0.683
Weak instruments *F* statistic	14.48 ***	11.59 ***	722.5 ***	33.43 ***	464.71 ***	14.54 ***
Sargan's *J* statistic					0.177	0.749

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

acquire enough connections to become a dealmaker in regional social networks which have a relative predominance of males.

Our second instrument is the number of pre-existing connecting channels, which are the directors from non-study industries that bridge connections between study industry dealmakers to companies operating other industries in 2010. One implication from the existing literature is that the quality of connections is likely to be more important than their raw quantity in their impacts on enhancing the ability to receive a diverse range of unique information, and thus on innovativeness in our study sectors (Kemeny et al., 2016; Feldman & Zoller, 2012). Connectors are important not just due to their own characteristics, but also because they act as part of the "relational infrastructure" expands the social reach of a given dealmakers' influence within regional entrepreneurial networks (Storper, 2018). We expect that connectors indirectly enhance the impact of dealmakers on patenting in the study industries, by providing channels to transmit novel information, thus improving dealmakers' ability to successfully bring together novel combinations of ideas and resources. Accordingly, connecting channels are defined as directors who work on the same company boards as at least one other director of a firm in the life sciences in the same region, and thus directly influence the number of dealmakers by construction. To align with their theorized role in enhancing the ability of dealmakers to benefit regional innovation via increased social network proximity to novel knowledge sources, connecting channels are linked to at least two other firms in total, and are also defined as not holding any positions on life sciences firms, in order to exclude company directors in firms that directly contribute to patenting in the life sciences. To further make the feasibility of any direct links with life sciences patenting even more remote, this last requirement is augmented by removing all companies listed as assignees in life sciences-related patents.

Both instruments are constructed from the company director dataset used to build the director interlock networks studied here. Tables 5 and 6 presents the IV estimation results, for the life sciences and information technology sectors respectively, run using the same basic specification as for the OLS models above, for the gender disparity and connecting channels instruments and for the overidentified model estimated with both instruments.

The weak instruments F statistic is significant for all IV models in the life sciences (Table 7), while the Sargan test of overidentifying restrictions is not close to significant at any conventional significance level for the overidentified model (Columns 5 and 6). These diagnostics suggests that the instruments are neither invalid, nor are they likely to be weak instruments. The coefficient for dealmakers is somewhat higher than in the OLS model for the IV models without controls (Columns 1, 3, and 5). The standard errors also remain small, and the IV estimations are significant at any conventional significance level. The dealmaker coefficients in the IV models with controls are higher than the OLS results for the life sciences (Column 11 in Table 3), while remaining highly statistically significant ($p<0.001$) for both the gender disparity and connecting channels instruments, and for the overidentified IV model.

The findings for information technology can be similarly described (Table 7), although there is a relatively smaller difference in the estimated coefficients for dealmakers between the models with and without controls. The standard errors are larger for the overidentified model with controls (Column 6) compared to the corresponding model for the life sciences, although they are nonetheless highly significant at the $p<0.01$ level in the former. Overall, these results are consistent with the OLS results and suggest a causal effect of dealmakers on regional innovation in both the life sciences and the information technology sectors.

One possible concern with this finding might derive from measurement issues over the reliability of the gender disparity indicator. As mentioned above, the gender disparity indicator is constructed from the company director data used to build the director interlock networks studied here. While there is no explicit data on individual directors' genders, we infer their gender using the other biographical information available in the dataset, and then account for their proportions accordingly for each TTWA. However, we are unable to conclusively identify the gender of all relevant directors from this information, particularly those with uncommon or unisex names. To prevent an unacceptably large proportion of individuals from being left out of the gender disparity measurement, we manually checked the gender for a subset of these individuals. This is a highly labour-intensive process that does not scale very well relative to the size of the data, and around four percent of individuals in the study sectors therefore remain without an unidentified gender in our dataset post-processing. This does not seem to warrant serious concern here, particularly given the strength of the findings reported above for two separately analysed high-tech sectors, except perhaps in a priori unlikely scenarios where the relatively small subset of individuals left out of consideration in constructing the indicator might have strongly biased our results: for instance if there are an unusually large share of dealmakers among these individuals without identified gender, while their gender distribution simultaneously differs very significantly from those with identified genders.

6. Conclusion

Dense webs of localized social interconnection have been found in economic geography and innovation studies to constitute an institutional source of interaction that benefits from firm and worker co-location and contributes to regional innovation. An emerging literature on highly connected individuals - sometimes termed "dealmakers" - has emerged to address the paucity of empirical research linking local social networks and regional economic performance, focusing on the connection between well connected network actors in the life sciences and information technology sectors and economic performance within leading high-tech clusters in the USA (Feldman et al., 2012; Kemeny et al., 2016; Pittz et al., 2019). However, there have previously been no relevant studies outside of the regions and firms studied in the USA. There has moreover been no direct investigation into the contributions of dealmakers to innovation and patenting more specifically within any empirical setting. This paper presents the first analysis on the topic to address both gaps. We have also addressed the network data coverage issues noted in the prior dealmakers work (Kemeny et al., 2016), by making novel use of open government data with census-like characteristics to construct the universe of company-director interlocks in the UK. This has also allowed us to construct a more complete picture of the importance of dealmakers and social capital in knowledge intensive high-tech clusters in the life sciences and biotechnology sectors. To ease comparability, we follow the empirical conventions set out in past dealmakers research to identify dealmakers and construct regional social capital indicators.

Our findings extend the literature by providing empirical support for the general importance of highly connected actors within local social networks for regional performance. We find that the regional distribution of dealmakers has a large and independent influence on patenting in both the life sciences and information technology sectors in the UK, while controlling for regional characteristics. This is consistent with the existing research in the USA empirical setting, which found that dealmakers have consistently positive substantive effects on both regional- and firm-level performance (Feldman et al., 2012; Kemeny et al., 2016). Feldman & Zoller (2012) has posited that dealmakers have a disproportionately large influence on regional innovative capacity and performance relative to all the other studied types of local network actors. Our findings are partially consonant with this argument. As the literature predicts, we find that dealmakers are more strongly associated than the aggregate membership size of localized social networks in the UK. This implies that dealmakers are not a unique feature of the American high-technology economy. An important potential extension of our finding is whether it applies still farther afield, as for example in China, and hence whether there are functional equivalents of the role played by dealmakers in very different institutional contexts.

Contrary to earlier findings, we find statistically and economically significant associations for the regional concentration of investors as we have for those actors we have defined as dealmakers. While the first-order effects of dealmakers for regional innovation appear to substantively significant and positive, this result suggests that the benefits of dealmakers on regional innovation is likely subject to a variety of contingent effects and intermediating processes that might influence knowledge diffusion, resource access, and the ability and incentives for dealmakers to act as robust network actors and enrich local social networks. Nonetheless, these comparisons are only suggestive, as our empirical analysis focuses on the UK context. Indeed, in the Silicon Valley context, "angel investors" are typically hands-on actors that link potential entrepreneurs to other actors and take an active ongoing role in coaching their financed start-ups to success; the role of dealmaker and investor would seem to overlap in these cases. Comparative research applying cross-country research designs should examine whether and how the seemingly preeminent role of investors reflects real differences in economic and institutional fundamentals between the US and the UK. Future work should also explore whether dealmaker effects generalize to other geographical and sectoral contexts, and on different economic outcomes.

Placed-based socioeconomic networks have long been seen as key drivers of local economic success. Our central goal here has been to identify the causal relationship between the local network structure and innovativeness productivity: viz. do highly connected actors cause social gains in regional patenting? Our results suggest an affirmative. While this question has long been central to economic geographical inquiry, the existing literature has tended to avoid directly addressing issues of causality. Nonetheless, our analysis obviously does not rule out other possible proximal and distal causes of local innovativeness. As relates to network structure, one such possible factor is the role of inter-regional network integration -- these so called "pipeline" connections have long been theorized to be highly impactful to place-based innovation success (Bathelt et al., 2004). Further research is thus needed to develop a causal understanding of the relationship between economic geography and socioeconomic networks. Likewise, while our focus on local patenting targets a mainstay research object in innovation studies, patenting represents only a subset of all economically productive urban innovation activities, and it thus remains an open question for future investigations into whether and how highly connected actors matter for innovation processes more generally.

As a first analysis of dealmaker effects outside of the original USA research setting, we have chosen to maximize comparability with the prior dealmakers research. This has also required that we follow the literature's empirical conventions. The literature has defined dealmakers as the actors with the greatest degree of local network interconnection. These more central positions give dealmakers comparative advantages in leveraging and organizing local social networks to realize benefits to economic performance. While dealmakers are also theorized to derive social capital from other positional network advantages (e.g., by brokering connections between otherwise disparate network communities), in practice the regional-scale empirical approach appears to be insufficiently fine-grained to consider these other network roles and micro-mechanisms, and identifies individual dealmakers solely through the quantity of their local connections. This is limitation is also salient in the present study. Further research should address the question of the extent and circumstances under which dealmakers have significant convening and brokering roles – and if so, to also disentangle the importance of being highly connected from these other forms of network centrality. Future research will need to do more to disentangle causality, specifically on whether something about the nature of contemporary high-tech industries seems to incentivize the emergence of dealmakers, as in the sociological theory of "structural holes" (Burt, 2004); or whether, instead, the regions that have strong dealmaker generation due to their antecedent histories tend to become innovation centres.

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Appendix A

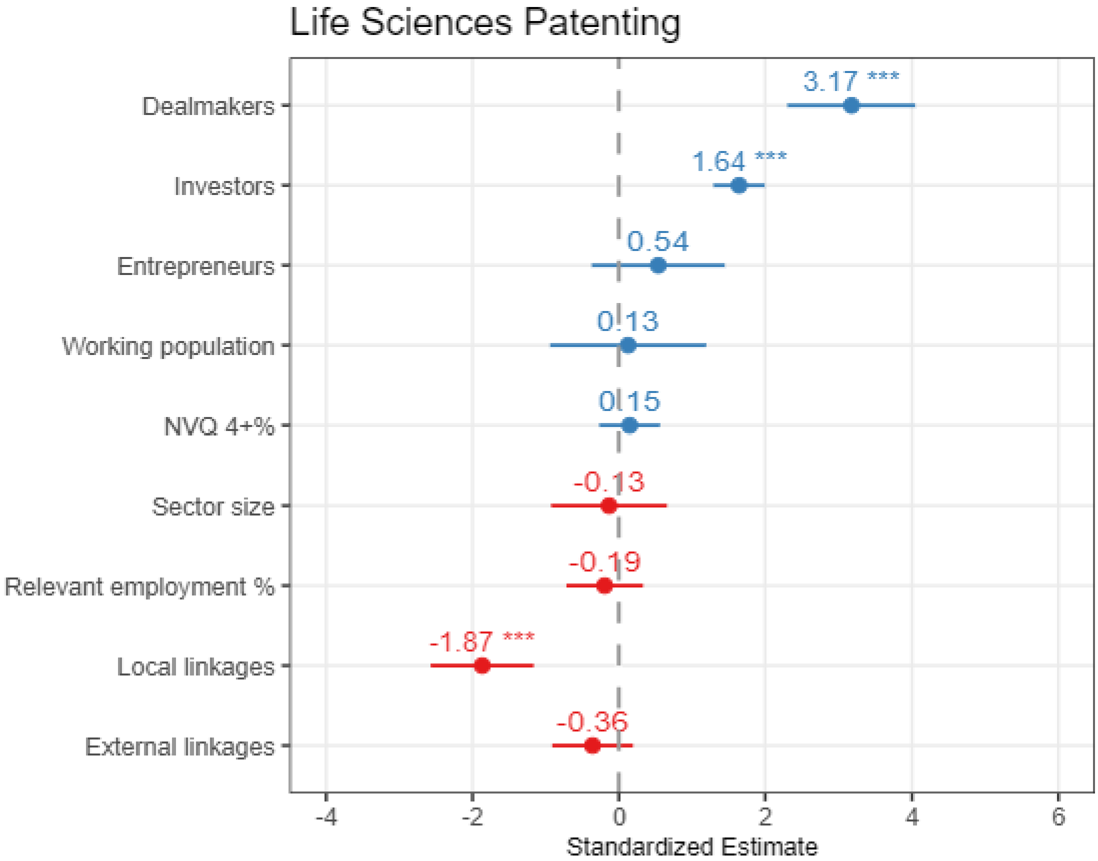

Figure S1. Dot-and-whisker plot showing standardized estimates for the regression model reported in Column 12 of Table 3 (0.95 c.i.).

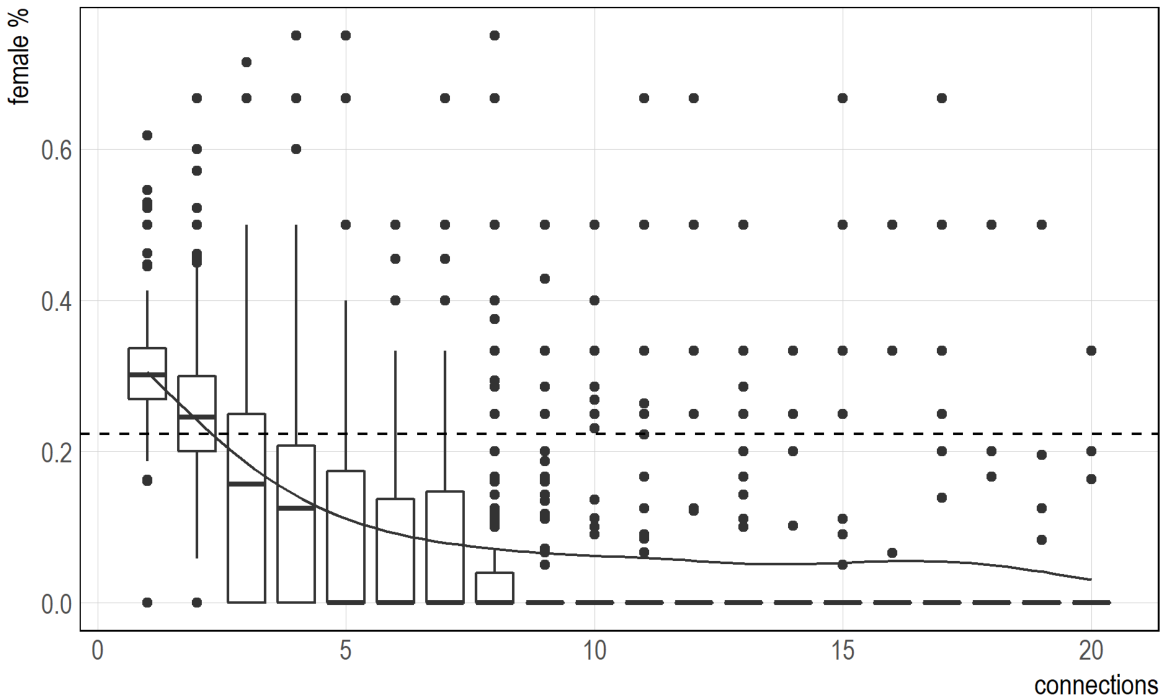

Figure S2. The regional share of female directors in the study regions is imbalanced and suggests a gender bias. The box plots summarise the gender distribution across the study regions. The total share of female directors across all study regions is shown by the dashed horizontal line, while the curve indicates the share of female directors by degree of connection across all study regions. We should expect that the regional share of female directors be invariant to the degree of connection (i.e. at the % indicated by the dashed horizontal line) if there were no gender bias for dealmakers – the trend towards zero as director connections increase suggests a systemic bias in favour of male dealmakers.

S1. List of Standard Industrial Classification (SIC) codes used

SIC 2007 code	5-digit SIC 2007 code	SIC 2007 heading	Industrial sector
21	21000	Manufacture of basic pharmaceutical products and pharmaceutical preparations	Life Sciences
21.1	21100	Manufacture of basic pharmaceutical products	Life Sciences
21.2	21200	Manufacture of pharmaceutical preparations	Life Sciences
26.6	26600	Manufacture of irradiation, electromedical and electrotherapeutic equipment	Life Sciences
26.70/1	26701	Manufacture of optical precision instruments	Life Sciences
32.5	32500	Manufacture of medical and dental instruments and supplies	Life Sciences
72.11	72110	Research and experimental development on biotechnology	Life Sciences
26.2	26200	Manufacture of computers and peripheral equipment	Information technology
58.2	58200	Software publishing	Information technology
58.21	58210	Publishing of computer games	Information technology
58.29	58290	Other software publishing	Information technology
61	61000	Telecommunications	Information technology
61.1	61100	Wired telecommunications activities	Information technology
61.2	61200	Wireless telecommunications activities	Information technology
61.3	61300	Satellite telecommunications activities	Information technology
61.9	61900	Other telecommunications activities	Information technology
62	62000	Computer programming, consultancy and related activities	Information technology
62.01	62010	Computer programming activities	Information technology
62.01/1	62011	Ready-made interactive leisure and entertainment software development	Information technology
62.01/2	62012	Business and domestic software development	Information technology
62.02	62020	Computer consultancy activities	Information technology
62.03	62030	Computer facilities management activities	Information technology
62.09	62090	Other information technology and computed service activities	Information technology
63.1	63100	Data processing, hosting and related activities; web portals	Information technology
63.11	63110	Data processing, hosting and related activities	Information technology
63.12	63120	Web portals	Information technology
95.11	95110	Repair of computers and peripheral equipment	Information technology

S2. Correlation matrix (Life sciences)

		1	2	3	4	5	6	7	8	9	10	11
(1)	Patents											
(2)	Actors	0.79***										
(3)	Entrepreneurs	0.78***	1***									
(4)	Investors	0.44***	0.35***	0.35***								
(5)	Dealmakers (4+)	0.81***	0.83***	0.82***	0.4***							
(6)	Working population	0.76***	0.9***	0.9***	0.34***	0.8***						
(7)	NVQ 4+	0.31***	0.25***	0.25***	0.18**	0.25***	0.073					
(8)	Relevant employment	0.120	0.17*	0.16*	-0.041	0.130	0.051	0.2**				
(9)	Local linkages	0.6***	0.74***	0.72***	0.26***	0.87***	0.71***	0.18**	0.130			
(10)	External linkages	0.58***	0.66***	0.65***	0.29***	0.79***	0.64***	0.19**	0.020	0.78***		
(11)	Connecting channels	0.75***	0.84***	0.84***	0.35***	0.83***	0.79***	0.31***	0.130	0.74***	0.71***	
(12)	Gender disparity	-0.17*	-0.34***	-0.33***	-0.080	-0.22***	-0.34***	-0.033	0.048	-0.23***	-0.16*	-0.21**

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

S3. Correlation matrix (Information technology)

		1	2	3	4	5	6	7	8	9	10	11
(1)	Patents											
(2)	Actors	0.76***										
(3)	Entrepreneurs	0.76***	1***									
(4)	Investors	0.78***	0.82***	0.82***								
(5)	Dealmakers (4+)	0.75***	0.96***	0.96***	0.82***							
(6)	Working population	0.69***	0.95***	0.95***	0.77***	0.93***						
(7)	NVQ 4+	0.37***	0.24***	0.24***	0.3***	0.24***	0.110					
(8)	Relevant employment	0.7***	0.78***	0.78***	0.66***	0.76***	0.66***	0.43***				
(9)	Local linkages	0.52***	0.79***	0.79***	0.59***	0.84***	0.78***	0.100	0.62***			
(10)	External linkages	0.55***	0.77***	0.77***	0.59***	0.81***	0.76***	0.2**	0.63***	0.84***		
(11)	Connecting channels	0.71***	0.93***	0.93***	0.77***	0.93***	0.88***	0.25***	0.73***	0.77***	0.78***	
(12)	Gender disparity	-0.17*	-0.33***	-0.33***	-0.19**	-0.3***	-0.37***	-0.026	-0.27***	-0.36***	-0.27***	-0.21**

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table S4. Lodged life sciences patents: Standardized OLS estimates for baseline and alternate specifications

Dependent variables:	Baseline	Baseline	Patenting / Capita	Patenting / Capita	Patenting Growth	Patenting Growth
Per capita dealmakers variable:		Y		Y		Y
Model:	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
Dealmakers	8.413** [7.15]	2.156* [2.22]	0.08* [7.15]	0.054* [2.22]	0.26* [6.14]	0.143* [2.31]
	(3.007)	(0.923)	(0.033)	(0.027)	(0.116)	(0.059)
Working population	1.633* [6.62]	5.438* [5.84]	-0.098 [6.62]	-0.052 [5.84]	-0.031 [5.86]	0.064 [5.85]
	(0.683)	(2.13)	(0.059)	(0.048)	(0.082)	(0.08)
NVQ 4+%	0.713* [1.52]	1.092* [1.54]	0.039** [1.52]	0.036** [1.54]	0.015 [1.47]	0 [1.54]
	(0.333)	(0.531)	(0.013)	(0.011)	(0.055)	(0.056)
Sector size	-0.481 [6.4]	-0.974 [6.37]	0.023 [6.4]	0.023 [6.37]	-0.023 [6.34]	0 [6.37]
	(0.287)	(0.509)	(0.045)	(0.039)	(0.045)	(0.046)
Relevant employment %	-0.591 [2.78]	-0.537 [2.9]	-0.016 [2.78]	-0.025 [2.9]	0.015 [2.74]	-0.024 [2.9]
	(0.831)	(0.836)	(0.03)	(0.028)	(0.056)	(0.057)
Local linkages	-4.708* [4.99]	-2.302* [4.46]	0.01 [4.99]	0.012 [4.46]	-0.155 [7.19]	-0.048 [4.52]
	(1.839)	(1.015)	(0.027)	(0.022)	(0.143)	(0.11)
External linkages	-0.779 [3.15]	0.673 [2.89]	-0.034 [3.15]	-0.024 [2.89]	0.012 [2.9]	-0.025 [2.9]
	(0.753)	(0.438)	(0.018)	(0.019)	(0.082)	(0.077)
Constant	1.288**	1.097*	0.061***	0.056***	0.206*	0.199*
	(0.458)	(0.451)	(0.012)	(0.013)	(0.086)	(0.092)
Observations	210	210	210	210	210	210
Region FE	Y	Y	Y	Y	Y	Y
R2	0.524	0.390	0.161	0.172	0.107	0.102

Appendix B

Individual records may be retrieved online from the API using HTTP GET requests (see the official documentation at https://developer.companieshouse.gov.uk/api/docs/index.html for more details). The large size and structure of the Companies House data necessitates the use of larger-than-memory data management and other "big data" programming techniques. The codebase is written in the R programming language with portions optimized in C++ and bash script. We abstract from the complexity of the software and programming implementation details here. We instead give a general overview of the methods used, focusing on the general steps and the guiding intuitions, in constructing the interlock social networks, and the dealmaker indicators from these networks. We proceed accordingly by presenting a stylized overview of the company-director interlock network's construction. Each company profile in the Companies House data includes a unique Company Registration Number. Individual company directors also have a unique identification number. These two features allow us to build a company-director interlock network connecting individual companies and their affiliated directors via an iterative algorithm. To illustrate, assume we have the company registration number for a single company in a sector of interest. We will refer to this as the so-called "seed". We begin by requesting the API for the company records associated with that company registration number. This will allow us to download that company's profile data. This profile data will contain the board of directors records associated with that company. We then query the API again, this time getting the data associated with the unique ids of the directors we obtained in the previous step. This gives us the company record data associated with the companies each of those directors are affiliated with. The availability of unique identifiers negates any further need to disambiguate individuals to prevent identifier collisions between any two similarly named companies, or persons that happen to have the same combination of surnames and forenames. The above steps are then reiterated until further queries do not net us any new, non-redundant records.

At this point, we will have obtained the entire set of company and director records emanating from the company-director connections of the seed. By following the algorithm described above, we will have implicitly traversed through the network of company-director affiliations by exploiting the inherently relational structure of the record data; simultaneously moving through linkages within- and bridging across industrial sectors, and through linkages across time. The latter obtains since the board of directors record for each company includes records for all current and historical company officer positions. Formally, this will have allowed us to define a bipartite network represented by a g × n incidence matrix B_{ij}, where g is the number of companies and n is the number of directors, such that B_{ij} is connected if and only if director n is/was on the board of company g. This is, in other words, a cross-sectional network defined by "board and firm tie interlocks", following the dealmaker literature's empirical conventions (Feldman & Zoller, 2012). Note that B_{ij} is not necessarily identical to the network defined by the ground truth network defined by the universe of company-director connections. The algorithm described above cannot discover companies that are in isolated network components (a network component refers to a network structure where all actors belonging to that component can trace an indirect path to each other). This means that companies that are not currently, and have never been, directly or indirectly connected to another company through director interlocks cannot be discovered by definition by this algorithm on its own; likewise for individual directors. The completeness of B_{ij} is also influenced by the initial selection of the seed for the same reason. In practice, however, we are not restricted to using only a single company as the seed. We can also circumvent this issue in practice by including directly downloaded records omitted by the algorithm, with the caveat of having to deal with the additional set of technical hurdles this would entail.

Paper 2 – Innovation in the pipelines: Dealmakers, non-local knowledge, and regional innovation

Augustin Boey

Abstract

An emerging literature shows the importance of well-connected individuals on multiple company boards – 'dealmakers' – for innovation in frontier sectors. At the same time, one of the longstanding debates in economic geography has been the relative importance of localised linkages ('buzz') compared to wider linkages ('pipelines'). Yet despite considerable effort to theorise these relationships, limitations of data have so far limited empirical analysis on these topics. This paper uses a unique dataset of individuals on all UK boards in the life sciences to integrate these two literatures and investigate the extent to which innovation is due to external 'pipeline' connections from dealmakers to non-local networks compared to pipelines intermediated by ordinary actors, while controlling for the 'buzz' generated through locally clustered connections. The results suggest that the effects of pipeline on regional innovation depend on the network positions of the individuals they connect to. Pipelines that are intermediated by dealmakers have an asymmetric enabling and catalysing effect on those that are connected to less influential individuals.

1. Introduction

Innovation remains remarkably concentrated within urban and regional clusters, despite strong secular reductions in transport and communication costs and the ongoing dispersal of routinized and standardized production in the context of contemporary globalization (Acs, 2003; Audretsch et al., 2011; Carlino & Kerr, 2015; Feldman, 1999; Feldman & Florida, 1994; Glaeser et al., 1992; Storper, 1997, 2013).

Scholars of regional innovation attribute the success of highly innovative regions, such as the Silicon Valley, to their enduring ability, fostered and sustained by vibrant and cohesive professional and informal social networks, to act as regional hotbeds of intense knowledge-enhancing collaborations and close interpersonal interactions (Acs, Stam, et al., 2017; Almeida & Kogut, 1999; Ferrary & Granovetter, 2009; Powell et al., 1996; Saxenian, 1996; Singh, 2005; Storper, 2018; Whittington et al., 2009). The joint effects of these localized webs of social linkages on the emergence of complex collective learning mechanisms has accordingly been conceptualized as a critical institutional source of regional advantage (Bathelt & Turi, 2011; Storper, 2018; Storper & Venables, 2004). More cogently, this so-called local buzz is also theorized to synergize with pipeline channels that connect and channel knowledge between clusters at regional and global scales (Amin & Thrift, 1992; Bathelt et al., 2004; Coe & Yeung, 2015; Feldman & Kogler, 2010; Gordon & McCann, 2000; Storper, 2013; Taylor, 2010; Wolfe & Gertler, 2004).

The complementary nature of both internal and external cluster linkages on knowledge creation is the central thesis of a prominent stream of research on the geography of innovation, which we refer henceforth as the pipelines literature (Bathelt, 2007; Bathelt et al., 2004, 2017; Bathelt & Glückler, 2011; Fitjar & Huber, 2015; Fitjar & Rodríguez-Pose, 2014; Li & Bathelt, 2018; Maskell, 2014; Maskell et al., 2006; Moodysson, 2008; Morrison et al., 2013; Tödtling et al., 2006; Trippl et al., 2009). The idea here is that, in a nutshell, the coming together of buzz and pipelines that characterize highly productive and innovative clusters. The dense web of social interactions that generate local buzz fosters trust relationships between local economic actors, which in turn supports collective action and encourages deeper and more complex forms of interactive knowledge exchange. High quality buzz environments thus provide conducive environments that facilitate novel information received from extra-local sources via pipeline channels to be efficiently diffused to the rest of the cluster.

But how exactly do socially interacting individuals matter in these buzz and pipeline dynamics? Despite the manifest importance of peer-to-peer social interaction in the transmission and diffusion of pipelined information, there has been little research systematically studying the relationships between the effects of pipelines on knowledge creation and the intermediating individuals with differential network roles and positions in regional networks[1].

This provides an apt conceptual entry point for the emerging dealmakers literature, which has provided growing evidence for the importance of well-connected individuals on multiple company boards for innovation in frontier sectors (Boey, 2020; Feldman & Zoller, 2012; Kemeny et al., 2016; Pittz et al., 2019). The central thesis advanced by this literature is that locally well-connected individuals have a disproportionate ability to augment economic performance, compared to those with an average degree of network connection, due to their positional advantages in leveraging regional connections to lower the costs of connecting people and transmitting information. Dealmakers are likely the lynchpin individuals responsible for generating and sustaining local buzz in realizing the benefits of local social networks. By virtue of their deeper embeddedness and unusual levels of network influence, they are also likely to be of disproportionate importance in influencing how quickly and efficiently the rest of the cluster is exposed to novel ideas. Moreover, given the primacy of interpersonal interaction established by the literature on buzz and its 'vital functions in coordinating deal making and relationships in the modern economy', the championing of regional ecosystems posited for dealmakers by the theoretical literature implies that these well-connected individuals are an integral part of the scarce supply of network 'leadership that convenes' within localized social networks (Storper, 2013: 227; Feldman & Zoller, 2012). Nonetheless, the nascent literature has yet to give sustained attention to empirically investigating potential mechanisms for dealmaker effects. While the dealmakers literature has proposed that

[1] See also Audretsch et al., (2018) for cognate comments from the perspective of the entrepreneurial ecosystems literature.

non-local connections likely influence the ability of locally well-connected actors to augment economic outcomes, this has thus far remained untested conjecture as the literature has yet to systematically address the relationship between dealmakers, pipeline connections, and regional innovation (Kemeny et al., 2016).

We thus situate this article to address the gaps located at the intersection of these two literatures, and explore:1) whether and how different types of dealmakers are substantively more important than others for regional innovation; and 2) whether and how pipelines from dealmakers matter in relation to pipelines from non-dealmakers for regional innovation.

This article focuses on the life sciences to build a comparable base of evidence with previous dealmakers research that had an empirical focus on innovation in the life sciences in the UK (Boey, 2020). This is also generally consonant with the focus of the broader literature, as extensive empirical research has established the life sciences as an archetype for knowledge-intensive high-tech industrial sectors strongly characterized by interactive learning and knowledge creation processes between collocated people and firms (Powell et al., 1996; Saxenian, 1996; Storper, 2018; Whittington et al., 2009). Our focus on the life sciences is also particularly salient to the ongoing concerted push from UK policymakers to develop globally competitive research capabilities and keep the country at the technological forefront in strategic areas of the life sciences, as part of industrial policy to drive longer-term growth[2].

In the next section, we briefly review how the pipelines literature conceptualizes the ways in which external connectivity augments regional innovation. We explain how this work inadequately accounts for the differential roles of networked individuals, using this as a point of departure to develop our hypotheses in connection to the dealmakers literature. Next, we describe how we use patent data and a novel dataset on the universe of company-director interlocks (Boey, 2020) in this article's analyses.

[2] See https://www.gov.uk/government/publications/eight-great-technologies-infographics, for example.

We outline how we construct the pipeline index, ending off the section by presenting some descriptive statistics on the relationships between regional patenting and pipeline extensiveness.

We then discuss the empirical model of regional innovation used here, before proceeding to present the estimation results. The findings from econometric tests of the effect of these social network indicators on regional patenting are consistent with our basic argument: the effect of pipelines on regional innovation depends on how these channels to extra-local knowledge sources are articulated into a region's innovation ecosystem through the differential roles and network positions of the individuals that intermediate these pipelines. Pipeline dealmakers have a complementary, but asymmetric enabling effect on the ability of locally oriented dealmakers to systemically contribute to regional innovation. Similarly, while the extensiveness of a region's pipelines is a substantively and statistically significant contributor to regional innovativeness, dealmakers asymmetrically enable and catalyse the benefits of less well-connected actors' external connectivity through dealmaker intermediated pipelines. This suggests that the distribution and quality of local dealmakers are critically important factors in divergent regional performance in the life sciences, and perhaps also more generally for high-skilled and knowledge-intensive industries at the innovative frontiers of the economy. The final section discusses these results, putting them in relation to their importance for policy and future research into regional innovation.

2. Individuals, pipelines, and social networks

The concepts of buzz and pipeline have been the subject of considerable research. The first view, dominant in initial research on the sources of innovation (Fitjar and Rodríguez-Pose, 2011), is that the source of innovation comes from local interactions – so-called 'Buzz'. These local interactions are seen as one of the important features underpinning the tendency of innovative activity to remain, even in the context of remarkable reductions in transport and communication costs, highly spatially concentrated within urban and regional economies (Acs, Audretsch, et al., 2017; Audretsch & Feldman, 2004; Duranton & Puga, 2004; Glaeser, 1999; Storper, 1997, 2013). This can be expressed as face-to-face contact (Venables and Storper, 2004).

The alternative view proposes that innovation is in large part due to linkages to the wider economy. This literature (henceforth the 'pipelines literature') theorizes that a well-developed network of pipelines provides the channels to external sources of novel knowledge requisite to a thriving and vibrant regional innovation ecosystem (Bathelt, 2005; Bathelt et al., 2004, 2017; Bathelt & Glückler, 2011).

This literature has developed significantly since the original seminal studies were published in the mid-2000s. Firms level studies have highlighted the importance of non-local links in innovative activity in London, UK (Gordon and McCann, 2005) and various Norwegian cities (Fitjar and Rodríguez-Pose, 2011; Fitjar and Huber, 2015). The general finding of this literature is that the two forms of connection matter differently for different types of innovation, and that they are often complements (Fitjar and Rodríguez-Pose, 2011). 'Buzz' and 'pipelines' may work together with local buzz generated and sustained by a critical mass of collocated actors interacting over dense localized social networks operating synergistically with extra-local pipeline linkages over wider geographical scales (Amin & Thrift, 1992; Bathelt et al., 2004; Gordon & McCann, 2000; Taylor, 2010; Wolfe & Gertler, 2004).

Yet the literature has some important limitations. One important limitation is that the literature on buzz and pipelines often removes the individual from their discussion of the mechanisms through which innovation happens. While the pipelines literature frequently invokes the idea of social networks, it nonetheless leaves unclear the extent to which we should regard network ties as having substantively meaningful roles beyond being an expressive metaphor used to describe transaction cost focused explanations of knowledge spillovers between collocated agents. What tends to get left by the conceptual wayside, in both the broader research on agglomeration and social networks and particularly in the pipelines framework, are systemic understandings of the differential roles and impacts of individual actors in collective learning and knowledge creating processes (Feldman & Zoller, 2012).

In contrast, in the much more nascent literature on dealmakers the focus of attention is much more explicitly on the individual. The literature suggests that unusually well connected individuals, or dealmakers, are important parts of localised social networks. In Kemeny et al.'s (2015) study, they argue that dealmakers can be an expression of local social networks, as they allow connections to the 'regional social network' through which 'workers can gain new ideas and human capital that might raise productivity, open new markets, help develop new products, or stimulate mergers, acquisitions or other types of liquidity events' (Kemeny et al., 2015: X). Yet, while there is some discussion of network positions in the dealmakers literature, empirical work has so far only considered dealmakers as a single construct.

The theoretical literature also argues that the first order effects of pipelines on regional innovation are not necessarily positive but is contingent on the presence of sufficient local buzz (Bathelt et al., 2004: 42):

> … both local buzz and global pipelines offer particular, albeit different, advantages for firms engaged in innovation and knowledge creation. Local buzz is beneficial to innovation processes because it generates opportunities for a variety of spontaneous and unanticipated situations where firms interact and form interpretative communities. The advantages of global pipelines are instead associated with the integration of multiple selection environments that open different potentialities and feed local interpretation and usage of knowledge hitherto residing elsewhere.

If this is correct, we might expect that pipelines and buzz are complements for regional patenting, with the optimal balance between the two depending on the specificities of the geographical and organizational context.

2.1 Hypotheses: Dealmakers and buzz vs. dealmakers and pipelines

Building on the theoretical literature above, and the results of the empirical research stated earlier, our principle hypothesis is that it is a combination of a thick local networks (buzz) and wider national networks (pipelines) which matter. This is because dealmakers who are fully locally oriented provide qualitatively different benefits to local innovation processes. Both types are thus likely contribute to regional enhancing the intensity and quality of local interaction by performing the network bridging and convening roles thus far emphasized in the dealmakers literature, thereby augmenting localized learning-by-interacting processes (cf. Storper, 2013).

> Hypothesis 1: The presence in a region of locally and nationally oriented dealmakers are complements, such that increasing the concentration of one will amplify the positive effect of the other on regional innovation, controlling for regional and local network characteristics.

By extending this argument to the dealmakers thesis, it is possible to conceive of two distinct types of dealmakers: 'ordinary' local dealmakers, who are exceptionally well-connected individuals within regional ecosystems, but lack substantive non-local connections; and pipeline-possessing dealmakers, who occupy comparably central positions within localized social networks, but who simultaneously hold 'pipeline' connections to the outside of their home regions.

Thus, we hypothesize that:

> Hypothesis 2: The regional extent of dealmaker-provided pipelines and non-dealmaker provided pipelines are complements, such that increasing the concentration of one amplifies the positive effect of the other on regional innovation, controlling for regional and local network characteristics

2.2 Hypotheses: Asymmetric enabling effects

Novel knowledge is typically sourced and transmitted socially by individuals in highly innovative industries, often requiring face-to-face interaction, due to the inherent pervasiveness of tacit knowledge and inherently high degree of uncertainty (Borgatti & Cross, 2003; Storper & Venables, 2004). The high costs of interactively transferring such information induces free-ridership and other agency and incentive problems that can be mitigated through the incentives for pro-social behaviour directly and indirectly created by face-to-face contact (Storper & Venables, 2004). Empirical research has likewise demonstrated that quid pro quo information exchanges on informal professional networks are a common knowledge transmission strategy even among competitors (Cowan & Jonard, 2004; Fleming et al., 2007). Such arrangements thus often have characteristics of a search and matching problem. They also often necessitate shared expectations and incentives for reciprocity since the informational payoffs are often not immediately gained by at least one party in the exchange. The relatively closed network structure in the cohesive core can perform the role of a stable in-group for the maintenance and collective enforcement of norms of social interaction (Granovetter, 2005). The structuring of relationships discussed above can also play a complementary role to face-to-face interaction here in promoting knowledge-enhancing pro-social behaviour by fostering an institutional setting conducive to endogenizing interactions. We expect that the resulting reduction in social distance and broadening of reachability raises incentives for reciprocal behaviour, while also promoting fuller commitment to exchanging information, by boosting the predictability and likelihood of repeated contact and interaction between two previously interacting agents. This in turn raises the value of knowledge-enhancing interaction. Assuming individuals are free to exit the region for greener pastures, this can thereby reinforce the ability of the localized network to further endogenize interaction by increasing the incentives for meaningful and repeated regional participation.

Actors may leverage the positional advantages conferred by their location and centrality within localized social network structures to coordinate knowledge-enhancing peer-to-peer interaction. The leveraging of weak ties via bridging and intermediating between socially distant groups and individuals is a potent mechanism for the cross-network sourcing of novel information and new ideas (Ahuja, 2000; Burt, 2015; Granovetter, 1973, 2005). Dealmakers are expected to play lynchpin roles here due both to their exceptionally high network influence, and the conducive network structure created by the strong ties of the cohesive dealmaker core connected via weaker ties to less deeply embedded participants in the regional ecosystem (Boey, 2020; Feldman & Zoller, 2012; Pittz et al., 2019). The pipelines literature emphasizes the importance of this relational mechanism, and in identifying weak ties with those between locally peripheral actors and with spatially distant ones connected through pipelines (Bathelt et al., 2004). Strong ties can have a stifling effect on the diffusion of novel information, as the pipelines literature argues, likely due to increased pressure to conform to conventions and a corresponding resistance to breakthrough innovations and increased propensity to engage in groupthink, between strongly connected and socially clustered actors (see also Fleming et al., 2007). Nonetheless, the strong ties between dealmakers do not exist in social isolation, but likely also provide the stable institutional backbones and network loci to facilitate cross-network bridging through their effects on reducing search and informational frictions.

Moreover, the complementary roles performed by the cohesive dealmaker core as regional switching boards facilitates a systemic reduction in social distance, and expansion in social horizons. This in turn creates the conditions for the formation of knowledge-enhancing social relationships, between a broader and more heterogeneous set of agents on a wider scale than would otherwise be reachable in the first place (Dodds et al., 2003; Newman, 2018; Watts & Strogatz, 1998). This also creates a variety of open and closed social contexts across the regional ecosystem that helps to manage the need for diversity in innovation, while helping to contain cohesion-damaging social tensions which could also dampen creativity by reducing willingness to receive and share information, that might arise from overexposure to culturally diverse agents (Bassett-Jones, 2005).

The creation of this cohesive in-group can help to reduce search and matching frictions only partially addressed by face-to-face contact, while also providing potential distributed signal processing and storage processes that help to address individual cognitive limits of representing complex systems, by supporting and fostering economies of scope in social metacognition (Borgatti & Cross, 2003; Casciaro, 1998; Cowan & Jonard, 2004; Garavan & McCarthy, 2008; Krackhardt, 1987). In contrast to the deep commitments and high transaction costs related to the knowledge transmission processes outlined above, such meta-information is more akin to professional gossip, and is more readily transmitted and exchanged through local buzz processes. Individuals with weak relationship ties are less likely to share negative gossip, compared to those with higher-trust ties, who are likely to share both positive and negative gossip, as shown in the organizational studies literature (Grosser et al., 2010). We might thus also expect that dealmakers share higher quality signals when they gossip, compared to any two given local actors, given that negative and positive evaluations are likely both important in making informed matching decisions.

Economic studies of social networks have shown that well connected agents are particularly effective in interactively diffusing new information to the broader community, particularly where there are effective time constraints to the information diffusing process (Alatas et al., 2016; Banerjee et al., 2013, 2019). Dealmakers are the obvious analogues here to these well-connected agents. Their advantageous network positions are likely particularly important for timely information transmission in highly competitive and knowledge-intensive industries. Dealmakers are moreover -- by their definition as especially well-connected agents – more likely to interact with others and thereby have opportunities to share and accumulate meta-information. Their broader social exposure is also expected to be instrumental in helping to address bounded rationality problems. The empirical social networks literature demonstrates that individuals tend to have fuzzy and myopic knowledge of their networks (Banerjee et al., 2019; Casciaro, 1998). Here, the relative stability and cohesiveness of the dealmaker core might allow its members to collectively act as a kind of distributed store of institutional memory for meta-information about the abilities, expertise, and attributes of regional agents that can augment search and matching decisions.

Moreover, differential exposure to information transmitted through central pipelines between dealmakers, and from peripheral pipelines to dealmakers via ties to ordinary agents, helps to drive specialization in meta-informational expertise, and effectively distributes complex relational knowledge such that it remains readily and quickly accessible through the grapevine. These dynamics creates an evolving regional knowledge ecology, where pipeline dealmakers have adaptive advantages in acquiring specialized expertise in the particular brand of knowledge they have first-hand exposure to via their positioned at the ends of central pipelines. The availability of this institutional store of meta-information reduces the need for costly signalling by supporting trust and reputation effects, and the joint effects of network structure on screening and matching processes help to mitigate the costs of coordination across the individuals within a region's innovation ecosystem.

The balancing of diversity and stability through network structure also incentivizes regional participation and commitment, and supports more complex and involved forms of knowledge-enhancing formal and informal relationships, including training and mentoring, and collaborations and strategic R&D alliances (Ahuja et al., 2009; Gulati, 1999; Newman, 2004; Powell et al., 1996; Uzzi, 1997). As discussed in the aforementioned, the benefits of peripheral pipelines are expected to accrue mainly to raising the volume and diversity of externally-sourced information, while the benefits of central pipelines are expected to have a greater impact on the systemic coordination of knowledge-enhancing interactions. Their joint complementarities thus raise regional innovation productivity by facilitating and incentivizing knowledge-enhancing communication, and thus act as an institutional source of regional advantage in innovative capabilities. We direct our attention here specifically to the systemic benefits to knowledge creation in clusters, making a conceptual and analytical distinction between two types of pipelines: 1) central pipelines, and 2) peripheral pipelines. The key differentiating observable characteristic between the two is that the entry points of the former into a given region are especially well-connected actors – i.e. dealmakers, while the latter are intermediated by actors that have an unremarkable degree of network centrality in their regions.

The specific setup in which pipelines are received and articulated through differentially connected regional network actors act as an important institutional component of a region's relational infrastructure (Storper, 2018). Differences in the embeddedness of intermediating actors, whose interactions are structured through social networks, lead to qualitatively different functions and substantively distinct effects for both pipelines types (Granovetter, 1985; Uzzi, 1996, 1997; Zukin & DiMaggio, 1990). How connections to extra-local knowledge sources enhance regional knowledge creation capabilities thus depends on how pipeline channels are articulated into the regional buzz generated and sustained by individual actors interacting on localized social networks. As shown by the empirical dealmakers literature, regional networks for the life sciences and information technology sectors in the US and UK tend to have a core of cohesively tied dealmakers within a more diffusely linked aggregate network (Boey, 2020; Feldman & Zoller, 2012). These well-connected dealmakers tend to have more experience within their regions and industries than the average actor, and collectively provide an institutional basis for the intertemporal persistence and growth of regional communities of practice (Amin & Cohendet, 1999, 2005). This also provides an enduring institutional setting to foster distinctive regional epistemic cultures with more cosmopolitan outlooks, through the tendency for dealmakers to have greater and more continuous exposure to the flow of novel information and ideas (Cetina, 2007; Wenger, 2010). Unlike ordinary actors, dealmakers also tend to be more continuously and consistently exposed to novel information and ideas from central pipelines by virtue of the densely clustered social ties between dealmakers. This also acts as a kind of centralized network foci that facilitates the bridging and interchanging of information received from peripheral pipelines in the aggregate network. In combination with the relatively high diversity of ideas received from peripheral pipelines and through the churn and labour mobility particularly among the younger urban demographic (Bleakley & Lin, 2012), this jointly facilitates the balancing of systemic resilience with the dynamism necessary for supporting recombinant and breakthrough interactive knowledge creation processes within the region.

Active pipelines provide unique benefits to regional coordination that are unlikely to have good substitutes in the benefits of peripheral pipeline. Moreover, given that the benefits central pipelines provide unique benefits to regional coordination only through its articulation into regional ecosystems through localized social networks, it is intuitive that the complementarities between pipeline providing dealmakers and exclusively locally oriented dealmakers are likewise asymmetric.

We thus posit that:

> Hypothesis 3: Pipeline-providing dealmakers have an enabling effect on local dealmakers’ positive effects on regional innovation, controlling for regional and local network characteristics, but not vice versa.
>
> Hypothesis 4: Pipelines from dealmakers have an enabling effect on the positive effects of pipelines from non-dealmakers on regional innovation, controlling for regional and local network characteristics, as well as the regional concentration of pipeline-providing dealmakers, but not vice versa.

3. Data and methods

To measure innovation, we use the log of total patent counts lodged in the UK per region for the life sciences using open patent data from the Intellectual Property Office. Patent data are a widely used measure of innovation, and is expected to be robust for our purposes -- while patent data is widely known to have inherent limitations, particularly when used as indicators for direct economic impacts, these limitations are not anticipated to have material implications here due to our focus on the creation of new technological knowledge in the life sciences (Acs et al., 2002; Lee & Rodríguez-Pose, 2013; Sonn & Storper, 2008).

Relevant patents are identified at the subclass level using International Patent Classification based industry classifications published by the OECD. Following (Lee, 2017), we use total patent application data from 2011-2016 to mitigate fluctuations in patent reporting, linking each patent to a TTWA region by the applicant postcode sector. While more recent patent data are available, we take the widely-used approach of truncating the patent dataset by three years to avoid missing values arising from lags in the patenting life cycle (Crescenzi et al., 2016; Hall et al., 2001). All other data used in this article are accordingly considered only over this study period.

We use the latest 2011 travel-to-work-area (TTWA) boundaries to represent UK regions. TTWAs are official spatial definitions of regional labour market areas that are commonly used in econometric analyses to approximate functional economic city-regions (Lee, 2014).

The dealmakers indicators are built using the universe of company-director interlocks in the UK, making use of a novel census-like dataset constructed based on publicly available company register data from Companies House (see Boey (2020) for more details on this dataset, on network construction and specific considerations in constructing the regional social network indicators, and on other implementation details). For the study period, we consider connections between around 1.4 million indirectly connected directors in UK regions and around 24,000 directors on the boards of life sciences firms. We allocate these nodes in turn into 210 TTWA regions by their postcode sector. As per the empirical conventions in the dealmakers literature, we identify those directors with at least four local affiliations in a region as a dealmaker for that region (Boey, 2020; Feldman & Zoller, 2012; Kemeny et al., 2016; Pittz et al., 2019). We additionally categorize these dealmakers as either exclusively locally oriented dealmakers – dealmakers with at least four local affiliations, that also do not have any pipelines, i.e. they are not connected to any external regions through director interlocks; or as pipeline providing dealmakers – dealmakers with at least four local affiliations, and with at least one pipeline connection.

3.1 Measuring pipelines

We construct indicators for pipelines to measure the degree of non-local connection through the geographical distance traversed by the extra-local linkages intermediated by the actors within a region's localized social network. We measure three distinct sets of connections: 1) central pipelines: pipelines intermediated by dealmakers; 2) peripheral pipelines: for those pipelines intermediated by non-dealmakers; and 3) the aggregate pipeline index: the pipelines intermediated by all actors.

To construct these indices, we first measure the distance for each non-local link by calculating the rectilinear distance between geographically adjacent TTWAs between the origin TTWA and the destination TTWA. As mentioned, TTWAs are meant to represent the UK's spatial economy as a set of discrete, functional labour markets. However, major employment clusters may not necessarily be located at the centre of each TTWA, and TTWAs are moreover not equally sized. We thus do not use the absolute linear distance between the origin and destination points, as we want to capture the intuition that extra-local linkages represent connections to external networks. We also exclude Northern Ireland, as it is a separate landmass from the rest of the UK, and therefore does not have any geographically adjacent TTWAs to those on the UK mainland.

These distances are normalized by a constant, which is the maximum distance between TTWAs. They are then summed for each pipeline intermediating actor for each TTWA, and subsequently divided by the total number of local connections per actor. Here, we might consider two cases: 1) an individual actor that has more pipelines than local connections, and 2) an individual actor that is almost fully locally oriented in their origin TTWA, but happens to have a single non-local connection to a distant region. It is intuitive that the first actor is more externally oriented than the second, and it is thus desirable to be able to distinguish between them. Assuming the total distance traversed by the pipelines in both these cases are identical, we can distinguish them by dividing each actor's aggregate pipeline distance by the revealed extent of their local orientation, thereby imposing a penalty for the distance traversed by their pipelines based on the number of their local connections. They are then aggregated for each TTWA. As the region with the highest pipeline index in the UK is consistently London throughout the study period, we then divide each region's index by the index of the region with the highest pipeline index. This facilitates interpretation of a region's pipeline index by setting its external connectivity through director interlocks relative to London's, thus putting it more clearly into broader context of UK patterns of extra-regional interconnection.

3.2 Descriptive statistics

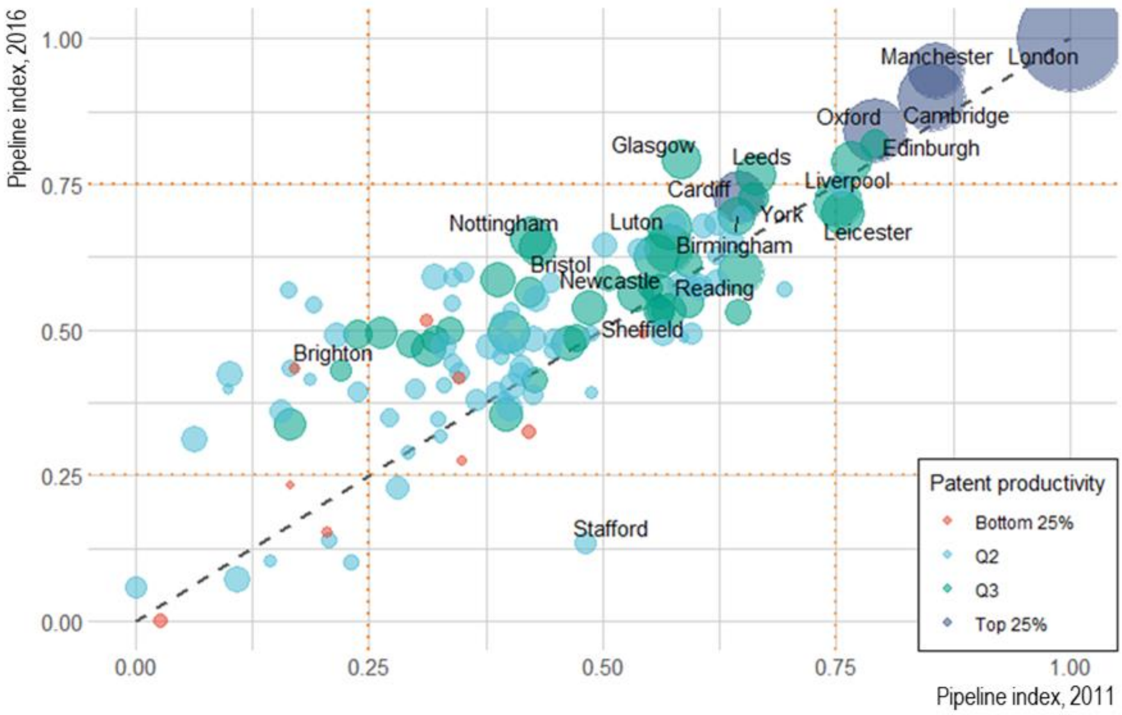

Figure 2. Changes in regional pipelines and patenting in the life sciences over the study period.

Figure 2 plots the pipeline index per region, for all actors, relative to London's, the most productive region's pipelines in 2011 and 2016 (the x and y axes, respectively). The points are scaled by the patent output of each region over the study period, and is assigned one of four colours to represent their relative innovative output – darker-coloured points belong to a club of regions that have higher patent productivity than lighter-coloured ones.

There is a direct relationship between the pipeline index and regional innovativeness, as indicated by the clustering of similarly coloured points in Figure 2. London also consistently has the highest pipeline index. The dashed diagonal line represents the average growth rate of London's pipeline index. Those points that fall to the right of the dotted line represent regions that had a relative decrease in their pipeline index over the study period. They appear to have generally smaller patent output.

There appears to be little turbulence, in terms of large-scale pipeline index movements, over the study period. The four dotted lines outline areas that might be interpreted as loosely defining the change in a region's relative pipeline index over the study period. For instance, the points within the area in the centre bounded by the four dotted lines represent regions that had a pipeline index in the midrange in both 2011 and 2016. We can notice that there appears to be little upward mobility, at least over the study period, particularly in terms of previously less externally connected regions becoming regions with a high pipeline index. Conversely, there are several regions that have moved from low-high, though the general trend is for regions to remain relatively close to their initial pipeline index from 2011 - 2016.

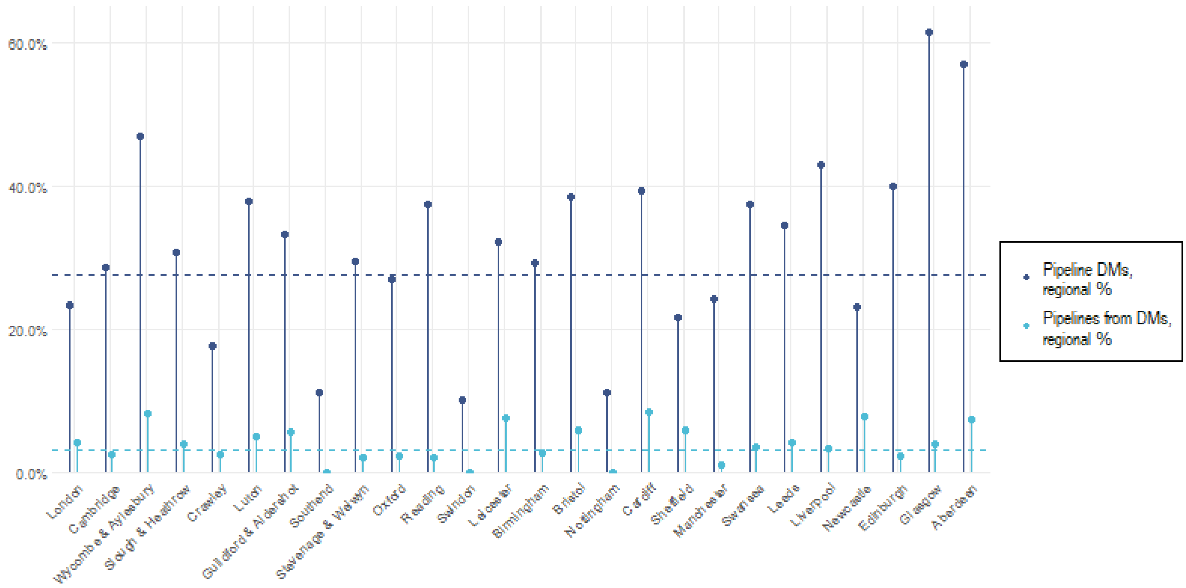

Figure 3. Active pipelines and the dealmakers that provide them in the life sciences for selected regions. Darker points show the regional percentage of pipeline providing dealmakers relative to all dealmakers within that region. Lighter points show the regional percentage of central pipelines (i.e. pipelines from DMs) to all pipelines within that region. The dotted lines show the mean value for each variable, corresponding to each colour. Regions are arranged in order of increasing distance from London, as calculated using the method described above, with patenting output used as the tiebreaker in event of a tie.

The correlation between the regional proportion of pipeline providing dealmakers, and the regional proportion of central pipelines, is positive and moderately strong at approximately 0.5. Regions tend to have a higher proportion of pipeline providing dealmakers with increasing distance from London (Figure 3). However, more distant regions do not obviously seem to have a higher proportion of central pipelines, as opposed to peripheral pipelines, compared to regions closer to London. Across the study region, pipelines appear to be sourced largely through non-dealmakers rather than dealmakers in the life sciences -- this is unsurprising since dealmakers generally comprise only a minority of a region's actors.

Table 2. Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
(1) Patenting																	
(2) Pipelines, all actors	.68 ***																
(3) Passive pipelines	.67 ***	1.00 ***															
(4) Active pipelines	.59 ***	.54 ***	.50 ***														
(5) Local linkages	.70 ***	.65 ***	.63 ***	.66 ***													
(6) External linkages	.64 ***	.58 ***	.56 ***	.76 ***	.81 ***												
(7) Relevant non-DM actors	.78 ***	.84 ***	.83 ***	.59 ***	.74 ***	.63 ***											
(8) Network density	-.51 ***	-.61 ***	-.60 ***	-.36 ***	-.46 ***	-.35 ***	-.75 ***										
(9) Actors in primary network	0.030	0.080	0.070	0.080	0.060	0.090	-0.010	0.030									
(10) DMs in primary network	0.110	0.130	0.100	.17 *	.26 ***	.19 **	.13 *	-0.100	.37 ***								
(11) Size of primary network	.71 ***	.69 ***	.68 ***	.54 ***	.69 ***	.67 ***	.74 ***	-.49 ***	0.090	.15 *							
(12) Working population	.76 ***	.74 ***	.73 ***	.59 ***	.74 ***	.64 ***	.90 ***	-.76 ***	-0.100	0.060	.75 ***						
(13) Relevant employment	0.060	.20 **	.20 **	-0.040	0.050	-0.050	0.070	-0.070	0.010	0.050	0.020	-0.020					
(14) Relevant firms	.80 ***	.81 ***	.80 ***	.61 ***	.79 ***	.67 ***	.99 ***	-.75 ***	-0.010	0.100	.77 ***	.92 ***	0.060				
(15) NVQ 4+ %	.32 ***	.31 ***	.31 ***	.19 **	.22 **	.26 ***	.24 ***	-0.100	0.060	-0.020	.30 ***	0.080	.13 *	.24 ***			
(16) Total dealmakers	.80 ***	.74 ***	.72 ***	.72 ***	.91 ***	.76 ***	.82 ***	-.52 ***	0.030	.15 *	.73 ***	.81 ***	0.090	.87 ***	.26 ***		
(17) Pipeline DMs	.73 ***	.61 ***	.59 ***	.79 ***	.86 ***	.92 ***	.68 ***	-.36 ***	0.080	.16 *	.68 ***	.67 ***	-0.020	.72 ***	.26 ***	.84 ***	
(18) Local DMs	.81 ***	.71 ***	.71 ***	.60 ***	.87 ***	.67 ***	.79 ***	-.48 ***	0.010	0.090	.71 ***	.78 ***	0.090	.83 ***	.25 ***	.96 ***	.77 ***

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Figure 4 illustrates this spatially. While there are pronounced differences in the distribution of pipelines from all actors and central pipelines across the study regions (panels d and e respectively), the distribution of all pipelines and peripheral pipelines appears almost identical (panels d and f respectively). The regional distribution of dealmaker intermediated pipelines and pipeline providing dealmakers has a moderately strong positive correlation across the study regions (Figure 3 and Table 2). However, pipeline dealmakers are more obviously regionally agglomerated in the

UK compared to exclusively locally oriented dealmakers (Panel c in Figure 4). This spatial distribution is even more pronounced when comparing central pipelines and peripheral pipelines (Panels e and f in Figure 4 respectively).

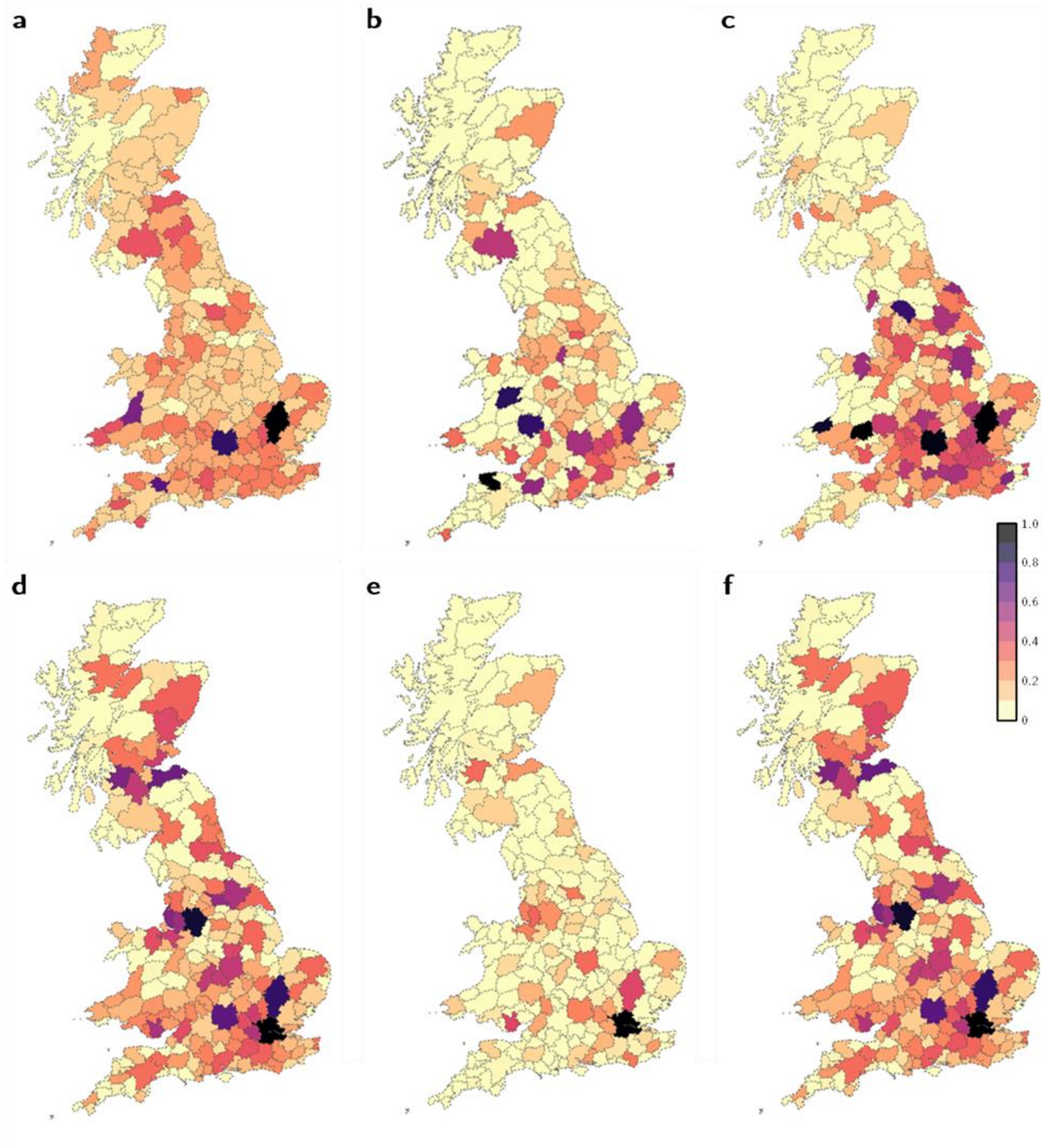

Figure 4. The regional distribution of dealmakers and pipeline connectivity for the life sciences in the UK. a-c Show the indicators at the TTWA level, normalized by working population, for all company directors (including non-dealmakers), pipeline providing dealmakers, and exclusively locally oriented dealmakers, respectively. d-f Show the pipeline index at the TTWA level for all pipelines, central pipelines (i.e. pipelines intermediated by dealmaker actors), and peripheral pipelines (i.e. pipelines intermediated by non-dealmaker actors), respectively. Higher regional values are mapped to darker colours, as shown in the colour bar.

4. Model

This paper explores the systemic relationship between regional network characteristics (i.e. pipeline connections and differentially positioned network actors) and innovation productivity. We use the regional level of analysis here, as we are interested primarily in system-wide impacts to regional innovativeness rather than the average impact for individual firms. The latter does not necessarily aggregate to the former due to potential social gains (Fleming et al., 2007).

As such, we model regional patenting in the life sciences from 2011-2016 within a modified regional knowledge production function (KPF) framework, where regional innovative productivity is assumed to be a function of locality-specific factors and knowledge sources (Acs et al., 2002; Griliches, 1979; Lee, 2017; Ó hUallacháin & Leslie, 2007; Rodríguez-Pose & Wilkie, 2019). Formally, we estimate the following empirical model for each TTWA i

$$\log(K) = \alpha + \beta_1 Z_i + \beta_2 CTRLS_i + \epsilon_i$$

where the dependent variable K is a proxy for knowledge – here, the number of patent applications in the life sciences lodged in the study period 2011-2016. The explanatory variables of interest are included in Z, and CTRLS are either vectors of control variables or region dummies for location fixed effects, with ϵ as the stochastic error term. We follow conventional regional KPF practice by log transforming all variables, except for region dummies and those variables representing percent regional shares.

We estimate two sets of models: the first focuses on exploring the differential roles of pipeline and local dealmakers on regional innovativeness, while the second focuses on comparing the systemic impacts of central pipelines and peripheral pipelines. The specifications of both models are identical except for the included explanatory variables of interest. For the dealmakers-focused models, the regional presence of dealmakers is broken down into two separate variables that are later interacted: pipeline DMs represent those dealmakers that have at least one external connection; while local DMs represent dealmakers that have four or more affiliations, but no non-local ones. Our general goal here is to unpack the roles between various types of dealmakers by teasing out the effects of pipeline providing dealmakers from exclusively locally embedded ones. Here, we follow the general approach in the previous work on dealmakers by focusing on the explanatory roles of the key individuals within regional ecosystems, rather than on aggregate network structure (Boey, 2020; Feldman & Zoller, 2012; Kemeny et al., 2016). The second set, the pipelines-focused models, distinguishes between the effects of pipeline development by their regional intermediation through either dealmakers or non-dealmaker individuals. As an exploratory and analytical strategy, it is also intended to build on the intuitions developed from analysing the first set of models. Here, central pipelines refers to the pipeline index, but constructed only for the subset of dealmakers in each region; whereas peripheral pipelines refers to the pipeline index constructed for all non-dealmakers in each region; with both combined in pipelines, all actors. The pipelines-related explanatory variables are present only in the specification of the second set of pipeline-focused models. This set of models also additionally include pipeline DMs as a control for regional pipelines development.

Both models use regional fixed-effects specifications to consider within-region variations only, and to control for idiosyncratic unobservable regional characteristics. As seen in Section 3.2, pipeline development appears to be characteristically clustered around London, the South East and the Northwest of England, and in Scotland. The latter also has a markedly greater proportion of pipeline providing dealmakers per TTWA compared to London. We might worry that dealmakers in Scotland, for instance, are systemically more likely to have more extensively pipeline connections due to their distance from London and the South East. Moreover, it is intuitive that substantive differences in governance structures and policies between the countries of the UK, and between broad regional groupings to a lesser extent, might materially impact regional innovation (Lee, 2017). Thus, for these dummies only, we use the regional statistical divisions defined at the NUTS 1 level to mitigate against the possibility of the results being driven by geographical location. These comprise Wales, Scotland, and the nine statistical regions in England (we exclude Northern Ireland, as explained in Section 3.1). These NUTS 1 regions are a proper superset of the TTWA study regions – there are no anticipated issues with mismatched spatial boundaries. Considering this paper's role as the first analytical cut into a complex but little understood topic, both sets of models are exploratory in purpose and do not control for simultaneity and selection issues. Accordingly, our analysis should be interpreted as descriptive associations, and not as causal effects.

3.1 Control variables

We include a vector of control variables for general regional characteristics that are each calculated for the study period from Office of National Statistics data. These comprise firstly of a control for agglomeration externalities – the log regional working population --that are expected to have a positive effect on regional innovative productivity via cluster size and urban density effects (Duranton & Puga, 2004; Lee & Rodríguez-Pose, 2013). We also include controls for the regional share of relevant employment in the life sciences, along with the log regional count of relevant firms, using Business Register and Employment Survey data. As an indicator of sector firm collocation, this is generally expected to be positively associated with regional innovation for similar reasons as the previous variable. It is also conventional for KPF models to include a measure of relevant industrial concentration as a proxy for industrial innovation networks not directly observed in the data (Acs et al., 2002). An indicator for human capital, usually in the form of regional education levels, is also typically included in regional KPF models (Lee, 2017). Here, we use the share of the regional population qualified up to NVQ (National Vocational Qualification) level 4 and above. This is expected to be positively correlated with innovation, as a measure of higher educational attainment, particularly due to the knowledge-intensive and high-skills characteristics of the life sciences.

Also common to the fully specified versions of both sets of models are controls for localized network characteristics. All of these variables are measured using the regional social networks constructed with the novel dataset of Boey (2020). These firstly include controls for first-order regional connectivity via the log regional count of external linkages, and likewise for local linkages. External linkages are a direct indicator of pipelines at the level of individual actors, while local linkages are a direct indicator of the number of ties between pairs of individual actors within each regional ecosystem. Including both these variables allow us to parsimoniously control for the fact that each individual actor, including dealmakers, holds a varying number of internal and external connections. This is particularly useful for the pipeline models, by helping to partial out variation that might otherwise bias the pipeline indices measure of the extensiveness of pipeline linkages.

We also include a second set of controls for localized network characteristics, this time focused on controlling for local buzz. This is desirable here since we want to distinguish the effects of dealmakers and pipelines from the benefits of local buzz to regional innovativeness. The idea that buzz environments, where there are increasing returns to the productivity and interactive learning benefits of face-to-face contact between co-present interacting individuals, is fundamental to economic geographical explanations of the virtues of colocation (Bathelt et al., 2017; Storper, 2013; Storper & Venables, 2004). Given firstly that buzz is theorized to result from effortful face-to-face interaction, and secondly that antecedent localized network structure shapes future opportunities for peer-to-peer contact, it follows that localized network structures have features that likely have strong influences on the intensity and quality of local buzz (Storper & Venables, 2004).

Here, local linkages perform a dual purpose as they are also an obvious candidate to partly control for buzz. To keep things parsimonious, we also adapt the network measures used in Feldman & Zoller (2012)'s dealmakers study. These measures were originally used in their study to compare the cohesiveness of dealmaker networks to the aggregate regional network in leading high-tech US clusters. Since it is intuitive that a region with stronger buzz is likely also more cohesive than a given region with generally weak interactions between local actors, these measures should provide get a reasonably valid set of controls for local buzz generated through local social network structure. Accordingly, we include a variable for the size of the primary network in each region. The primary network (also known as the primary component) contains the largest set of actors without any isolates in a social network. This is expected to have a positive correlation with regional innovativeness, since the aggregation of previously isolated actors into larger network components should augment knowledge spillovers and access to novel and diverse information (Fleming et al., 2007). We also include the regional network density to control for the overall level of connectivity between local actors, since the density of a network is defined by the ratio between the number of actual ties and the number of potential ties (Newman, 2018). Here, we follow Feldman & Zoller's (2012) example by including controls for the share of actors in the primary network, and the share of dealmakers in the primary network, to account for the differential cohesiveness of these groups of actors.

5. Results

5.1 Dealmakers results

We report the modeling results for the dealmaker model in Table 3. The models presented in Columns 1-4 include the dealmaker-related explanatory terms individually, then their interaction. The models in Columns 5-8 follow suit, this time including controls for regional characteristics and regional fixed effects. The models in Columns 9-12 additionally include local network characteristics, while those in Columns 13-16 also control for regional connectivity through local and external linkages. Unless stated otherwise, we focus below on the results of the full dealmaker model.

The effect of the dealmakers interaction term is robust. It is consistently positive and highly statistically significant (at the p<0.001 level) across all interaction models (Columns 4, 8, 12, and 16). All of the models demonstrated a consistently positive and generally significant association between the concentration of exclusively locally oriented dealmakers with regional patenting. The influence of pipeline providing dealmakers on regional innovation is also generally positive, though it is not significant in the full model. While the main effects of either of these two dealmakers-related variables imply a complementary relationship, the results reported in Table 3 are conditional on the other variable being held at zero. Knowing this is of limited practical value, however, as it is not unusual for many study regions to host both types of dealmakers.

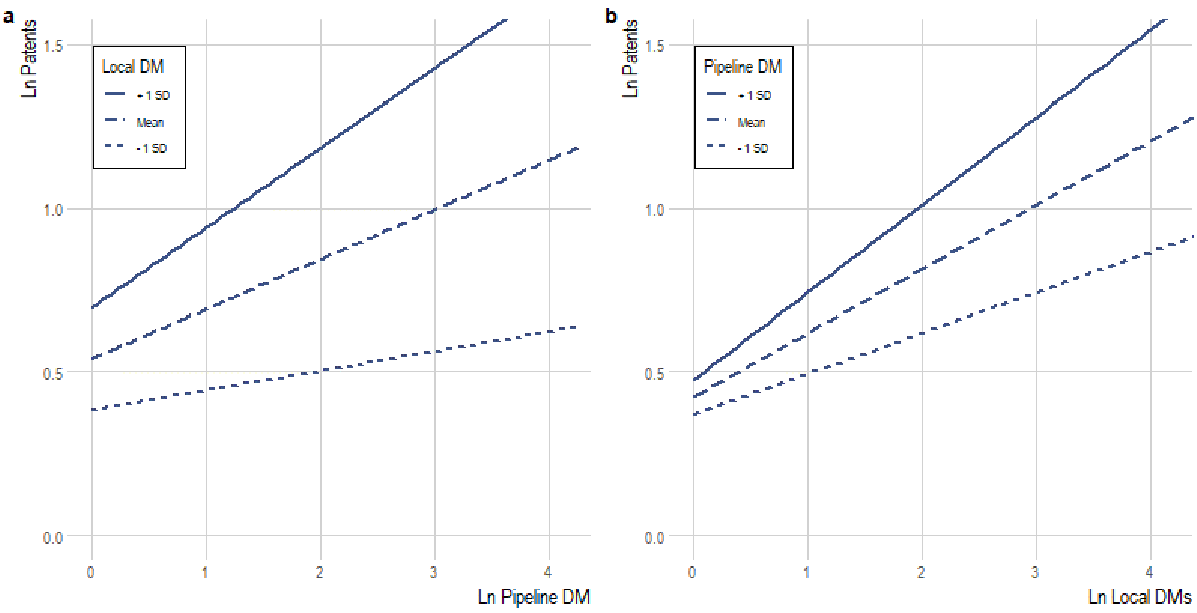

Figure 5. Conditional effects: Local dealmakers and pipeline-providing dealmakers. Non-interacted variables are mean-centred and held constant to simplify interpretation.

More cogently, the main effects do not inform us how the effect of pipeline dealmakers changes conditional on the effect of local dealmakers (and vice versa). Moreover, their apparently mutually complementary relationship might only obtain depending on relative regional dealmaker endowments. Such a scenario might lead us to draw very different substantively conclusions than in the generally complementary case. For instance, as a straightforward extrapolation from the hollowing out argument proposed in the pipelines literature might suggest (Bathelt et al, 2004), it might be the case that having too many pipeline providing dealmakers could prove detrimental for regions with a poorly anchored dealmaker network. It is thus plausible that increasing a region's pipeline providing dealmakers might have an increasing marginal effect on innovation in regions well-endowed with locally oriented dealmakers, while also having an opposite conditional effect in regions that do not have enough locally oriented dealmakers. Nonetheless, as Figure 5 illustrates, we do not find compelling empirical evidence for such a relationship in our data. The regional concentration of pipeline dealmakers appears to have a consistently positive influence on patenting whether the regional concentration of local dealmakers is held constant at their mean value or held at -1 or +1 SD (Panel a in Figure 5. Note that all figures in this section have logarithmic axis scales.). This is likewise true for the effect of local dealmakers on regional innovation conditioned on pipeline dealmakers (Panel b in Figure 5). We infer from these results that the interaction between pipeline providing dealmakers and exclusively locally oriented dealmakers has generally complementary effects regional innovation in the life sciences.

The statistical significance of the interaction term also belies the possibility that neither type of dealmakers necessarily has significant effects throughout the entire range of the observed data. We should therefore also further consider the values at which the slope of either dealmaker-related variable is likely to have a significant effect. This is shown in Figure 6 for the conditional slope of pipeline providing dealmakers, and the conditional slope of exclusively locally oriented dealmakers (viz. on the y-axes of Panels a and b in Figure 6, respectively). The darker shaded region in either panel shows the interval where either respective dealmaker variable is expected to be statistically different from zero. Approximately 0.4 pipeline providing dealmakers are required, on average, for the slope of local dealmakers to attain statistical significance (Panel b in Figure 6). Since fractional quantities are not substantively meaningful in this instance (as dealmakers are individual persons), we interpret this result as suggesting that regions need at least one pipeline-providing dealmaker for the concentration of local dealmakers to have a statistically significant effect on regional innovation. The implications of this are likely to be consequential, since around 25% of regions have at least one exclusively locally oriented dealmaker but do not have any pipeline-providing dealmakers

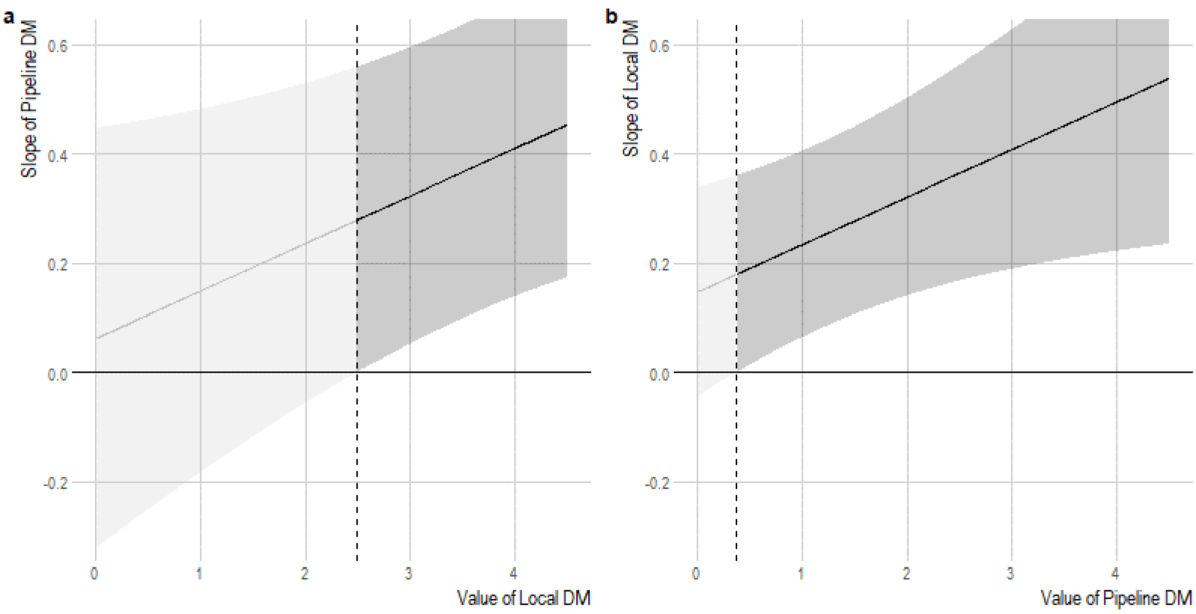

Figure 6. Johnson-Neyman plots for pipeline providing dealmakers and exclusively locally oriented dealmakers. a Conditional slope of pipeline providing dealmakers by local dealmakers. b Conditional slope of local dealmakers by pipeline providing dealmakers. The darker shared region in each plot indicates the interval where the predictor differs significantly from zero ($p<0.001$), adjusted to control the false discovery rate using the procedure detailed in (Esarey & Sumner, 2017).

Around 11 exclusively locally oriented dealmakers are required, on average, for the slope of pipeline dealmakers to be statistically different from zero (Panel a in Figure 6). Nonetheless, while this is markedly higher than the converse relationship, it is relatively unusual for a region endowed with pipeline dealmakers to not meet the requisite minimum threshold for exclusively locally oriented dealmakers – this amounts to only around 5% of the study regions. We interpret this pronounced asymmetry as providing indirect evidence with our underlying argument that pipeline providing dealmakers and exclusively oriented dealmakers have qualitatively different effects on regional innovation ecosystems. Moreover, the much lower minimum thresholds for pipeline dealmakers vis-a-vis local dealmakers observed in our data suggests a different set of substantive implications, as we discuss in the final section below. We therefore infer that a shortage of exclusively locally oriented dealmakers is of less consequence to innovation in a given region than an insufficient supply of pipeline providing dealmakers. These results thus support the first two hypotheses on pipeline providing dealmakers and exclusively locally oriented dealmakers and their relationship with regional innovation in the life sciences: 1) the two types of dealmakers are complements; and 2) there is an enabling effect, such that a minimum threshold of pipeline providing dealmakers is required for regions to benefit from exclusively locally oriented dealmakers.

Table 3. Dealmakers and Innovation, OLS Results: Lodged life sciences patents, mean 2011-2016 (Ln)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Pipeline DMs (Ln)	0.547 ***		0.200 ***	-0.021	0.223 ***		0.134 **	-0.118 *	0.160 ***		0.102 *	-0.142 *	0.428 ***		0.366 ***	0.063
	(0.035)		(0.045)	(0.062)	(0.041)		(0.044)	(0.058)	(0.044)		(0.046)	(0.060)	(0.082)		(0.079)	(0.109)
Local DMs (Ln)		0.472 ***	0.352 ***	0.286 ***		0.252 ***	0.192 ***	0.089 *		0.200 ***	0.166 ***	0.079		0.289 ***	0.249 ***	0.148 **
		(0.023)	(0.035)	(0.036)		(0.039)	(0.043)	(0.043)		(0.043)	(0.045)	(0.044)		(0.054)	(0.052)	(0.057)
Pipeline DMs (Ln) X Local DMs (Ln)				0.097 ***				0.110 ***				0.115 ***				0.087 ***
				(0.020)				(0.018)				(0.020)				(0.022)
Local linkages (Ln)													-0.040	-0.092 **	-0.127 ***	-0.072 *
													(0.029)	(0.034)	(0.033)	(0.035)
External linkages (Ln)													-0.157 ***	0.055	-0.097 *	-0.052
													(0.045)	(0.032)	(0.044)	(0.044)
Relevant non-DM actors (Ln)									-0.021	-0.001	0.018	0.003	-0.086	-0.044	-0.084	-0.051
									(0.108)	(0.106)	(0.105)	(0.097)	(0.107)	(0.106)	(0.101)	(0.098)
Network density (Ln)									2.598 **	2.127 *	1.768 *	0.712	2.417 **	1.947 *	1.394	0.755
									(0.858)	(0.855)	(0.862)	(0.815)	(0.836)	(0.854)	(0.820)	(0.807)
Actors in primary network %									0.214	0.183	0.157	0.123	0.199	0.142	0.101	0.099
									(0.282)	(0.277)	(0.274)	(0.253)	(0.274)	(0.273)	(0.260)	(0.251)
DMs in primary network %									0.081	0.117	0.085	0.188	0.174	0.219	0.271 *	0.268 *
									(0.119)	(0.115)	(0.115)	(0.108)	(0.121)	(0.122)	(0.116)	(0.112)
Size of primary network (Ln)									0.023	0.032	0.021	-0.024	0.036	0.024	0.024	-0.011
									(0.034)	(0.033)	(0.033)	(0.031)	(0.033)	(0.033)	(0.031)	(0.032)
Working population (Ln)					0.159 **	0.137 *	0.138 *	0.144 **	0.240 ***	0.207 **	0.199 **	0.198 **	0.248 ***	0.191 **	0.191 **	0.193 **
					(0.056)	(0.055)	(0.054)	(0.050)	(0.067)	(0.066)	(0.066)	(0.060)	(0.065)	(0.066)	(0.062)	(0.060)
Relevant employment %					4.788	-1.219	1.142	3.965	6.57	1.254	2.496	4.419	6.16	2.409	3.294	4.427
					(4.852)	(4.741)	(4.705)	(4.350)	(4.873)	(4.868)	(4.849)	(4.486)	(4.829)	(4.851)	(4.611)	(4.457)
Relevant firms (Ln)					0.121 *	0.09	0.063	0.085	0.147	0.088	0.049	0.076	0.231	0.147	0.184	0.145
					(0.056)	(0.055)	(0.055)	(0.051)	(0.129)	(0.128)	(0.128)	(0.118)	(0.131)	(0.131)	(0.124)	(0.120)
NVQ 4+ %					0.013 **	0.010 *	0.010 **	0.009 *	0.016 ***	0.013 **	0.012 **	0.011 **	0.016 ***	0.012 **	0.012 **	0.011 **
					(0.004)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	0.374 ***	0.194 ***	0.206 ***	0.276 ***	-2.132 ***	-1.821 **	-1.781 **	-1.736 ***	-3.317 ***	-2.869 ***	-2.674 ***	-2.332 ***	-3.423 ***	-2.652 ***	-2.551 ***	-2.341 ***
	(0.034)	(0.034)	(0.033)	(0.034)	(0.568)	(0.560)	(0.548)	(0.504)	(0.712)	(0.713)	(0.711)	(0.659)	(0.690)	(0.714)	(0.679)	(0.657)
Observations	210	210	210	210	210	210	210	210	210	210	210	210	210	210	210	210
Region FE					Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.540	0.661	0.690	0.723	0.736	0.749	0.760	0.798	0.751	0.762	0.768	0.803	0.769	0.771	0.794	0.810

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table 4. Pipelines and Regional Innovation, OLS Results: Lodged life sciences patents, mean 2011-2016 (Ln)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Pipelines, all actors (Ln)	0.243 ***				-0.010				-0.015				-0.016			
	(0.018)				(0.027)				(0.027)				(0.026)			
Passive pipelines (Ln)		0.236 ***		0.477 ***		-0.009		0.284 ***		-0.010		0.267 ***		-0.007		0.234 ***
		(0.018)		(0.049)		(0.026)		(0.047)		(0.026)		(0.052)		(0.025)		(0.053)
Active pipelines (Ln)			0.182 ***	0.286 ***			0.038 *	0.213 ***			0.020	0.188 ***			-0.013	0.152 ***
			(0.017)	(0.031)			(0.016)	(0.028)			(0.016)	(0.031)			(0.019)	(0.037)
Passive pipelines (Ln) X Active pipelines (Ln)				0.053 ***				0.049 ***				0.045 ***				0.039 ***
				(0.008)				(0.007)				(0.007)				(0.008)
Pipeline DMs (Ln)													0.427 ***	0.427 ***	0.448 ***	0.333 ***
													(0.083)	(0.083)	(0.087)	(0.085)
Local linkages (Ln)													-0.039	-0.039	-0.042	-0.026
													(0.029)	(0.029)	(0.029)	(0.028)
External linkages (Ln)													-0.156 ***	-0.156 ***	-0.152 **	-0.152 ***
													(0.045)	(0.045)	(0.046)	(0.043)
Relevant non-DM actors (Ln)									-0.048	-0.053	-0.066	-0.064	-0.063	-0.075	-0.083	-0.096
									(0.117)	(0.118)	(0.110)	(0.108)	(0.114)	(0.115)	(0.107)	(0.108)
Network density (Ln)									3.563 ***	3.557 ***	3.338 ***	1.906 *	2.430 **	2.425 **	2.426 **	1.509
									(0.845)	(0.845)	(0.856)	(0.823)	(0.837)	(0.838)	(0.837)	(0.808)
Actors in primary network %									0.298	0.293	0.258	0.212	0.216	0.207	0.205	0.183
									(0.293)	(0.293)	(0.291)	(0.269)	(0.275)	(0.276)	(0.274)	(0.259)
DMs in primary network %									0.135	0.133	0.115	0.235 *	0.171	0.171	0.182	0.279 *
									(0.122)	(0.122)	(0.122)	(0.115)	(0.121)	(0.122)	(0.122)	(0.117)
Size of primary network (Ln)									0.045	0.045	0.042	-0.004	0.037	0.037	0.033	0.004
									(0.035)	(0.035)	(0.034)	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)
Working population (Ln)					0.170 **	0.170 **	0.159 **	0.137 *	0.273 ***	0.272 ***	0.257 ***	0.224 ***	0.250 ***	0.249 ***	0.253 ***	0.227 ***
					(0.060)	(0.060)	(0.060)	(0.053)	(0.068)	(0.068)	(0.069)	(0.064)	(0.065)	(0.065)	(0.065)	(0.061)
Relevant employment %					2.758	2.685	3.398	6.074	6.464	6.302	6.317	7.303	6.767	6.422	6.103	6.419
					(5.354)	(5.356)	(5.135)	(4.751)	(5.143)	(5.147)	(5.022)	(4.723)	(4.937)	(4.936)	(4.835)	(4.638)
Relevant firms (Ln)					0.226 ***	0.224 ***	0.186 **	0.179 **	0.243	0.244	0.236	0.225	0.22	0.226	0.229	0.245
					(0.064)	(0.063)	(0.057)	(0.057)	(0.131)	(0.132)	(0.130)	(0.121)	(0.132)	(0.133)	(0.131)	(0.125)
NVQ 4+ %					0.014 **	0.014 **	0.014 **	0.011 **	0.017 ***	0.017 ***	0.017 ***	0.015 ***	0.016 ***	0.016 ***	0.016 ***	0.014 ***
					(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Constant	1.762 ***	1.734 ***	1.688 ***	2.992 ***	-2.546 ***	-2.530 ***	-2.033 **	-0.675	-4.067 ***	-4.016 ***	-3.575 ***	-1.889 *	-3.592 ***	-3.496 ***	-3.554 ***	-2.073 **
	(0.087)	(0.087)	(0.102)	(0.166)	(0.659)	(0.657)	(0.622)	(0.633)	(0.777)	(0.773)	(0.755)	(0.802)	(0.744)	(0.743)	(0.715)	(0.782)
N	210	210	210	210	210	210	210	210	210	210	210	210	210	210	210	210
Region FE					Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
R2	0.460	0.449	0.345	0.616	0.695	0.695	0.704	0.766	0.735	0.734	0.737	0.780	0.770	0.769	0.770	0.798

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

5.2 Pipeline results

Table 4 presents the modelling results for the pipeline indices. As per the above section, we run a set of models in a stepwise fashion. Columns 1-4 report the basic results, while Columns 5-6 show the estimates after including controls for regional characteristics. Likewise, the models Columns 9-12 additionally control for regional network characteristics, and Columns 13-16 also include controls for internal and external linkages, with Column 16 reporting results for the full model. To ease interpretation, all pipeline index variables are scaled in relation to the region with the highest pipeline index (London at both the start and end of our study period; see Figure 2). We thus interpret a unit increase in a pipeline index variable as the average effect of bringing a region's non-local reach closer to the leading region.

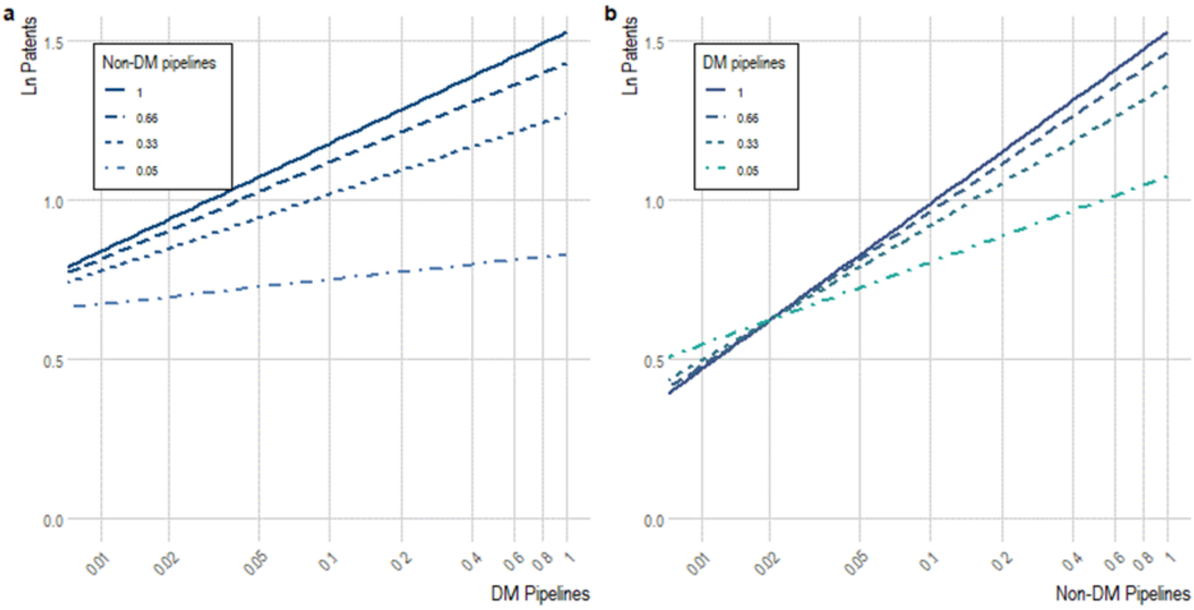

Figure 7. Conditional effects: Active (dealmaker intermediated) pipelines and passive (non-dealmaker intermediated) pipelines. Non-interacted variables are mean-centred and held constant to simplify interpretation.

Apart from the first set of models without controls, all model results from Columns 5-16 follow a similar pattern: neither central pipelines or peripheral pipelines by themselves, nor the direct sum of the two are statistically different from zero.

However, the coefficient of central pipelines can thus be observed to depend on the value of non-dealmaker pipelines, non-DM, and vice versa. All the models that include the interaction between central pipelines and peripheral pipelines (Columns 8, 12, and 16) demonstrate highly statistically significant and positive coefficients for the interaction term and the terms for both types of pipelines. Moreover, the terms for pipelines intermediated through non-dealmakers, and those for pipelines intermediated through all actors are negative when controls are introduced (Columns 5, 6, 9, 10, 13, 14), yet their estimated coefficients are positive in their corresponding interaction models. These results suggest that regions require both types of pipelines for the geographical reach of their extra-local connectivity to influence region-level innovativeness.

Following the reasoning discussed above for the dealmakers models, we show that marginal increases in active, dealmaker intermediated, pipelines are consistently associated with progressively greater marginal returns om regional patenting over a broad range of moderating values for passive, non-dealmaker intermediated, pipelines (Panel a in Figure 7; likewise for the converse relationship, as shown in Panel b). This provides empirical support for the hypothesis (H2) that the regional extent of central pipelines and peripheral pipelines are complements for regional innovation, even after controlling for regional and local network characteristics.

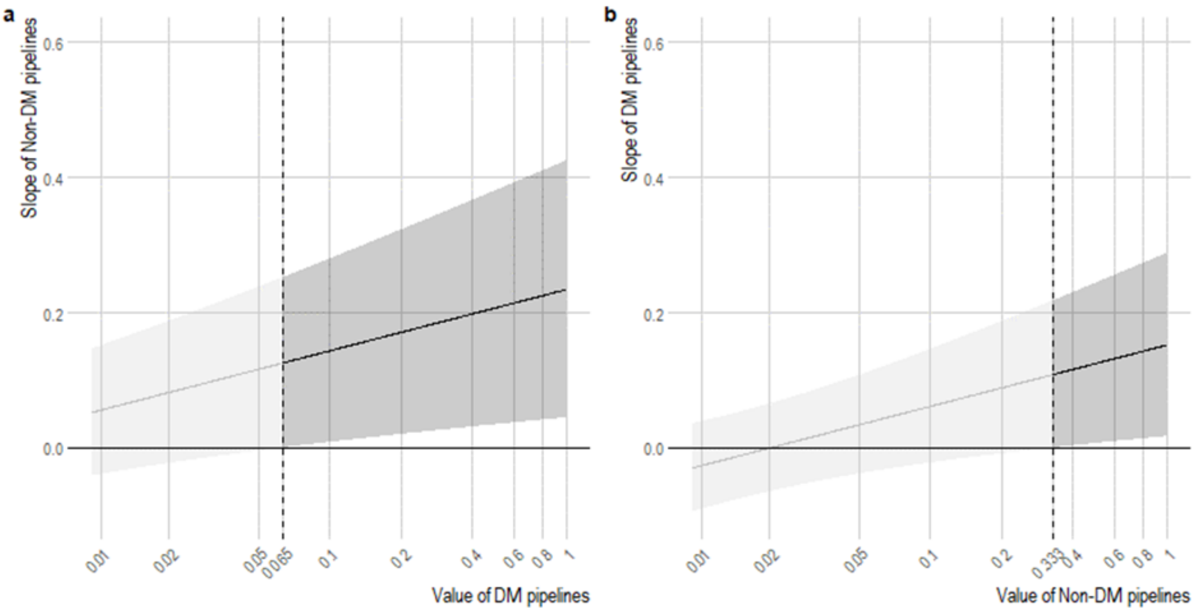

Figure 8. Johnson-Neyman plots for dealmaker provided and non-dealmaker provided pipelines. a Conditional slope of non-dealmaker pipelines by dealmaker provided pipelines. b Conditional slope of dealmaker-provided pipelines by non-dealmaker pipelines. The darker shared region in each plot indicates the interval where the predictor differs significantly from zero ($p<0.001$), adjusted to control the false discovery rate using the procedure detailed in (Esarey & Sumner, 2017).

Figure 8 shows the changes in the conditional slopes of the pipeline-related terms, and provides a further illustration of the mutually complementary nature of both pipeline-related terms. Each panel in Figure 8 also indicates the statistically significant intervals, demonstrating a clear asymmetry in the minimum thresholds for dealmaker provided and non-dealmaker provided pipelines. More specifically, a pipeline index of around 0.07 in terms of central pipelines is the minimum threshold necessary, on average, for regions to have statistically significant effects from their local endowment of peripheral pipeline connections intermediated through non-dealmakers (Panel a in Figure 8). Conversely, regions require a minimum threshold pipeline index of around 0.33 for their peripheral pipelines, on average, for them to have statistically significant effects from their central pipelines (panel b in Figure 8). This supports the hypothesis (H4) that central pipelines play an enabling role, such that a minimum threshold of dealmaker pipelines is necessary for a given region's life

Table 5. Standardized OLS estimates for baseline and alternate specifications for dealmakers and innovation

Dependent variables:	Baseline	Baseline	Patenting / Capita	Patenting / Capita
Per capita explanatory variables:		Y		Y
Model:	(1a)	(1b)	(2a)	(2b)
Pipeline DMs (Ln)	0.238	-0.132	0.048	-0.008
	(0.152)	(0.086)	(0.025)	(0.014)
Local DMs (Ln)	0.42***	0.144*	0.086**	0.053*
	(0.114)	(0.07)	(0.032)	(0.022)
Pipeline DMs (Ln) X Local DMs (Ln)	0.314***	0.432***	-0.002	0.038*
	(0.082)	(0.108)	(0.014)	(0.018)
Local linkages (Ln)	-0.273*	-0.063	-0.056**	-0.033
	(0.135)	(0.127)	(0.021)	(0.027)
External linkages (Ln)	-0.125	0.13	-0.025	0.009
	(0.122)	(0.134)	(0.019)	(0.019)
Relevant non-DM actors (Ln)	-0.154	-0.238	-0.064	-0.073
	(0.242)	(0.291)	(0.109)	(0.105)
Network density (Ln)	0.063	0.273**	-0.052	-0.029
	(0.068)	(0.089)	(0.033)	(0.029)
Actors in primary network %	0.016	0.023	-0.02	-0.018*
	(0.026)	(0.036)	(0.01)	(0.008)
DMs in primary network %	0.113**	0.137*	0.038*	0.038*
	(0.041)	(0.058)	(0.018)	(0.017)
Size of primary network (Ln)	-0.026	0.066	0.02	0.024
	(0.083)	(0.1)	(0.025)	(0.025)
Working population (Ln)	0.441**	0.658***	-0.119**	-0.07
	(0.132)	(0.149)	(0.044)	(0.038)
Relevant employment %	0.042	0.04	-0.002	-0.004
	(0.044)	(0.044)	(0.013)	(0.012)
Relevant firms (Ln)	0.403	0.602	0.065	0.075
	(0.267)	(0.306)	(0.089)	(0.087)
NVQ 4+ %	0.162**	0.228***	0.018*	0.024*
	(0.051)	(0.059)	(0.009)	(0.01)
Constant	0.64***	0.693***	0.048***	0.047***
	(0.087)	(0.097)	(0.012)	(0.013)
Observations	210	210	210	210
Region FE	Y	Y	Y	Y
R2	0.809	0.761	0.248	0.246

*Hereoskedacity-robust standard-errors in parentheses. *p<0.05, **p< 0.01, ***p<0.001* sciences patenting to benefit from marginal increases in the external connectivity intermediated through non-dealmakers.

5.3 Robustness checks

Before concluding, we address potential estimation biases emanating from the influence of regional scale. The discussion here is brief, as the motivating concerns—e.g., from the use of unscaled dependent and explanatory variables—have been examined in the preceding chapter. While the dependent variable is regional patenting productivity in both the dealmakers and pipelines models (as presented in Tables 3 and 4 respectively), these risks are likely more acute for the former because it uses local stocks of networked agents for the explanatory variable. Accordingly, we report standardized estimates for the preferred and alternative specifications as a sanity check for the dealmakers model in Table 5. By contrast with the previous chapter, we do not report variance inflation factors (VIFs) here since they are largely uninformative in this setting. High VIFs are a natural consequence of interacting the explanatory variables, as they are then collinear by construction, thereby also mechanically leading to inflated VIFs.

The standardized estimates in Table 5's 'baseline' columns (Columns 1a & 1b) correspond to the fully specified dealmakers model (Column 16 of Table 3), where Column 1b has additionally normalized the explanatory variables by local working population. Columns 2a and 2b follow suit, and additionally normalize the dependent variable by working population. We might be reassured that the findings are generally consistent, with the estimates and their statistical significance remaining largely stable across the baseline and alternative model specifications.

Finally, although it is straightforward to obtain the corresponding estimates for the pipelines model, we elect not to do so as the measurement of the pipelines index already implicitly accounts for regional scale. More cogently, it is not obvious how the results of such an exercise might be interpreted to make meaningful comparisons. As the measure indirectly accounts for scale at the dyadic level, subsequently normalizing the pipeline index at the regional level emits a quantity that appears substantively distinct from the pipeline index, but otherwise does not clearly have an intuitively accessible interpretation.

6. Discussion and conclusions

The perennial debate among the geography of innovation scholarship on the value and significance of localized and geography-spanning linkages remains inconclusive on how, and when, social network-based structures and processes might hold greater explanatory salience for regional innovativeness than traditional proximity-centric accounts of knowledge spillovers (Acs, Audretsch, et al., 2017; Audretsch et al., 2011; Audretsch & Link, 2019; Bathelt & Glückler, 2011; Boschma, 2005; Boschma & Frenken, 2018; Crescenzi et al., 2007; Feldman, 1999; Gordon & McCann, 2000, 2005a, 2005b; Hoekman et al., 2009; Iammarino & McCann, 2006; Kemeny et al., 2016; Lobo & Strumsky, 2008; Marrocu et al., 2013; Powell et al., 1996; Sonn & Storper, 2008; Storper, 2013, 2018). Current understandings are thin when it comes to addressing the means and conditions through which knowledge channelled through distant sources eventually augment localized innovative capacities (Storper, 2013). This study makes a novel contribution to the gap formed at the theoretical intersection of two prominent strands of economic geographical explanation – 1) the pipelines literature on the roles of region-spanning connections linking places to extra-local networks as critical entry points for external sources of knowledge, and their importance in leveraging variations across localized knowledge pools, and 2) the emerging dealmakers literature on the economic importance of locally well connected agents. While extra-local knowledge transmission channels are seen to be critical in explaining the performance of regional innovation ecosystems, our understanding of the role of interacting individuals in moderating the benefits of these pipeline connections has thus far been limited (Audretsch et al., 2018; Kemeny et al., 2016; Storper, 2013). In the foregoing, we thus provide a new perspective on why the effectiveness of pipelines differs between regions, making key distinctions firstly between pipeline providing and exclusively locally oriented dealmakers; and secondly between central pipelines and peripheral pipelines (i.e., pipelines directly intermediated by dealmakers, and those directly intermediated by non-dealmakers, respectively).

We first analysed the role of locally oriented dealmakers and pipeline providing dealmakers in fostering innovativeness in the UK's life sciences sector across the country's regions. The findings generally affirm the importance of dealmakers and provides new insight into the channels underlying the disproportionate importance of well-connected actors, relative to other actors with less central network positions, found in previous dealmakers research (Boey, 2020; Feldman & Zoller, 2012; Kemeny et al., 2016). We find that pipeline-providing dealmakers and exclusively locally oriented dealmakers are mutually complementary for patenting in the life sciences at the regional level, after controlling for variations in regional characteristics and local buzz. Moreover, the results imply that a minimum threshold of pipeline-providing dealmakers is a conditional requirement for local dealmakers to have statistically significant effects on regional innovation. We also find evidence for an even higher minimum threshold for the converse relationship. This asymmetric behaviour is consistent with our supposition that locally oriented dealmakers and pipeline dealmakers provide qualitatively different benefits to their regional innovation systems. Nonetheless, much fewer of the study regions in our data meet the requisite threshold for pipeline dealmakers but not for local dealmakers, than the converse scenario. This suggests that pipeline providing dealmakers play an enabling role for their exclusively locally oriented counterparts, but not vice versa.

Having thus demonstrated the importance of pipeline-providing dealmakers, we then turned our attention towards the role of central pipelines directly intermediated through dealmakers, in relation to peripheral pipelines intermediated through less well-connected local actors. Paralleling the findings of the preceding analysis, we find that both active and peripheral pipelines have a mutually complementary positive effect on regional innovativeness, even after additionally controlling for the regional concentration of pipeline providing dealmakers. We find that regions need to meet a minimum threshold of central pipelines for non-dealmaker pipelines to yield statistically significant benefits to local innovation. However, we also find a comparatively higher minimum threshold value for peripheral pipelines required for central pipelines to yield regional benefits.

This suggests that the marginal returns to augmenting regional pipelines has a piecewise structure – a given region obtains large benefits to its innovativeness from central pipeline development as it acquires sufficiently extensive central pipelines over the minimum enabling threshold (assuming it also has peripheral pipelines in place); and subsequently only experiences tangible benefits to its innovativeness from further central pipeline development after developing an extensive network of peripheral pipelines. This was not a directly anticipated result, and we interpret it as implying compounding advantages to those select few regions belonging to the club of regions exceptionally well endowed with both types of pipelines. We speculate that this might be part of the constitutive differences between leading and less successful regions – a key component of the former's 'local genius' (Storper, 2013) – that enable the former group to consistently out-develop and out-perform the latter group. One plausible explanation is the acquisition of unique advantages in inter-regional (and international) coordination by these leading regions (Coe & Yeung, 2015). Nonetheless, since peripheral pipelines comprise the vast majority of the extensiveness of pipelines in the life sciences for any given UK region (Figure 4), this suggests that central pipelines catalyse and enable the benefits of peripheral pipelines on regional innovation over a more substantively significant range than the converse. This suggests, in turn, that the results remain broadly consistent with the hypothesized relationships. It is worth pointing out here that the enabling effect from a relatively low threshold of central pipelines on regional innovation ecosystems found here is also consonant with canonical results in social network theory demonstrating the emergence of sweeping transitions in overall cohesiveness from relatively small changes in micro-scale connectivity between individual network actors (Newman, 2003, 2018; Watts & Strogatz, 1998).

Considered more closely in relation to our motivating theory, these findings also appear to support our assumptions that the regional benefits of central pipelines on innovation obtain largely via their indirect effects on enhancing how efficiently and effectively newly-arrived knowledge is transmitted and utilized through localized social networks, rather than through their direct effects in channelling externally-sourced knowledge. Passive pipelines conversely more likely have the function of channelling the bulk of non-local knowledge into a given region, particularly given the scarcity of well-developed central pipelines as a regional resource (even relative to pipelines in general; see Figure 4). We might thus expect marginal improvements in central pipelines to have a potentially transformative effect on regional innovativeness, depending on whether the region previously had sufficiently developed central pipeline connectivity, while the regional impact of peripheral pipelines generally appear to be more incremental and evolutionary in character.

Our findings contribute to the limited research into the differential roles of individuals in moderating the benefits of extra-local interconnection for fostering regional innovation performance. It also builds upon the emerging dealmakers literature, by contributing to the hitherto absent empirical research on how dealmakers augment innovation. The regional concentration of local linkages is similarly found to consistently have a negative effect. One way this result might be interpreted is as indicative support for the idea that excessive levels of local buzz might be inimical for local learning processes by causing a ‘congestion effect’ (Bathelt et al., 2004). If we assume that this interpretation is commensurate with the ground truth, then this finding might be seen to provide evidence that is contrary the pipeline literature’s theorizations that localized social networks intrinsically provide filtering mechanisms that prevent local buzz from transforming into unproductive noise. Moreover, we consistently find that the regional concentration of external linkages is consistently negative throughout both sets of results presented above, particularly once controls for regional and local network characteristics are introduced. This provides evidence for the hollowing out effects resulting from excessive external linkage proposed by the pipelines literature (Bathelt et al., 2004). The raw regional concentration of pipeline linkages thus appears to have an equivocal effect at best, underscoring the salience of the general thesis advanced here – that rather than the volume of pipeline connections in itself, it is the relative connectedness and roles of the individuals intermediating geographically-spanning ties that are more meaningful for regional innovation outcomes. Considered as a whole, these findings suggest that unevenness in strong network leadership across regions amplifies divergence regional performance in highly innovative and knowledge intensive industries, and thus also provide additional credence to the dealmakers thesis. Thus, if clusters might be said to be the key nodes in the globalized economy (Amin & Thrift, 1992), then it follows that pipeline dealmakers are the keystone actors that influence the benefits of intra-locational connection between these key regional nodes.

Interest in network and ecosystem approaches to unpacking and managing regional innovation has been resurgent among scholars and policymakers (Acs, Stam, et al., 2017; Audretsch et al., 2018; Feldman et al., 2016, 2019; Pittz et al., 2019; Spigel, 2017; Stam & Spigel, 2018). The pipelines literature has called for greater institutional support for the development of pipelines, noting that the 'automatic' nature of knowledge spillovers through local buzz implies that much of the ongoing policy effort to foster local interactions might be more productively diverted toward promoting geography-spanning ties connecting localities to external regions (Bathelt et al., 2004; Bathelt & Glückler, 2011). While we agree that regions gain unique innovation advantages from having coexisting local buzz and pipelines, our findings suggest that these policy prescriptions need to be nuanced. In the first instance, as mentioned above, the regional concentration of external linkages consistently demonstrates a negative and significant effect. Regional authorities might thus find that pursuing unqualified pipeline development makes for blunt policies with potentially counterproductive effects.

Crucially, it is the critical agents (i.e. dealmakers) that appear to matter more for regional innovativeness than aggregate connections (Feldman & Zoller, 2012). Localized knowledge spillovers are not inevitably augmented as an inevitable result of extensive regional pipeline development. As our findings imply, the ability to access and leverage high levels of regional buzz is not automatically available to all members of a cluster but depend on the pattern of connections between individual actors in differential roles and influence within localized social networks. Rather than trying to balance efforts to foster aggregate internal and external linkages, regional policymakers might thus be better advised to evaluate the sufficient availability of well-connected actors at the local entry points of knowledge transmitting pipelines. Policymakers should likewise also consider ensuring that sufficient institutional support is provided to generating and sustaining local buzz around these critical agents.

These policy implications are presented only tentatively. As a preliminary analytical cut exploring the relationships between extra-local pipelines and local dealmakers, our findings focus on associations, and should not be interpreted as indicating causal effects. While this empirical strategy might be appropriate for our current purposes, subsequent work might consider adopting a causal framework. As such, we suggest that future studies should address these key limitations and empirical gaps. However, as highlighted in previous dealmakers research, well-connected network actors are likely to behave in a way that is endogenous to some extent with their embeddedness within regional ecosystems and the outcomes of interest (Boey, 2020; Feldman & Zoller, 2012; Kemeny et al., 2016). Yet our understanding of how individuals moderate and interact with the economic benefits of local and extra-regional connectivity within localized innovation ecosystems is still fledging and has pervasive gaps, including on the mechanisms through which individuals sort into in varying network positions and degrees of network centrality, and how this plays into the emergence and evolution of knowledge diffusing and generative interactive processes (Audretsch et al., 2018; Pittz et al., 2019; Storper, 2013). Given the inherently endogenous nature of social capital and social networks, these critical missing pieces will make it particularly difficult to anticipate lurking endogeneity problems and thus craft well-founded causal estimation strategies, and suggests a need for a combination of econometric and non-econometric approaches by further investigations (Jackson, 2010; Kemeny et al., 2016). Detailed characterisations and close analyses produced through well-designed qualitative and mixed-methods research might, for instance, prove particularly helpful for future attempts to disentangle more precisely the relative roles of pipeline providing and exclusively locally oriented dealmakers, and likewise for the differential roles of pipelines intermediated through dealmakers and through less well-connected individuals.

While the pipeline literature defines pipelines as connections to extra-local sources of knowledge in general, we have kept consideration here specifically to pipelines between regions in the UK. While this was motivated in part by our exploratory goal, we were also constrained to the national scale of analysis by the pervasive paucity of high-quality relational data necessary to construct social network-based indicators, such as those used here. To the best of our knowledge, even the present study would not be possible except for the novel UK dataset created in Boey (2020). Future work might thus attempt to address these data availability issues and expand their empirics to encompass both national and transnational pipelines. Similarly, further work might be done on testing whether similar findings also obtain for other high-tech production, such as in the information technology sector, and in other empirical settings outside of the UK. Subsequent research might also consider using a multisectoral approach, controlling for technological relatedness, or physical and other forms of proximity (Boschma, 2017; Crescenzi et al., 2017; D’Este et al., 2013; Lee & Rodríguez-Pose, 2013).

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Paper 3 – Do open social networks foster high-tech growth?

Augustin Boey

Abstract

Does social network structure influence the growth of high-technology clusters? Policymakers and scholars studying technology clusters often argue that success of high-tech and knowledge-intensive industries and city-regions is underpinned by flatter and more open social networks, yet there is relatively little systematic empirical evidence for such social gains. This paper investigates the relationship between local network openness on high-tech growth, constructed using relational data on the universe of UK firms and their top teams from 2010-2019 to construct career affiliation networks and measures of region-industry network openness based on the local concentration of network connectivity. It finds that initial network openness in 2010 has a statistically and economically significant and positive effect on employment growth in high-tech industries over the subsequent decade. Likewise, we also find similarly positive associations for digital tech -- the subset of high-tech specifically focused on the digital economy – and for STEM-intensive industries – the superset of industries including high-tech – more broadly. To test the idea that open networks have a causal effect on high-tech cluster growth, we instrument our measure of open networks using a novel measure of institutional openness and find a persistent causal link between open network structure and high-tech employment growth.

1. Introduction

Scholars studying innovation and economic development have been very interested in high-profile Silicon Valley-style concentrations of high-technology firms (Porter, 1990; Saxenian, 1991; Ellison & Glaeser, 1997; Krugman, 1997; Kenney, 2000; Bathelt et al., 2004; Storper, 2013; Ferrary & Granovetter, 2017). Hoping to create their own Silicon Valleys, policymakers around the world are also keen for insights into the localized sources of breakthrough creativity and entrepreneurial dynamism of leading high-technology clusters at the technological frontier (Acs, 2003; Casper, 2013; Spigel, 2017; Lee & Clarke, 2019; Crescenzi et al., 2020; Yeung, 2021). In many of these debates, localized networks are seen as the social backbone of successful firms and places (Uzzi, 1996; Burt, 2004; Owen-Smith & Powell, 2004; Uzzi & Spiro, 2005; Fleming et al., 2007; Whittington et al., 2009; Eagle et al., 2010; Feldman & Zoller, 2012). A central explanation distinctively links local high-tech performance to open socioeconomic networks and city-regional institutions and has become well-known through studies of highly innovative agglomerations, most famously on high-tech industry in the San Francisco Bay Area (Piore & Sabel, 1986; Almeida & Kogut, 1999; Brown & Duguid, 2000; Storper et al., 2015).

In an influential analysis, Saxenian (1994) tells a contrasting tale of two city-regions competing in the then-emerging semiconductor industry. Boston's Route 128 high-tech cluster was dominated by conservative corporate culture and associated norms of in-house control and self-reliance. This led to largely mutually exclusive concentrations of social connections within hierarchically organized firms. By contrast, a 'Bohemian' culture of experimentation and open interaction pervaded the Silicon Valley (cf. Lécuyer, 2005; Granovetter, 2017; Storper, 2018). These distinctive 'Californian cultural traits' fostered densely intersecting networks of technical experts and entrepreneurs, providing a supportive environment in which people, ideas, and resources moved relatively quickly and flexibly across organizational boundaries. The Valley's open and flatter social structure thus sustained a higher quality and quantity of localized interactions than Boston's comparatively closed and centralized networks and, in turn, gave the Silicon Valley's high-tech industry a lasting 'regional advantage' in continuous innovation, collective learning, and ultimately, high-technological specialization.

A growing body of research, including on technological clusters, innovation systems, and organization management, increasingly endorses the idea that open social structures lead to better economic performance (Grabher, 1993; Kenney & von Burg, 1999; Boschma, 2005; Breschi & Malerba, 2005; Casper, 2007; Saxenian & Sabel, 2008; Smith & Reilly, 2013; Chesbrough et al., 2014; Crescenzi et al., 2016; Huggins & Thompson, 2021). Unfortunately, many fundamental questions about open networks are still unsettled despite the idea's influence on a wide range of disciplines. We know little whether place-based open networks really matter for local high-tech performance and, if they do, when their benefits are likely to be economically significant. The tendency for empirical studies to focus on high-profile (largely American) high-tech clusters leaves uncertain whether open networks generate similar social gains outside these cases (cf. Storper, 2018). Moreover, while often invoked in the past three decades, the 'open networks' concept is still unclearly defined, and the lack of metrics that meaningfully quantify the key terms in this complex debate remains an obstacle to rigorous understanding and effective policy.

This article addresses these gaps by systematically targeting beliefs about open networks that have pervaded thinking on high-tech clusters particularly since Saxenian's (1994) study. We test these claims by examining the relationship between local network openness and high-tech employment growth in UK regions. The regional focus allows us to evaluate widespread assumptions that place-based open networks produce systemic benefits for entire regional high-tech ecosystems. The UK is an excellent context to systematically test the importance of open networks in high-tech industries in a substantively distinct but broadly comparable setting with the motivating literature. Like the US, the UK has consistently ranked amongst the most innovative advanced economies globally, yet also experiences significant regional disparities in high-tech performance (WIPO, 2021; McCann, 2016). We develop a new measure of network openness based on degree centralization, using it to quantify the openness of regional networks constructed from a unique dataset on the universe of UK firms and their top employees. We find a robust positive association between network openness in 2010 and high-tech job growth over the subsequent decade. A novel instrument on the historical openness of regional institutions suggest that this is a causal relationship for high-tech and digital economy, but not for STEM.

We make several substantive contributions to the literature. First, we synthesize the essence of open networks from the multidisciplinary literature and propose a formal definition that rigorously quantifies its essential kernel. In doing so, we address the conceptual fuzziness and imprecision that has impeded further understanding of its effects and implications. Second, we provide the first country-wide empirical analysis of the systemic impact of open networks on regional high-tech performance in a major advanced economy. Third, we show the wider impact of open social structure outside of leading U.S high-tech clusters. Finally, we find new evidence that suggest substantive limits to the importance of open networks, even when only science- and technology-oriented industries are considered, contradicting expectations based on the motivating literature. Our results provide the first systematic demonstration that the openness of local social structures matters for local high-tech success. They also suggest that the social gains from open networks are less economically significant further from the technological frontier. These findings have significant theoretically- and policy-relevant implications that warrant further study.

The rest of the article is structured as follows. Section 2 identifies the conceptual essence of open networks and discusses the role of open networks on economic performance. Section 3 describes the data; presents our measure of network openness; and briefly describes the geography of open networks in UK high-tech industry. Section 5 presents our empirical model and the estimation results. We end the section by discussing the findings and implications for future research. The final section concludes.

2. Literature review

2.1 Geography, institutions and open networks

Interdependent firms connected by flat and inclusive networks of open communication and exchange are often argued to provide greater performance and flexibility in highly innovative industries versus relatively closed networks. The idea that highly innovative clusters have open and decentralized social structures has been popularized through noted analyses of two well-known cases: the apparel industry of the 'Third Italy' and high-tech industry in the Silicon Valley (Piore & Sabel, 1984; Saxenian, 1994). Table 2 summarizes the key regional differences in Saxenian (1994) between the Silicon Valley and Boston's Route 128. But why do some places have more open networks than others, and how does this relate to economic performance? The general argument advanced in this literature has a causal narrative with three distinct parts. There is firstly geographical heterogeneity in place-specific social institutions[3]. This engenders place-specific differences in how people regularly behave and interact. This distinctiveness secondly impacts network formation and development processes, creating localized variations in the 'propensities for connection' that lead to city-regional differences in localized social structures (Storper et al., 2015). Thirdly, patterns of connection in localized social networks affect economic outcomes by acting as a relational framework that structures opportunities and incentives for productive interaction.

[3] Differences between city-regions at the sub-national scale of analysis largely involve heterogeneity in informal institutions—broadly defined here as the relatively stable set of shared norms, established rules and cultural conventions, shared beliefs, common routines and practices—that provide regularity to how individuals and groups behave and interact (Mahoney & Thelen, 2009; Lundvall, 2010).

Table 2. Key differences in local institutions and interfirm networks between high-tech clusters in California's Silicon Valley and Boston's Route 128 (summarized from Saxenian, 1994)

Regional aspect	Silicon Valley – *Open, Decentralized, Cooperative*	Route 128 – *Closed, Hierarchical, Autarkic*
1. Institutions	'Culture of decentralization'	Culture of corporate 'self-sufficiency'
2. Institutions	Norms of 'open communication', collaboration and informal exchange	Conservative norms of 'secrecy' and corporate 'loyalty'
3. Networks	'More open and networked' and 'interdependent' firms	'Vertically integrated' firms; 'Autarkic structure' of interfirm organization
4. Networks	'Dense', 'diverse' and 'cross-cutting' social networks	Fragmented networks concentrated within organizations and workplaces
5. Networks	'Interpenetration' of 'labor markets and social structures'	Limited job mobility across organizational boundaries

In this view, patterns of connections are seen as endogenous to places, such that certain places develop and sustain relatively more open networks than others. Economic action is thus said to be socially 'embedded' within the intermediating 'relational infrastructure' of place-based social networks which are, in turn, embedded within the macro-level institutional context (Granovetter, 1985; 1992; 2017; Zukin & DiMaggio, 1990; Hess, 2004; Storper, 2018) [4]. Geographical heterogeneity in relatively enduring localized institutions therefore fosters city-regional differences in the openness of localized network structures, leading to subsequent differences in regional economic performance. Thus, as Saxenian (1994) argues, the Silicon Valley's 'regional advantage' versus Route 128 was underpinned by the Valley's relatively open social networks of communication and exchange across firms, which were in turn fostered by a distinctive culture and norms of interaction encouraging collaboration, risk-taking and informal exchange [5]. Subsequent research on the Silicon Valley and other high-tech clusters have also

[4] Embeddedness thus also provides a channel for individuals and groups to shape regional institutions. While any given individual is unlikely to have much influence over broader cultural processes, regional cultures may potentially also evolve through collective interpersonal interaction (Boschma, 2005; Granovetter, 2017).

[5] California had distinctive state laws against 'non-compete' employment contract clauses—which might encourage higher interfirm knowledge worker mobility—but these legal institutions cannot fully explain the Silicon Valley's success versus Boston, particularly when considering the divergent performance of other Californian high-tech clusters (Gilson, 1999; Casper, 2009; Storper et al., 2015).

generally affirmed the importance of the characteristics in Table 2 (Grabher, 1993; Almeida & Kogut, 1994; Lee et al., 2000; Acs et al., 2002; Fleming et al., 2007; Casper, 2009; Storper et al., 2015; Huggins & Thompson, 2021).

2.2 Open networks and economic performance

The overall economic benefits of place-based open networks are generally due to regional social gains from better information flow and a relatively higher quality and intensity of interfirm and interpersonal relationships versus a comparable closed network. Here, we synthesize a multidisciplinary literature to discuss five broad channels through which open city-regional networks might positively impact local economic performance.

Open networks heighten regional innovative capacity by enhancing information diffusion. A relatively high density of interfirm ties between technical experts, entrepreneurs, and other workers can quickly and effectively diffuse cutting-edge technical information and business intelligence across a region's organizations. The ubiquity of connections across blurred firm and organizational boundaries is also a central feature distinguishing open and closed networks (Table 2). Connections are relatively less concentrated within an open network, and this means any given pair of agents within an open network are more likely to be directly or indirectly reached through multiple connecting paths than in a closed network. The large-scale open social structure formed by such cross-cutting interfirm networks enables a larger variety of fresh ideas to reach firms from external sources, more effectively and reliably than in a closed network with relatively sparse knowledge flows between self-contained firms (Granovetter, 1973; Almeida & Kogut, 1999; Lee et al., 2000). The timely availability of novel and non-redundant information enables local firms and inventors to adapt more quickly to new technologies and markets, helping mitigate the high levels of uncertainty and volatility endemic to industrial sectors with high rates of technological innovation (Saxenian, 1994; Fleming et al., 2007; Chesbrough et al., 2014).

These information diffusion dynamics also support a dynamic and flexible local labour market. Interfirm communication channels in open networks support high interfirm mobility by effectively transmitting information about job opportunities to individuals. This gives workers ready access to more alternate employment options and helps mitigate the risks of working in a high-technology start-up (Saxenian, 1994; Casper, 2009). Similarly, shorter network distances and a wider social interface connecting firms in an open network reduces frictions in hiring suitable knowledge workers by augmenting search processes and matching skills to tasks. The enhanced labour mobility in an open network also potently amplifies collective learning capabilities by giving greater access to new information through both weak and strong ties. Higher mobility helps sustain diverse webs of loose interfirm affiliations that supports the high-levels of face-to-face interaction important for innovative activities (Storper & Venables, 2004). Enhanced interfirm job mobility also facilitates the more widespread formation of strong career affiliation ties across firms, thereby enhancing the diffusion of embodied technical knowledge with tacit characteristics that require close interpersonal interaction to transfer (Storper, 2013; Granovetter, 2017). Thus, relative to a given closed network, an open network is systemically more effective at sustaining a higher and more widely diffused volume of both diverse low-bandwidth information flows (e.g., through industry gossip), and high-bandwidth transfers of complex knowledge (e.g., via in-depth discussions between inventors) across a high-tech cluster (cf. Aral & Van Alstyne, 2011). Moreover, whereas potentially disruptive entrants might be excluded or marginalized by relatively few gatekeepers with vested interests in a closed network, an open network has a substantially higher social 'surface area' and provides more points of entry for workers and entrepreneurs with atypical ideas to successfully enter and participate in the local economy. This helps renew and circulate a diversity of technologies, skills, and perspectives in an open network – that might otherwise have been concentrated within fragmented communities, or excluded entirely, in a closed network. An open network systemically creates a bigger and less concentrated 'marketplace for ideas' and diverse influences than a closed network (Casper, 2009) – thus helping to prevent staleness and regional lock-in (Boschma, 2005).

Place-based open networks thus promote technological and entrepreneurial dynamism by providing favourable conditions for firms and people to develop and bring innovative ideas to the market more quickly. It is easier to start new firms in an open network due to broader interfirm contacts. The availability of flexible labour markets and access to venture capital makes it easier and less risky for inventors to commercialize an innovation through a technology start-up (Casper, 2009). Network openness might thus raise regional performance due to higher pecuniary incentives to participate in risky initiatives (Boschma, 2005). As Saxenian's (1994) analysis vividly illustrates, individuals in open networks are more likely to undertake risky but innovative activities than less autonomous workers due to more conservatively-oriented reward structures in closed networks. Operating within open networks makes it easier to bring together flexible combinations skills, knowledge, and inputs from different firms, thus enabling more widespread interfirm collaborations, alliances, and subcontracting arrangements (Powell & Sandholtz, 2012; Storper et al., 2015). This enables firms to reduce sunk costs by externalizing R&D and other specialized functions to other firms (Granovetter, 2017). Collaboration also enables inventors to effectively collectively pool their knowledge to develop more complex and impactful innovations (Powell et al., 1996; Wuchty et al., 2007; van der Wouden, 2020). Moreover, open networks provide supportive conditions for creating knowledge of a markedly different character than in relatively closed networks. Open networks provide an appropriate social infrastructure for path-breaking innovation by supporting more effective innovation strategies. Whereas traditional high-tech innovation strategies emphasize consolidating research efforts in large corporate R&D labs, open innovation strategies favour a flexible mix of smaller R&D teams and externally-sourced inputs (Chesbrough, 2011). Furthermore, large-scale empirical studies of innovation dynamics have shown that the latter type of R&D strategy tends to be more impactful at driving scientific and technological innovation.

Although bigger and more centralized teams are more effective at consolidate existing knowledge, smaller and flatter interdisciplinary teams are more likely to produce more disruptive and novel research (Wu et al., 2019; Xu et al., 2022). The comparative ease of assembling small interdisciplinary teams through flexible collaborative arrangements in an open network thus raises regional transformative capacities by facilitating the strategic application of decentralized and heterogenous inputs.

Feedback processes moreover tend to reinforce gains to regional performance in open networks. There are potential synergistic feedbacks, such as through the complementarities from coevolving labour mobility and information diffusion processes in open networks discussed above. Network structure also plays an important role in the spread and social enforcement of localized norms (Granovetter, 2005). As such, the expansion of an open network might further contribute to a generally open regional context by transmitting and strengthening conventions, attitudes and norms favouring openness over a broader subset of interacting participants in the region. Building shared beliefs and attitudes is a particularly important mechanism for the performance of large-scale open networks as they 'serve as a decentralized coordinating force under uncertainty' (Storper, 2018: 219; North, 1990). The cross-cutting nature of open networks also provides opportunities for transformative spillovers of industry-specific institutions into the broader regional context. The spillover of open network structures and norms of interaction from the Silicon Valley's semiconductor industry into other high-tech sectors has been used to explain the region's successful forays into emerging high-tech industries such as biotechnology (Casper, 2009; Storper, 2018). More generally, open networks also tend to become better connected and thus produce larger social gains over time. Empirical analyses consistently find thriving clusters have generally better interconnected networks that often tend to become progressively more so over time (Almeida & Kogut, 1999; Fleming et al., 2007; Casper, 2009; Feldman & Zoller, 2012; Boey et al., 2020; Huggins & Thompson, 2021). Storper (2018), for example, argued that repeated rounds of entrepreneurship and collaboration that drew on the Californian Bay Area's cross-cutting informal high-tech networks contributed to exponential network growth. This catalysed circular causation as the growing pool of networked people recursively increased the network's effectiveness at supporting more ventures and projects.

Open networks also give rise to emergent capabilities for innovative activities unlikely to develop in closed networks. City-regions with open networks host a complex web of cross-cutting interdependencies that make them potent 'social reactors' for the creation of new organizational ecologies (cf. Bettencourt, 2021). For instance, the flatter distribution of connections in an open network also enables more well-connected individuals to emerge outside of the corporate hierarchies of large firms. These so-called 'dealmakers' might then contribute to regional economic performance by coordinating resources, information and interactions over a dynamic regional network (Feldman & Zoller, 2012; Kemeny et al., 2015). The broader availability of dealmakers might thus raise the regional capacity to channel widely distributed resources and information into productive collective arrangements. Local dealmakers also impact regional innovation dynamics as they are crucial determinants of how well the value of knowledge sourced from outside the region is captured through gains in regional innovativeness (Boey, 2020). Interactions between a diversity of agents spanning different domains also create unique opportunities for transformative organizational innovation through novel cross-domain spillovers (Padgett & Powell, 2012; Granovetter, 2017). An important consideration here is that the kinds of specialized functions and actors that might emerge in specific open networks is also shaped by localised historical and institutional trajectories. A prominent example is the emergence of Silicon Valley's venture capital financing industry, which created a new dominant model of high-tech financing – pioneered by former engineers from local ICT firms with deep regional networks and a novel active investment style – disrupted the old arms-length style of high-tech finance by non-domain finance specialists. The Silicon Valley's venture capitalists have since acquired a more general importance by taking on a variety of important functions beyond traditional financing roles and become vital to the robust performance of the region's complex innovation system (Ferrary & Granovetter, 2009).

2.3 The conceptual kernel of open networks

As the foregoing highlights, open networks shape regional economies through their systemic impacts on local innovation and entrepreneurial dynamics. Nonetheless, the many virtues of open networks suggest that they might have more general roles in supporting urban success than previously considered. Consider, for instance, the role of knowledge spillovers in agglomeration externalities. Economic geographers and urban economists have long held that people and firms locate near each other in cities to help them become more innovative by getting ideas from others (Marshall, 1890; Jacobs, 1960; Gordon & McCann, 2000; Glaeser et al., 2010; Storper, 2013). But if people agglomerate to access knowledge spillovers through serendipitous encounters and other productive interactions, it follows that frequent opportunities for productive interpersonal interaction are necessary at the city-regional level, particularly in technologically volatile market segments where inter-industry Jacobs spillovers of tacit knowledge are critical (cf. Casper, 2013; Grillitsch, 2019). This suggests that the effectiveness of knowledge spillovers depends on an appropriate underlying social infrastructure – i.e., an open network – that makes frequent interaction possible. If so, then localized differences in network openness might be a key explanation why a small club of leading city-regions (including the Silicon Valley) have sustained their disproportionately high performance for decades, despite contemporary globalization and rapid technological change – and thus perhaps also the development trajectories of the complementary set of disproportionately low performing city-regions (cf. Bettencourt et al., 2010; Storper, 2018).

Unfortunately, a lack of conceptual specification impedes further investigation into such possibilities. Despite widespread influence, one odd feature of the existing literature is that the central concept 'open networks' is still not well defined. The terms commonly used to describe such place-based networks— e.g., ‘open’, ‘decentralized’, ‘dense’, ‘flatter’, ‘inclusive’, ‘diverse’ —are used in ways that are evocative and intuitively appealing, but imprecise and often inconsistent. Studies of open networks have moreover largely focused on a small set of high-profile clusters, and it remains unsettled whether the postulated benefits of open networks generalize beyond the idiosyncrasies of these limited empirical settings. The existing literature has also tended to focus on a few industrial sectors (mostly ICT and biotechnology), and it is unclear whether we should expect similar gains from open networks in other high-tech sectors. The pervasive lack of clarity into the concept’s essential characteristics thus undermines rigorous understanding of the economic significance of place-based open networks by hindering systematic empirical testing and realistic assessments of policy relevance. We therefore lay the conceptual groundwork for further analyses here by identifying the essential characteristics of open networks.

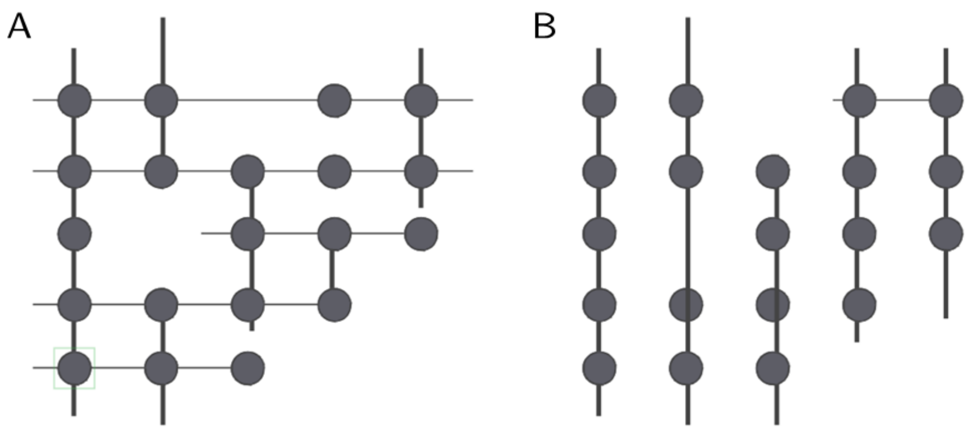

Figure 9. Open versus closed networks: stylized schematic representations of the pattern of interfirm connections in a. Silicon Valley and b. Route 128. The filled circles represent individual economic actors; vertical lines represent hierarchically structured ties internal to vertically integrated firms; and horizonal lines represent Interpersonal social ties across organizational boundaries (after Brown & Duguid, 2000).

Returning to Saxenian’s (1994; Table 2) contrasting descriptions of Silicon Valley and Route 128, we submit that the core traits of open networks are made more obvious when we consider what these contrasts entail for their network topology. Figure 9 presents stylized representations of the pattern of interfirm connections in an open and closed network (i.e., in Silicon Valley and Route 128 respectively) following Saxenian (1994). It is intuitive that cutting-edge technical information might be more effectively diffused in Figure 9's network A in than in B. The relatively more closed network in B is quite clearly dominated by hierarchically structured ties. Conversely, the actors in the more open network (A) are relatively more connected and extensively linked through ties that cut across organization boundaries.

We therefore propose that the essence of open networks is that they are comparatively: 1) better connected at the macro scale, such that 2) connections are relatively less concentrated within organizational silos. This parsimoniously encapsulates the *necessary* conceptual kernel of open networks in cities and regions, since none of the theoretical mechanisms discussed in the foregoing would work if the networks in question lacked these features[6].

Accordingly, we hypothesize that regions with higher initial network openness in high-tech will have stronger subsequent growth in those high-tech industries. Moreover, based on the motivating literature, we also expect that open networks will have economically significant effects on subsequent job growth across all substantively science- and technologically-oriented industrial sectors.

3. Data and measuring network openness

3.1 Defining regional high-tech industries

We focus on the regional scale to better investigate the potential systemic social gains that are widely assumed to obtain from open social networks at the regional level in the motivating literature. Our units of analysis are travel to work areas (TTWAs) to represent UK regions. TTWAs are official spatial definitions of functional regional labour market areas widely used in econometric analyses of the UK to approximate

[6] This formulation is deliberately parsimonious to avoid conceptual fuzziness. It is not intended to capture every relevant aspect of open networks, but only their most essential and foundational features.

functional economic city-regions (Lee, 2014). We use the latest 2011 TTWA boundaries published by the Office of National Statistics (ONS), giving us 218 total TTWAs in Great Britain. We exclude Northern Ireland due to the lack of appropriate regional level data.

We study high-tech job growth using data from the Business Register and Employment Survey (BRES). We also use data from the Annual Population Survey to construct some of our controls. We focus on the decade from 2010 to 2019, excluding 2020 to avoid capturing exogenous shocks from the COVID-19 pandemic.

Sectoral boundaries are defined using Standard International Classification (SIC) 2007 code definitions at the 5-digit level. While there is no single definition of high-tech, we define our study sectors with reference to widely used official industry definitions. We define three industrial groupings that provide progressively wider coverage over industrial subsectors related to science and technology. They do this in a manner somewhat analogous to spatial bands, except within the SIC industry classification space instead of physical space. This design allows us to systematically assess the economic significance of open networks for industrial groupings commonly seen as having a strong technological orientation.

Our focal industry grouping is high-tech, defined using the SIC codes published by the ONS Economic Review (2018). The high-tech sector comprises ‘high technology manufacturing’, ‘medium-high technology manufacturing’, and ‘high-tech knowledge intensive services’. High-tech is constructed as the strict superset of the digital economy sector. In turn, high-tech is also constructed as the strict subset of the STEM sector. High-tech is thus the intermediate ‘band’ between digital economy and STEM.

We define digital economy according to the official SIC definition used by the UK government (Tech Nation, 2018; Lee & Clarke, 2019). Digital economy comprises selected 5-digit SIC codes in ‘computer and electronic manufacturing’ and ‘digital and computer services'. Digital economy is the narrowest industry 'band' comprising the highly innovative and non-routinized ICT-related subsectors of the high-tech sector, aligning closely with the idea of leading-edge ICT clusters in the style of the Silicon Valley. The digital economy sector is thus of special interest to industrial policymakers aiming to foster innovation-led growth, including in the UK (Tech Nation, 2018).

Finally, we define our broadest 'band', STEM, using the Science and Technology (S&T) SIC classifications published by the Office of National Statistics (Office for National Statistics, 2015). STEM is defined as all 5-digit SIC codes classified as belonging to the ONS's Science and Technology classification, and comprises 'digital technologies', 'life sciences and healthcare',

3.2 Measuring open networks

We develop our open network metrics by making novel use of a unique census-like dataset constructed based on administrative company register data from Companies House publicly available through a web API. The Companies House data offers a window of unparalleled depth into the network structure of UK firms. The dataset comprises the universe of all UK companies and affiliated company officers from 1844 to the present, and contains comprehensive data including all board appointments, modification, and resignations; company profiles and associated SIC codes; filed accounts; and company officer biographical data.

The relational nature of the data allows us to construct regional socioeconomic networks that completely characterize the bipartite network structure of 'top team' networks[7]. Relevant firms are identified using the company SIC codes in their company profile data. Company and director nodes are allocated into 218 regions based on the postcode sector details contained within the company register data to

[7] Sometimes also referred to as 'career affiliation networks' or 'board interlock networks'.

provide relatively fine-grained regional boundaries. See Boey et al. (2020) for more information on this dataset, and the specific considerations and implementation details for constructing the regional company-officer networks.

We construct regional metrics to quantify the network openness of regional high-tech networks. As discussed in Section 2, the conceptual kernel of open networks is that they are 1) better connected at the macro scale, such that 2) connections are relatively less concentrated within organizational silos. We operationalize the intuition that open networks essentially have relatively less concentrated social connections captured as the degree centralization of their regional network. Degree centralization parsimoniously quantifies the conceptual kernel of open networks because it measures how concentrated connections are within a given network.

Simply put, if a given network is relatively highly concentrated, then it is not an open network, and the degree centralization measure will be relatively high; versus another given network that has a relatively low degree centralization and is thus an open network. The open networks measure thus reflects the concentration of social connections in a region. Formally, we measure the network openness for a given network g as

$$\text{Open networks}_g = \frac{1}{\sum_{i=1}^{N} s_i^2}$$

where N is the number of actors and S_i is the share of connections (i.e., the degree centrality) held by a given actor i. We use this measure to quantify initial regional network openness for each high-tech industry sector grouping at the TTWA level for all TTWAs in 2010.

One plausible concern with this measure is a potential skewing effect from large firms. We might worry that the presence of tech giants like Microsoft or Facebook might distort the open networks measure for that region. However, it turns out that the average UK high-tech top team size lies between 2-3 persons for both individual regions and the whole UK. The removal of these very large firms from the data thus does not make a noticeable difference to the regional open networks indicator. There is moreover sublinear scaling of board size versus firm size – i.e., even though a tech giant might be orders of magnitude larger than a given high-tech start-up, the tech giant does not have a commensurately larger board versus the high-tech start-up.

3.2 Descriptive statistics

We benchmark the open networks measure against commonly used network statistics. Table 3 shows that our open networks indicator is significantly correlated with commonly used network structure metrics, which might reassure us that our measure has sufficient construct validity, in that it is meaningfully measuring aspects of regional network structures.

Table 3. Correlation statistics. Upper: UK high-tech sector variables. Lower: UK high-tech local social networks in 2010 (n=218)

	1	2	3	4	5
(1) High tech growth					
(2) Open networks	0.18**				
(3) Employment share	-0.064	0.21**			
(4) Working population	0.18**	0.55***	0.18**		
(5) High skill share	0.13	0.26***	0.12	0.2**	
(6) LC size	0.1	0.16*	-0.22**	0.19**	0.24***

* p < 0.05, ** p < 0.01, *** p < 0.001

	1	2	3	4	5	6
(1) Open networks						
(2) Tie density	-0.12*					
(3) Clustering	-0.37***	0.14*				
(4) Clustering in LC	-0.19**	0.13*	0.61***			
(5) Ave path length in LC	0.50***	-0.14*	-0.44***	-0.30***		
(6) LC Small-world-ness	0.82***	-0.04	-0.30***	-0.13	0.43***	
(7) Size of LC	-0.06	0.89***	0.03	0.13	-0.02	-0.08

* p < 0.1, ** p < 0.05, *** p < 0.01

The open networks indicator is least correlated with the size of the largest network component (LC) in each TTWA (the largest component is also sometimes referred to as the primary component). LC size is also the only metric our open networks indicator has essentially no correlation with.

The most correlated network statistic with our open networks indicator is the Small-word-ness of the largest component (LC Small-world-ness)[8]. The regional small-world-ness metric has well-studied properties and has some plausible theoretical correspondence with the idea of open networks. However, we do not make further use of it in this paper because, as Figure 10 shows, all UK TTWAs were small-worlds in 2010. The universality of small-worlds in real-world-networks (Jackson, 2010; Newman, 2018) suggests that small-world-ness might not meaningfully explain open network structure nor regional economic performance.

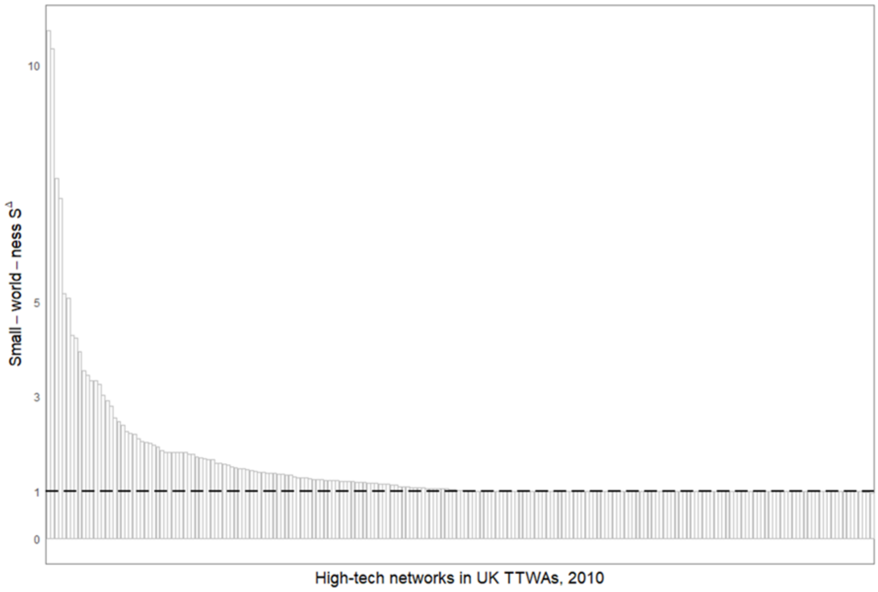

Figure 10. Small-world structure in high-tech across UK sectors in 2010. The dashed horizontal line indicates the minimum threshold (at least 1 S^{Δ}) for a given network to have small-world structure.

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[8] We measure the small-world-ness metric S^{Δ} as defined in Humphres & Gurney (2008). $S^{\Delta} = (C^{\Delta}_{g}/C^{\Delta}_{rand})\ /\ (L_{g}/L_{rand})$ where C^{Δ}_{g} is the transitivity and L_g is the average path length for a given observed network. These are normalized by C^{Δ}_{rand} and L_{rand}, which are the expected values in an ensemble of equivalently dense random graphs. Transitivity is a measure of a network's global clustering coefficient and is defined as the fraction of transitive triples (Newman, 2018). We calculate the randomized metrics as the average over 1000 randomized networks generated for each TTWA using a degree distribution preserving edge rewiring algorithm with 100 rewiring steps per vertex. Networks with $S^{\Delta} \geq 1$ are considered small-worlds.

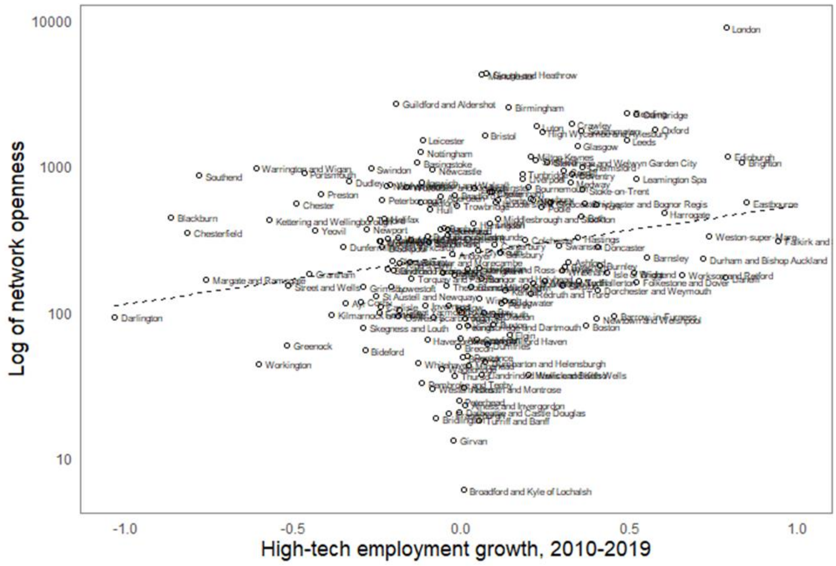

Figure 11. High-tech growth and initial network openness, 2010-2019.

Figure 11 shows the positive association between the log of our network openness measure and subsequent high-tech job growth over our study period. The figure shows the expected relationship between open networks and regional performance. While only a simple correlation, this might nonetheless assure us that we are likely on the right track.

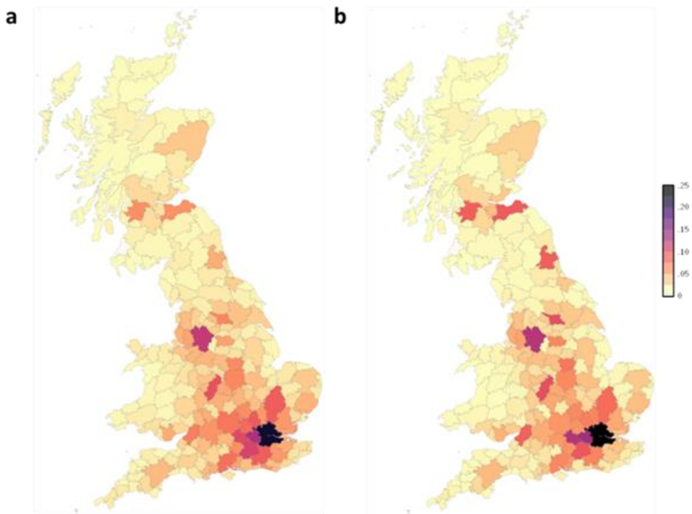

Figure 12. Local social network structure and high-tech employment in the UK. a. Shows initial network openness in 2010 at the TTWA level, b. Shows the corresponding regional high-tech employment in 2019. All values are expressed as a share of the national total to facilitate comparability. Higher regional values are mapped to darker colours, as shown in the colour bar.

Figure 12 depicts the regional distribution of initial network openness in 2010 and regional-high tech employment in 2019 and provides another view of the positive association shown in Figure 11. We can also observe obvious regional variation in Figure 12, which is unsurprising considering the differences in regional histories and devolved governance across the UK

4. Model and results

4.1 Empirical model

Our core estimation examines employment growth. We adapt a widely used empirical design taken from the urban-regional growth literature (Glaeser et al., 2015; Grillitsch et al., 2021) to focus on localized social network macrostructure. We estimate models of the form

$$ln\left(\frac{\text{Employment}_{i,2010}}{\text{Employment}_{i,2019}}\right) = \alpha + \beta_1\, ln\left(\text{Open Networks}_{i,2010}\right) + \gamma\ \text{Other Controls}_{\text{i}} + \epsilon_i,$$

where *i* indexes TTWAs. The dependent variable is the change in the log number of high-tech jobs over the decade from 2010 to 2019. We follow previous research by focusing on employment growth rather than wage growth since the latter is likely to be limited by workers' spatial mobility (Glaeser et al., 2015). *Open Networks* is the log of initial network openness in high-tech industries in TTWA *i* in 2010. The other controls account for initial TTWA characteristics which affect subsequent employment growth, and the error term is ϵ

The coefficient β on high-technology industries is the key figure of interest and describes the correlation of initial network openness and future employment growth for high-tech industrial clusters. A positive coefficient thus indicates that network openness is associated with growth in high-tech. This is what we should expect to find based on widespread claims in the theoretical literature on the myriad region-specific advantages that emerge from, and are fostered by, flatter and more open localized networks in highly innovative social milieus (Saxenian 1994; Storper 2013; Huggins & Thompson, 2021). To test this idea, our interest is therefore whether initial network openness leads to changes in high-tech industry jobs in the study period. Accordingly, we favour a cross-sectional design over a year-on-year or dynamic panel model to better align with the idea that these network-wide social gains are not immediately observed but have emergent and cumulative effects that are better identified over the medium- and long-run at the relevant regional and ecosystem scales. Moreover, while we have data on individual firms, our primary interest in testing the idea of regional social gains – as opposed to average effects on individuals, firms, or a particular subgroup of firms and individuals within localized social network – necessarily precludes the inclusion of firm-level fixed effects.

We include several controls widely used in the empirical literature. Aside from the social network metrics, all controls for regional observables are calculated using official statistics from the Business Register and Employment Survey and the Annual Population Survey published by the UK Office of National Statistics (ONS).

We firstly include 10 region dummies for location fixed effects at the NUTS 1 level. These control for the role of unobserved regional characteristics and differing regional governance and policy regimes. They should also help to partial out unobserved initial differences in high-tech employment across regions. Secondly, we include the share of the local population qualified with National Vocational Qualification (NVQ) level 4 and above (i.e., higher education qualifications) as a control for human capital. This is a commonly used indicator of high skills in the UK setting that is expected to be positively associated with high-tech growth (Lee, 2017). Thirdly, we include the log of the total working population to control for the expectation that larger TTWAs positively correlate with growth in high innovation and knowledge-intensive industries due to scale and urban density effects (Duranton & Puga, 2004; Lee & Rodriguez-Pose, 2013). We also include the initial share of relevant employment to control for the potential agglomeration economies that might arise due to collocation.

Finally, we include a variable for the log size of the primary (i.e., the largest) network component relative to each regional network to control for the extent of network aggregation. This is expected to have a positive association with network growth since regions with larger values are relatively more connected and thus provide potentially better and quicker access to network resources than regions that have relatively smaller primary components (Fleming et al., 2007). Another motivation for including this control is that this is only network statistic discussed in the preceding section that is essentially independent, and thus providing non-redundant information about regional network structure, with our measure of Network Openness in our empirical setting. We also try including other frequently used controls taken from the urban-regional growth literature such as specialization and absolute diversity. However, their inclusion does not materially change the substantive message of our findings, while simultaneously reducing model precision by lowering the adjusted R-squared. We therefore omit these other controls in the interest of parsimony, especially since we do not have compelling or principled theoretical reasons to include them as covariates here.

4.2 Instrumental variable strategy

We might anticipate potential issues with endogeneity in our model. More open local social networks might directly promote local high-tech job growth, but network openness might also be the result of high-tech growth if growing technology clusters tend to attract people that have more open networking behaviour. An unobserved policy that promotes science park development, for instance, might also jointly influence both local high-tech job growth and network openness.

These challenges are addressed using an instrumental variable (IV) strategy that makes use of the motivating literature’s causal story. As discussed in Section 2, micro-level economic life is theorized to be embedded within socioeconomic networks, which are in turn embedded at the macro-level within regional institutions. Openness might lower barriers to interpersonal communication, particularly between individuals from different backgrounds, and people embedded within a regional culture of openness are thus more likely to interact with others more broadly and with less strict adherence to organizational boundaries (Qian, 2013). This suggests a channel through which regions with open macro-level institutions might foster more open networks versus those with relatively closed regional institutions. An ideal instrument might therefore model regional variations in institutional characteristics that systematically influence the openness of regional high-tech networks, while not directly influencing high tech job growth.

Figure 13. The cuisine space. The minimum spanning tree of the cuisine projection of the bipartite graph of TTWAs and country-of-origin cuisines in 2005 is depicted. Nodes represent the country-of-origin of culinary influences. Each node is sized by their relative ubiquity, and is coloured by their World Bank macro-region, as per the legend. The node for Great Britain's culinary influence is indicated by the black arrow above the legend.

In his 'creative class' thesis, Richard Florida famously drew the link between city-regions with 'open' and 'bohemian' mindsets and cosmopolitan urban environments ‘seething with the interplay of cultures and ideas’ (Florida 2002: 227; 2005). Taking inspiration from this work, we use the relative cosmopolitan composition of regional cuisines as our instrument for macro-level institutional openness[9]. The intuition here is that places with relatively more ‘cosmopolitan’ influences on F&B demonstrate a revealed cultural preference for openness. This instrument thus is not about local cuisine per se, but rather the general openness of macro-level regional culture. A cursory glance through any popular food guidebook will corroborate the intuition – one is far more likely to find cuisines from distant places and unexpected culinary fusions in, for instance, Los Angeles than in Louisville, or in Brighton than in Bristol. The mix of country influences on regional F&B cuisine therefore captures localized variations in the institutional demand for openness across regions – i.e., the openness of ‘regional cultures’ – that, in turn, affects the evolution of localized network openness. Because regional culture might also evolve through the embedded interactions between actors on localized networks, we measure the IV historically in 2005 to mitigate reverse causality.

We develop the instrument with the extensive profiling and biographical data on the F&B industry in the company register database, using the economic complexity network measure (Hidalgo & Hausmann, 2009; Hidalgo, 2021; Balland et al., 2022) as a dimensionality reduction technique to summarize the complex spatial patterns of relative country-of-origin influences on regional cuisines. The IV is measured as the regional culinary complexity: the economic complexity of the bipartite graph of TTWAs and the countries of origin of their F&B cuisines[10]. This measure

[9] Florida (2002; 2005) also focuses on the role of open regional institutions and sociocultural diversity in attracting highly talented workers as the main mechanism linking macro-level cultural openness to city-regional success. This is our point of departure from Florida’s position as, contrary to his claims, regional diversity is more likely an outcome rather than a direct cause of urban success (Peck, 2005; Storper, 2013).

[10] More specifically, the IV is constructed using the comprehensive company register data as follows. We first identify F&B using SIC information. Then, for each F&B company in each TTWA, we accord a fractional share for each restaurateur’s country-of-origin nationality. We then aggregate the totals of each country-of-origin for each region. This is then used to construct the bipartite graph of TTWAs—cuisines used for the complexity measure. The main assumption here is that the country-of-origin of F&B proprietors substantively influences food preparation because people from different national

appropriately quantifies the intuition that a regional cuisine that has more culinary influences from countries that are relatively uncommon across the country likely has a relatively more cosmopolitan range of influences on its F&B – and thus a more complex regional cuisine – than a regional cuisine with mainly local influences. The IV satisfies the exclusion restriction since the development of the F&B industry is almost certainly orthogonal to local high-tech growth.

Figure 14. The regional distribution of culinary complexity and the cuisine space in selected UK regions. Darker coloured regions on the map have higher culinary complexity. Filled nodes in each panel indicate the countries-of-origin of culinary influences that the region is relatively specialized in and are coloured by their World Bank macro-region as per the legend.

backgrounds prepare even nominally similar dishes differently (e.g., consider the innumerable local variations of fried chicken). We follow best practice (Hidalgo, 2021) and cut countries-of-origin that are outliers on the left tail of the distribution so that we consider only culinary influences from countries of origins that have a meaningful overall presence in the UK.

There are two obvious objections to the IV. We might expect that restaurants tend to set up in highly populated regions to access more customers. We may also suspect that the demand for more complex cuisines might be higher in regions with relatively more highly skilled workers due to the latter's more cosmopolitan consumption preferences. While these are valid concerns, they are unlikely to present any issues here as the influence of general agglomeration effects and the share of highly educated workers are already controlled for in our empirical model.

One might also have practical concerns about construct validity over our novel use of economic complexity to construct an IV. Does our IV reasonably approximate the ground truth UK culinary landscape? Direct validation is not possible here given the lack of suitable data sources on UK restaurants and their menus. Fortunately, we can indirectly assess the proximity network underlying the IV. Figure 13 depicts the cuisine space, the network connecting relatively similar country-of-origin culinary influences across UK TTWAs in 2005. Popular knowledge about the UK might have us expect that South Asian and British cuisines to be very closely related on substantive grounds, and it is reassuring that this is exactly what Figure 13 shows. We can also see that geographically proximate cuisines also tend to be topologically clustered in the cuisine space, which makes sense if we consider that the cuisines from spatially proximate countries are likely more similar than those between far-flung countries. We might also be encouraged that nearby TTWAs specialize in relatively similar cuisines (Figure 14), reflecting the expected behaviour as established in the empirical economic complexity literature. Finally, we might note important differences between the spatial distribution of cuisine complexity in 2005 shown in Figure 14, and the regional distribution of network openness in Figure 12 – most notably that while London does have the highest cuisine complexity in 2005, it does not have the obvious dominance seen in Figure 12.

Table 4. Impact of open networks on high-tech growth, 2010-2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	Full	Full	No London	Full	Full	No London	Full	Full	No London
Open networks	0.066***	0.188***	0.189***	0.143***	0.833**	0.880**	0.156***	0.866*	0.917**
	(0.019)	(0.064)	(0.064)	(0.037)	(0.399)	(0.400)	(0.046)	(0.458)	(0.463)
Employment share		-0.145***	-0.147***		-0.288***	-0.236***		-0.232***	-0.241***
		(0.044)	(0.045)		(0.068)	(0.070)		(0.073)	(0.076)
Working population		-0.088*	-0.087		-0.650*	-0.688*		-0.678*	-0.720*
		(0.053)	(0.053)		(0.357)	(0.358)		(0.407)	(0.412)
High skill share		-0.049	-0.049		-0.622	-0.662*		-0.65	-0.695
		(0.114)	(0.114)		(0.379)	(0.383)		(0.432)	(0.438)
LC Size		0.050*	0.051*		0.035	0.035		0.034	0.035
		(0.027)	(0.027)		(0.037)	(0.038)		(0.038)	(0.040)
Constant	-0.249*	-0.051	-0.071	-0.603***	4.252	4.527	-0.756***	4.465	4.77
	(0.138)	(0.542)	(0.546)	(0.233)	(2.872)	(2.885)	(0.283)	(3.256)	(3.295)
First stage results									
Cuisine complexity, 2005				0.287***	0.035***	0.036***	0.231***	0.029**	0.031**
				(0.034)	(0.013)	(0.013)	(0.0365)	(0.012)	(0.013)
First stage F-statistic				24.879	284.015	267.523	19.958	282.074	265.619
R squared	0.110	0.207	0.202						
Weak instruments test statistic				52.839	9.451	9.307	28.171	7.762	7.626
Weak instruments test p-value				0.000	0.002	0.003	0.000	0.006	0.006
Endogeneity test p-value				0.009	0.040	0.024	0.021	0.054	0.035
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218	218	217	218	218	217	218	218	217

Notes: Robust standard errors are reported in parentheses. The outcome variable is log high-tech employment growth for TTWAs in England, Scotland, and

Table 5.. Impact of open networks on high-tech, digital economy and STEM, 2010-2019.

	Digital economy			High-tech			STEM		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Sample	Full	Full	No London	Full	Full	No London	Full	Full	No London
Open networks	0.157**	0.884*	1.174**	0.143***	0.833**	0.880**	0.058***	0.081	0.106
	(0.061)	(0.512)	(0.540)	(0.037)	(0.399)	(0.400)	(0.019)	(0.144)	(0.143)
Employment share		-0.420***	-0.514***		-0.288***	-0.236***		-0.133**	-0.140**
		(0.153)	(0.160)		(0.068)	(0.070)		(0.053)	(0.055)
Working population		-0.579	-0.796*		-0.650*	-0.688*		-0.016	-0.036
		(0.415)	(0.441)		(0.357)	(0.358)		(0.130)	(0.129)
High skill share		-0.565	-0.763*		-0.622	-0.662*		-0.012	-0.031
		(0.384)	(0.414)		(0.379)	(0.383)		(0.136)	(0.137)
LC Size		0.043	0.059		0.035	0.035		0.046**	0.047**
		(0.039)	(0.044)		(0.037)	(0.038)		(0.019)	(0.019)
Constant	-0.413	2.710	4.007	-0.603***	4.252	4.527	-0.324**	-0.335	-0.214
	(0.336)	(2.794)	(3.017)	(0.233)	(2.872)	(2.885)	(0.130)	(1.012)	(1.007)
First stage results									
Cuisine complexity, 2005	0.235***	0.032***	0.033***	0.287***	0.035***	0.036***	0.289****	0.047****	0.049****
	(0.036)	(0.013)	(0.012)	(0.034)	(0.013)	(0.013)	(0.032)	(0.011)	(0.011)
First stage F-statistic	20.803	284.879	268.007	24.879	284.015	267.523	23.885	343.533	321.438
Weak instruments test statistic	29.492	9.977	8.710	52.839	9.451	9.307	57.092	20.589	19.528
Weak instruments test p-value	0.000	0.002	0.004	0.000	0.002	0.003	0.000	0.000	0.000
Endogeneity test p-value	0.068	0.151	0.206	0.009	0.040	0.125	0.628	0.822	0.963
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	217	217	216	218	218	217	218	218	217

4.3 Open networks and high-tech job growth

Table 4 presents the results for the impact of network openness on subsequent employment growth in high-tech city-industries in the United Kingdom. The estimations are unweighted and report robust standard errors in parentheses. The first three columns describe the basic OLS relationship between local network openness and digital-tech city-industry growth. Columns 4-6 show the instrumental variable results with the culinary complexity instrument, while Columns 7-9 show the corresponding results using the non-discretized version of the same instrument. The corresponding first stage relationships are also reported in each column. The weak instruments tests p-values are computed with the first stage F test statistic, under the null hypothesis that the instruments are weak. We report p-values from Wu-Hausman endogeneity tests, allowing for robust variance estimation, under the null hypothesis that all the variables are exogenous and give consistent OLS estimates; a rejection of the null hypothesis thus indicates the need for instrumental variables estimations.

The first column begins with all 218 TTWAs by including only the region dummies and the second column also includes the other controls. The estimated OLS coefficient is positive, with a larger magnitude in the second column, and is statistically significant at the 1% level in both. With all controls included, a one standard deviation increase in 2010 network flatness is associated with a 0.19 standard-deviation increase in high-tech job growth over the following decade. Column 3 addresses the concern that London might account for an unduly large influence on the estimates because of its disproportionate size. London is a primate city but there is no analogous city in the United States – the empirical setting of much of the influential analyses on social networks and technology clusters – due to its comparatively decentralized urban hierarchy[11]. Nonetheless, there is little substantive

[11] Our concern here is simply that London is considerably larger than other cities in the United Kingdom to a degree not found in cities in the United States and is agnostic to the ongoing debates on the scaling behavior of city sizes in the urban dynamics of the US or elsewhere (Batty 2006; Bettencourt, 2021).

change to the results when London is excluded. The stability of these associations suggest that they are not simply driven by urban primacy effects or straightforward differences between high-tech cluster growth.

Table 6. Standardized estimates of the impact of open networks on high-tech growth, 2010-2019.

	(1)	(2)	(3)
Estimator	OLS	OLS	OLS
Sample	Full	Full	No London
Open networks	0.186*** [1.65]	0.296*** [3.8]	0.278*** [6.07]
	(0.054)	(0.087)	(0.104)
Employment share		-0.204*** [1.85]	-0.203*** [1.88]
		(0.064)	(0.065)
Working population		-0.023* [1.64]	0 [3.06]
		(0.013)	(0.057)
High skill share		0.007 [1.48]	0.008 [1.52]
		(0.053)	(0.054)
LC Size		0.089* [1.64]	0.087* [1.64]
		(0.048)	(0.048)
Constant	0.100	0.134	0.134
	(0.078)	(0.081)	(0.081)
Observations	218	218	217
Region dummies	Yes	Yes	Yes
R squared	0.11	0.207	0.202

Robust standard errors shown in parentheses. VIFs are reported in square brackets. All estimates are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We briefly consider possible collinearity with reference to the results Table 6. The OLS specifications presented in the first three columns of Table 4 are shown in Table 6 with standardized estimates with VIFs in square brackets reported alongside. Small effects might be drowned out in the presence of high VIFs, and our particular concern here is to detect whether this untoward situation might obtain from the influence of regional scale. Opinions divide amongst researchers on the appropriate minimum VIF threshold indicating potential multicollinearity. VIF thresholds of 5 and 10 are often suggested – none of the variables seem particularly worrisome by these standards. Our concerns might also be allayed by the stability of the results across all OLS models: the coefficient on open networks are the largest across the standardized and standardized estimates, and the ordinal relationship for the coefficient on each term is robust to standardization.

The effect of initial network openness on subsequent high-tech growth is higher than the basic results when using cuisine complexity as an instrument. The instrumental variables estimate with and without additional controls in Columns 4 and 5 is 0.14 and 0.83, more than double and quadruple the OLS coefficients in Columns 1 and 2, respectively. When London is omitted in Column 6, we find a relatively modest increase of the network openness coefficient of around 5%; a similar impact as we saw in the corresponding least squares results in Column 3. Although there is some loss of precision compared to the OLS estimates, the instrumental variable effects remain significant at the 1% level in Column 4, and at the 5% level in both Columns 5 and 6.

Columns 7-9 repeat the analysis with the non-discretized version of the cuisine complexity instrument, to address the concern that the instrumented results might be unduly driven by the discretization step during the construction of the culinary complexity measure. The coefficients are similar in magnitude to the instrumented results reported in Columns 4-6, albeit with a modestly higher estimate in the open networks coefficient across Columns 7-9, and a modest loss in precision in the models with additional controls (Columns 8 and 9). The robustness of the instrumented estimates across Columns 4-9 suggest that the results are not arbitrarily driven by the discretization procedure. These results suggest instrumented elasticities for high tech job growth between 0.83 to 0.92 (Columns 5-6 and 8-9).

The OLS coefficient estimates (Columns 1-3) show the strong positive relationship between high-tech job growth over the decade 2010-2019 at the TTWA level and initial network openness in 2010. The empirical associations are economically and statistically significant, even when London is excluded from the sample, and suggest that network openness is positively associated with subsequent local high-tech job growth. The pattern of the OLS findings is broadly mirrored by the instrumental variable results within Columns 4-6 and 7-9 respectively. The estimated coefficient on network openness is positive even without additional controls, and the size of the instrumented effects fall within a relatively narrow range. The substantive findings are also robust to the inclusion of London in the study sample. Both the discretized and non-discretized versions of the culinary complexity instrument work well and the variable for open networks is statistically significant throughout Columns 4-9. The diagnostics suggest that neither version of the instrument appear to be weak. The F-statistic is well above acceptable levels and the weak instruments test is rejected at the 1% level. The first stage relationships are also strong and highly significant from zero throughout: regional culinary complexity in 2005 is strongly related to network openness at the start of our regression study period in 2010.

The consistently larger elasticities found in the instrumental variable estimates suggests that endogeneity might downward bias the OLS results. If this reflects the ground truth, then the instrumental variable estimates correctly show larger elasticities because the instrumental variables capture the persistent features of open local network structure that have a stronger positive effect on longer-run high-tech cluster growth than the endogenous aspects also captured by the least squares estimates. This suggests that the culinary complexity instrument(s) capture exogenous sources of variation of localized social network structure in high-tech. The instrumental variable estimates thus report higher estimates because they are only influenced by the variation from the exogenous variation captured by the instrumental variables. The Wu-Hausman endogeneity test null hypothesis of OLS estimator consistency is rejected in all instrumented variables estimates, and thus provides an econometric justification for this explanation.

Substantively, the most important implication then is that initial network openness has a causal impact on subsequent regional high-tech employment growth. This explanation is corroborated by the strength and stability of the results and the associated performance of the diagnostics discussed above. An objection to this interpretation is that that the covariates might indirectly measure pertinent structural characteristics, such as the edge density, of the localized social networks under consideration. While this is a plausible issue, it nonetheless does not seem particularly worrisome here since variables such as population size are typically too general to be reliably used as social network metrics, especially given the high degree of specialization required in high-tech industries (Gordon & McCann, 2000), and the exceedingly wide range of possible structural variation between even two identically sized networks. Moreover, the fact that the coefficients consistently remain economically and statistically significant even without additional controls across the OLS and instrumental variable results provides comfort that our results are not simply explained by general factors as the size of urban-regional agglomerations or education levels. These findings thus provide new systematic evidence for high-tech industry in the United Kingdom and is consistent with widely promoted theories on the economic value of flatter and more open social networks for the long-run success of highly innovative technology clusters.

4.4 The limits of open networks?

We next extend our analysis to consider other high-tech industry sector groupings. Table 5 reproduces our preferred high-tech growth specification (Columns 4-6 in Table 4), for ease of comparison, in Columns 4-6. We repeat our preferred specification for digital economy and STEM-related industry growth in Columns 1-3 and 7-9 respectively. The three industry groupings presented in Table 5 provide progressively wider coverage over industrial subsectors related to high technology. This allows us to systematically evaluate whether open networks are generally economically significant across all science- and technology- related industrial activities[12]

[12] Note that we separately model each sector grouping instead of using sub-industry fixed effects since our primary interest is not to compare relative effect sizes.

Table 5 shows that the general pattern of instrumented results from high-tech (Columns 4-6) is maintained in Columns 1-3 for the digital economy subsector. The open networks coefficient is statistically and economically significant in all columns. The diagnostics also continue to present no cause for concern. Given that we have already established the substantive importance of open networks for job growth in the high-tech sector, it would be surprising result if open networks were also not important for the innovation-focused subset of firms engaged in the digital economy. As set out in Section 3, the digital economy sector is the strict subset of high-tech firms engaged in non-routinized ICT and represents Silicon Valley-style innovation-intensive ICT. Digital economy thus corresponds to the fast-paced and highly uncertain environments close to the technological frontier the motivating literature has extensively studied, where we would expect open networks to matter for regional performance.

However, similar findings do not obtain for STEM (Columns 7-9). The open networks coefficient does not approach any conventional level of statistical significance in the fully specified model (Column 8). Similar results obtain when London is omitted (Column 9). The diagnostics nonetheless do not indicate any potential weak instrument issues. This is an unanticipated result. On the one hand, as the strict superset of the high-tech sector, the STEM sector naturally encompasses a larger range of industrial activities than either high-tech or digital economy. On the other hand, the breadth of included activities alone is not sufficiently explanatory here. We would expect from the motivating theory that open networks would continue to be substantively important in STEM's growth. Unlike firms in the digital economy sector or, to a smaller extent, the high-tech sector, STEM firms do not collectively share an obvious common technological orientation. Yet, it is precisely in such situations where the systemic advantages to decentralized coordination and information diffusion afforded by open networks might be expected to be particularly impactful (e.g., by fostering Jacobs spillovers and interdisciplinary collaboration).

How then might we explain this unexpected result? We can only briefly speculate here given the lack of relevant theory and empirical findings in the existing literature. It might be that open networks are truly not economically significant for the STEM sector. As Table 5 shows, although the largest component size is far from any conventional level of significance in digital economy and high-tech, it is significant at the 5% level in STEM (Columns 8 and 9). While null results do not necessarily mean an absence of effect, the coefficient for open networks is also not significant in these columns. One possible interpretation that might be further explored is that other structural features of the localized network might instead become more important as the sectoral boundaries transition from high-tech and STEM. In this case, it is plausible that there exists some threshold beyond which the critical mass of interpersonal connections provided by a sufficiently large degree of network aggregation (as measured by the size of the regional network's largest component) matters more even as open network structure's role diminishes (cf. Fleming et al., 2007). It remains for future research to investigate the dynamics of such a transition; where the threshold between relevant and irrelevant industrial boundaries might lie; and to identify the underlying mechanisms. Alternatively, it might be that open networks are still substantively important, but the networks in STEM were simply not sufficiently open to significantly impact subsequent growth. However, STEM had a similar regional distribution of initial levels of network openness as did high-tech or digital economy. Likewise, it might be that STEM is too large for open networks to be effective – yet open networks seem similarly impactful in both high-tech and the smaller digital economy sector (Table 5). It is plausible that larger sectors and greater intra-sectoral diversity both require more network openness, but there is little existing research that might tell us when and why more openness might be required.

We might also consider if open networks seem irrelevant here only because of how STEM is defined. Although our study sectors are defined according to widely accepted official industry definitions, perhaps the STEM definition contains substantively unrelated activities that were included in the official definition for administrative purposes. However, since we deliberately defined STEM as the strict superset of the high-tech sector, then why do open networks appear to have causal importance in high-tech but not in STEM? It is plausible, for instance, that open networks are substantively important only in highly-innovative sectors close to the technological frontier. If so, we might suspect that the addition of firms engaged in miscellaneous 'Other scientific/technological services' might explain the non-significant results in STEM. However, higher education is also included in this miscellaneous category, and the importance of university-industry spillovers for high-tech cluster success is well established (Bathelt et al., 2010; Casper, 2013; Spigel, 2017; Storper, 2018). Moreover, even though the 'Publishing & Broadcasting' subsector is included in the STEM definition, the rise of the new media industry suggests that this is not necessarily a less innovative subsector. To summarize these findings, while we have systematically demonstrated the importance of open networks for digital economy and high-tech here, much remains unsettled about the factors that determine which economic activities might mutually benefit from being embedded on an open network.

5. Conclusions

Social networks have long been seen as important for regional growth, particularly in highly innovative industries close to the technological frontier. Yet there is a 'pervasive folklore' (Kemeny et al., 2016) about the economic value of social networks that has rarely been closely examined. While localized network structure is often argued to be important, there is little systematic evidence to support these bold hypotheses despite burgeoning interest in the phenomenon over the past decades. There remains insufficient causal evidence that geographically bound socioeconomic networks are important for local innovativeness.

In particular, the idea that localized social networks that have comparatively open and decentralized patterns of interconnection foster high-tech growth has had a profound influence on how place-based social networks are understood across a multidisciplinary literature (Piore & Sabel, 1984; Grabher, 1993; Saxenian, 1994; Almeida & Kogut, 1999; Kenney & von Burg, 1999; Brown & Duguid, 2001; Breschi & Malerba, 2005; Fleming et al., 2007; Saxenian & Sabel, 2008; Casper, 2009; Smith & Reilly, 2013; Chesbrough et al., 2014; Spigel, 2017; Storper, 2018; Huggins & Thompson, 2021). This paper studies UK high-tech and systematically tests the ubiquitous, yet little scrutinized, belief that open network structure underpins local high-tech success, using a unique dataset on the universe of UK firms and their top teams to construct appropriate regional high-tech networks.

We clarify the conceptual fuzziness around the fundamental terms of this complex debate that has long hindered the development of more systematic understandings of the roles and importance of open social networks. This allows us to inductively identify the essential characteristics of open networks and propose a formal definition that rigorously quantifies its conceptual kernel. We provide, for the first time, country-wide empirical evidence for the economic benefits of open regional networks in a major advanced economy. We also provide new evidence for the United Kingdom and contribute to a broader understanding of the role of social networks beyond the more frequently studied technology clusters in the United States. The paper also provides a definitive first step towards identifying exogenous sources of variation in local network structure. Instrumental variable analysis using a novel instrument for institutional openness indicates that initial network openness has a causal effect on subsequent job growth over the next decade from 2010-2019 in the digital economy and high-tech sectors, but not in the broader STEM sector.

Our findings provide systematic evidence that supports the view that localized network openness is a significant driver of regional high-tech growth. However, while the motivating literature often suggests that open networks are generally important for innovation-led local growth, we also provide new evidence for the underexplored issue of identifying and explaining the substantive limits to open networks. These results contradict expectations from the motivating literature and raise important theoretical questions. Given the wide-ranging conceptual influence of the idea of open networks, more research is critically required to understand the factors and settings that determine when the systemic advantages afforded by open networks are expected to have economically significant roles.

There are also significant policy implications that underscore the need for further research. Policymakers around the world have long sought to emulate the success of the Silicon Valley and other technologically dynamic regions. Ideas about the importance of place-based open networks for innovation-led growth motivate industrial strategies and local development policies worldwide that feature networking initiatives that promote inter-organizational collaboration and generally 'putting people in the same room' (Casper, 2013). More direct spillovers into the policymaking world are also in evidence in emerging regulatory tools and practice (e.g., 'anticipatory governance') targeted at supporting high-tech innovation normatively and explicitly oriented around ideals of decentralization, diversity, inclusiveness, flexibility and open engagement (Nesta, 2019). Our findings corroborate prevailing perspectives on the importance of such open network-building initiatives for Silicon Valley-style clusters of digital economy firms. Nonetheless, we still know little about the limits to the substantive importance of open networks, nor the underlying mechanisms that determine open network effectiveness. Although our results also suggest such networking initiatives would be impactful in the high-tech sector, the indeterminate industrial boundaries between high-technology and STEM implies that we remain unable to predict whether the public expenditure for such initiatives might be well justified for any given high-tech cluster policy, or even to provide general cautionary guidelines to prevent situations when such initiatives might lead to counterproductive outcomes.

Future work might also extend this study by analysing the extent to which these findings generalize to other industrial sectors where open social networks are reputed to be important, such as knowledge-intensive services, finance, and the creative industries; and the role of open network structure for other important outcomes such as regional innovativeness productivity. It is moreover important to evaluate the role and substantive importance of open networks on other economically significant networks, such as in the networks of patent inventors. There is also a continued need for comparative case studies and qualitative investigation into the proximate causes, key actors, and ideal conditions to foster flatter and more open social networks.

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Paper 4 – Open networks drive new industry success: antecedent industries and the emergence of UK fintech

Augustin Boey

Abstract

How do new industries develop in local economies? The growth of existing industries has long been studied by urban economists and economic geographers, yet there is limited empirical understanding of budding industries at the technological frontier. We study the growth of financial technology (fintech), a major new industry, in the UK from 2010-2019. While fintech has been in the public spotlight, it remains an open question as to how it has developed, and how much its development has been driven by antecedent regional capabilities in finance and digital technology. We provide a first empirical exploration of these questions using a novel dataset that integrates big data sources and administrative data on the universe of UK firms and top employees. We find that open networks in fintech's primary antecedent related industries in the finance and digital economy industries encourage regional fintech firm growth. The moderating effect of digital economy network openness on finance openness in fostering regional fintech entrepreneurship is robust to controls for specialization and absolute diversity. The evidence suggests that the growth of disruptive frontier industries might be biased towards regions that are already comparatively advantaged with open entrepreneurial networks in more technologically sophisticated antecedent industries.

1. Introduction

Economic geographers and urban economists have long sought to identify the sources of sustained city-urban development. A burgeoning literature has deeply enriched our understanding of the central role of urban environments with a diverse mix of economic activities and dense concentrations of highly-skilled workers for the growth of localized industries. But considerably less attention has been given to studying entirely new industries, and the broad structural factors that widely seen to explain the growth of established industries leave much unexplained about the innovation infrastructure that support the emergence and development of new high-technology industries in local economies. This represents an important gap in our understanding given the importance of technological innovation to long-term growth. The mainstay tools—diversity, specialization, and relatedness—offer little insight into how Boston's Kendall Square, for example, became a leading biotechnology hub despite lacking a strong history in biology-related specialization. At a larger scale, the technological dynamism of the Silicon Valley is sometimes attributed to gains from dense agglomerations of high-skill industries, but such accounts provide substantively unsatisfying explanations for the Valley's unflagging ability to foster new high-technology industries, breakthrough after breakthrough (Saxenian, 1994; Glaeser, 1998; Kenney & von Burg, 1999; Brown & Duguid, 2000; Acs et al., 2002; Storper et al., 2015).

It is therefore timely and opportune for the present study's exploration of the emergence and development of Fintech in the UK. Fintech refers to financial services innovation through digital technological integration. Fintech entrepreneurs are frequently finance industry 'outsiders' that attempt to disruptively compete with incumbents in the financial services sector by transforming how financial services are used and provided (Goldstein, Wei & Karolyi, 2019). Fintech is perhaps the most highly publicized industry popularly associated with the so-called Fourth Industrial Revolution. Global investment into fintech has grown exponentially since the industry’s inception from USD 1.8 billion in 2010 to 165 billion in 2019 (KPMG, 2021). Fintech has simultaneously become increasingly strategically important to policymakers worldwide, particularly in leading financial centres such as New York, Shanghai, and Toronto. The United Kingdom is no exception and has seen extremely rapid growth in the new industry since 2010 (Figure 15). The UK hosts several prominent fintech ‘unicorns’ [13] that offer disruptive alternatives to traditional financial services – e.g., Revolut, which offers mobile app-based digital banking services that also allow users to convert currencies into popular cryptocurrencies, and Wise, which allows users to quickly and inexpensively internationally transfer money with a mobile app. UK policymakers have championed the fintech industry as a core future growth industry since 2010, and have positioned the UK as the ‘undisputed FinTech capital of the world’ (DIT, 2019: 17; Bank of England, 2019; HM Treasury, 2018; 2021). However, despite the nascent industry’s growing importance, there has been relatively little scholarly research on fintech even in the finance literature (Goldstein, Wei & Karolyi, 2019). Many questions thus remain unsettled about how fintech has developed, and how much of that development has been due to existing local capacity in finance or high-tech.

[13] Unicorns are start-ups that have reached a valuation that exceeds USD 1 billion.

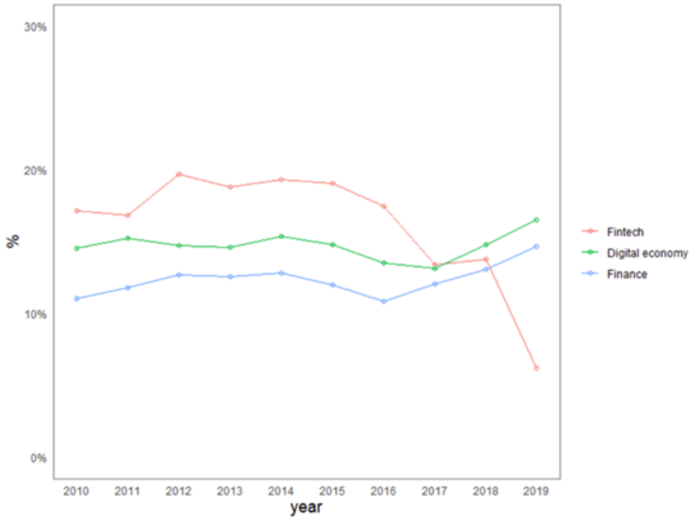

Figure 15. Growth rate in number of firms in fintech, finance, and digital economy. Growth rate is measured as the percentage of new firm entries over existing firms in the Companies House register. Fintech firms are not included in digital economy or finance.

The rise of fintech is popularly understood as the disruptive coming together of the financial services industry and 'deep tech' (DIT, 2019; Lai & Samers, 2020). However, we still know little about how the development of this new sector has depended on the merging of finance and tech. Do places that have stronger finance and non-routine ICT capabilities experience higher fintech growth? If so, what are the localized capabilities that really matter? Here, we draw on a multidisciplinary literature that emphasizes the decisive role of open and decentralized place-based socioeconomic networks in the technological and entrepreneurial dynamism of city-regions (Piore & Sabel, 1986; Almeida & Kogut, 1999; Brown & Duguid, 2000; Storper et al., 2015; Boey, 2022). The UK's status as a global leader in a major new industry gives us a unique opportunity to explore the relative importance of open social macrostructure and standard explanations of city-industry growth. Using a novel dataset combing comprehensive administrative data with more dynamic emerging data sources also us to explore the conditions that might influence which economic activities might mutually benefit from being embedded on an open place-based network. Focusing on the finance and digital economy (the subset of ICT engaged in Silicon Valley-style non-routine activities) industrial sectors, we examine the relationship between initial specialization and the network openness of fintech's antecedent industries on subsequent fintech firm growth in 2010-2019 in UK regions.

Regional specialization in either finance or digital economy industries appears to have no statistically significant impact on subsequent fintech growth, particularly once we account for the effect of open networks. We also find that diversity has a generally positive but inconsistent effect on regional performance. Initial network openness in regional fintech in 2010 has an unambiguously positive effect on fintech growth over the following decade. The effect of initial network openness in fintech's antecedents is asymmetric. Initial levels of openness in finance and digital technology have complementary effects, and regions that have high initial levels in both antecedent industrial sectors generally have the strongest future fintech growth. Regions that conversely have low initial levels in both antecedent industrial sectors generally have little future fintech growth. Contrary to initial expectations, the combination of high initial finance openness with low initial digital economy openness is the least performant combination of network openness in antecedent industries. We also find that fintech firms in relatively more open regions tend to specialize in similar economic activities as the breakthrough successes (i.e., the fintech unicorns and scaleups), while fintech firms located in relatively more closed regions specialize in a comparatively broader and more diffuse set of activities. This suggests a potential channel through which open networks in the disrupting industry might foster stronger economic performance. We generally interpret these findings as indicating that relatively open networks in the 'active' disrupting industry (i.e., in digital economy) is a critical ingredient for local success in fostering disruptive new industries.

We make several contributions to the literature. First, we provide the first analysis to our knowledge that relates the openness of socioeconomic networks in antecedent industries to the development of an emerging frontier industry. Second, we provide use this data to discuss key trends of interest in UK that have thus far been little examined. Third, we provide a new perspective on the underexplored question of how regions adapt to disruptive innovation. Finally, we construct a novel dataset that integrates comprehensive administrative data on the universe of UK firms and their top employees with emerging big data from business intelligence platforms and make that data open for further research.

The rest of the article is structured as follows. Section 2 reviews the literature. Section 3 describes the data and briefly discusses our data matching and validation process. Section 4 explores the emerging geography of UK fintech. Section 5 presents our empirical model and the estimation results. The final section concludes.

2. Conceptual review

How do new and highly-innovative industries emerge and take root in in local economies?[14] Urban economists and economic geographers often focus on broad structural characteristics that influence the effectiveness of agglomeration economies (Glaeser et al., 1992; Ellison et al., 2010; Diamond, 2016; Grillitsch et al., 2021). Human capital and technological spillovers between industries are seen as particularly impactful in sparking breakthrough innovation through serendipitous recombination (Jacobs, 1960). Diverse city-regional economies are therefore widely believed to be crucial in creating the local informational environments that facilitate the inter-industry information flows that result from such productive interactions (Feldman & Audretsch, 1999; Duranton & Puga, 2001). In a similar vein, evolutionary economic geographers focus on the role of industry relatedness and argue that prior specialization in technologically antecedent industries has strong path-dependent effects on future regional technological trajectories (Neffke et al., 2011). City-regions with high industrial concentrations of finance and non-routine ICT activities might therefore be relatively advantaged over other given regions that are not similarly

[14] Please refer to Paper 3 for an extended conceptual discussion on network openness.

endowed with a critical mass of requisite skills embodied within industry-specific labour pools.

Given our present purposes, it is important to consider these channels in relation to popular beliefs that the emergence of fintech 'is as much about the "Tech" as it is the "Fin"' (DIT, 2019: 11), UK policymakers often argue that the emergence of UK as a 'leading global FinTech hub' is founded on the country's 'leading international financial services sector' in combination with its 'thriving tech scene' (DIT, 2019: 7; HM Treasury, 2018). This is a strong claim given that Silicon Valley-style nonroutine ICT and the finance industry are not typically seen as closely connected industrial sectors. Arguments about the value of diversity and local antecedents assume that these factors create a local interactional environment with abundant opportunities for knowledge and resources to disseminate from these antecedent industries to fledging fintech clusters. But workers in unrelated industries are generally unlikely to interact with enough depth and frequency for the kinds of boundary-crossing spillovers necessary to support the emergence and growth of new frontier industries. An apt comparison might be made with the venture capitalist industry in the Silicon Valley – its emergence and ongoing dominance is partly driven by deep incompatibilities in technical expertise, technological orientations, and institutional characteristics between high-tech firms at the innovation frontier and traditional arms-length financing arrangements (Lee et al., 2000; Granovetter, 2017). Finance and cutting-edge IT were, in other words, fundamentally unrelated industries in the Californian context. If fintech's antecedent industries are also largely unrelated in the UK setting, then it follows that neither diversity nor specialization in antecedent industries are likely sufficient conditions for local fintech success. As such:

> Hypothesis 1: The impact of greater industrial diversity, if any, on subsequent fintech growth is positive.
>
> Hypothesis 2: The impact of greater specialization in fintech's antecedent industries, if any, on subsequent fintech growth is positive.

By contrast, a distinct approach foregrounds the central role of place-based socioeconomic networks in fostering geographically localized innovative environments that support technological and entrepreneurial dynamism (Powell et al., 1996; Whittington et al., 2009; Lundvall, 2010; Kemeny et al., 2016; Spigel, 2017). City-regional social networks are thought to provide a regional context for innovation, and geographical differences in their intensity and structure thus contribute to differences in local performance. In this perspective, while local factor endowments remain important, the emergence of economic institutions—including the establishment of new industries—arises through complex processes of interaction between geographically localized agents. The sustained performance of high-tech clusters and their 'capability to generate and develop breakthrough innovations that create new industrial domains and to redesign radically its industrial value chain' thus depend on localized socioeconomic structures that influence economic outcomes by guiding and constraining how agents behave and interact (Powell et al., 2012; Casper, 2013; Granovetter, 2018; Storper, 2018). Granovetter and McGuire, for instance, analysed the emergence of the United States's electricity industry in the late 19th century and argued that the emergence of breakthrough industries is 'socially constructed by the mobilization of resources and influence through social networks' (Granovetter & McGuire, 1998: 167).

Other empirical analyses have likewise found that places with supportive social infrastructures have a distinct geographical advantage in generating and sustaining breakthrough innovations and new industries (Saxenian, 1994; Casper, 2013; Storper et al., 2015; Ferrary and Granovetter, 2017). A key generative mechanism in this process is 'cross-network transposition, whereby experience, status, and legitimacy in one domain are converted into 'fresh' action in another' (Padgett & Powell, 2012). The empirical literature on new organizational emergence show that this process of 'lashing up' elements from across multiple networks diverse elements become interactively stable (Powell & Sandholtz, 2012). Casper (2009), for example, demonstrated that decentralized place-based social networks linking individuals across firms and organizations created deep and flexible labour markets that were critical to the success of fledging biotechnology clusters in San Francisco and San Diego. By contrast, an open social structure did not take root in Los Angeles, and the city-region failed to develop a large biotechnology industry despite favourable initial conditions and hosting Amgen, an early biotechnology leader.

Casper's study connects with a growing and multidisciplinary body of research that emphasizes the importance of open and decentralized placed-based networks for high-tech industry success (Boschma, 2005; Breschi & Malerba, 2005; Saxenian & Sabel, 2008; Chesbrough et al., 2014; Crescenzi et al., 2016; Huggins & Thompson, 2021; Boey, 2022). City-regions with comparably open networks systemically facilitate bringing together a diversity of people, ideas, and resources more rapidly, effectively and flexibility versus a comparable relatively closed network – traits that are widely considered crucial in highly-innovative sectors close to the technological frontier. Given that fintech's antecedents do not share an obvious common technological orientation, the systemic gains to decentralized coordination and information diffusion fostered by open networks might be expected to be particularly impactful by fostering Jacobs spillovers, cross-organization partnerships, and interindustry collaboration. We therefore posit that:

> Hypothesis 3: The impact of open social networks in fintech in 2010 on subsequent fintech growth is positive.
>
> Hypothesis 4: The impact of open social networks in fintech's antecedent industries in 2010 on subsequent fintech growth is positive.
>
> Hypothesis 5: The interaction effect between initial network openness in finance and digital economy is significant, such that the effects of initial network openness in fintech's antecedent industries are complementary.

3. Data

3.1 Measuring regional characteristics

Our units of analysis are travel to work areas (TTWAs), which are official spatial definitions of functional regional labour market areas widely used in econometric analyses of the UK to approximate functional economic city-regions (Lee, 2014). We use the latest 2011 TTWA boundaries published by the Office of National Statistics (ONS). We are unable to include Northern Ireland due to the lack of appropriate regional level data. This gives us 218 total TTWAs in Great Britain.

We study fintech firm growth over the decade from 2010 to 2019. Our start year is 2010, as it is the first year included in the UK government's Fintech Sector Strategy (HM Treasury, 2018). Substantively, 2010 also sits comfortably between key fintech milestones – e.g., the first bitcoin transaction was in 2009 and the term 'fintech' was coined in 2014 (Lai & Samers, 2020). Although we also have access to more current data, we do not consider 2020 to avoid inadvertently capturing exogenous shocks from the COVID-19 pandemic.

Our main data source is a unique census-like database of administrative company register data made publicly available by Companies House through a web API. The data comprises the universe of all UK companies and their affiliated company officers from 1844 to the present. It includes comprehensive microdata including company profiles and associated SIC codes; financials; postcodes; complete records on board appointments, modification, resignations; and all associated company officer biographical data.

The relational nature of the data allows us to construct regional socioeconomic networks that completely characterize the bipartite network structure of 'top team' networks[15]. We identify firms in fintech's antecedent industries, finance and digital

[15] Also often referred to as 'career affiliation networks' or 'board interlock networks'.

economy, using the firm-level SIC information available for each firm on the company register. We match these to widely-used industry sectoral boundaries defined for SIC codes at the 5-digit level by the UK government (ONS, 2015; Tech Nation, 2018; Lee & Clarke, 2019)[16]. Company and top team member nodes are allocated into 218 regions based on their postcode sector details to provide relatively fine-grained regional boundaries. See Boey et al. (2020) for more information on this dataset, and the specific considerations and implementation details for constructing the regional company-officer networks. The industrial sectors of interest comprise approximately 1.4 million relevant actors in our study period.

These networks are used to construct metrics that quantify initial network openness at the region-industry level using the measure developed in Boey (2022):

$$\text{Open networks}_g = \frac{1}{\sum_{i=1}^{N} s_i^2}$$

where N is the number of actors and S_i is the share of connections (i.e., the degree centrality) held by a given actor i. We use this measure to quantify initial regional network openness for each high-tech industry sector grouping at the TTWA level for all TTWAs in 2010. The associations between local fintech growth and open networks are presented in the correlation matrix in Table S1.

3.2 Identifying fintech firms with frontier data

The Companies House data offers unparalleled detail on the evolving structure of the UK economy, and it would be ideal to identify fintech firms by their SIC codes just as we do for digital economy and finance. Unfortunately, the newness and boundary-disrupting nature of the fintech industry precludes this straightforward option. As we discuss in the next section, there is substantial overlap between the SIC codes in

[16] Digital economy comprises selected 5-digit SIC codes in ‘computer and electronic manufacturing’ and ‘digital and computer services’.

fintech and in digital economy and finance. There is also substantial heterogeneity in the economic activities of fintech firms. These traits mean that we cannot reliably detect fintech firms from SIC information alone as there fintech does not have a distinct SIC 'signature' that might be used to positively identify fintech firms.

We address this problem in a way that broadly resembles Nathan & Rosso's (2017: 143) approach to integrating high-quality administrative data with more dynamic but less reliable big data sources using data science techniques to facilitate 'a more detailed and better measure of some of the most dynamic [industrial] sectors', although our approaches are distinct as we deal with different substantive constraints. We focus here on describing our approach in broad strokes as the implementation details are involved and largely tangential to the rest of this paper. We use microdata on UK fintech firms from business intelligence platforms that track emerging industries, including fintech as a core platform offering. These platforms use a combination of scraping, machine learning and community validation to integrate new data sources, that often have 'big data'-like characteristics, to dynamically track companies, entrepreneurial, and investment activity in emerging market segments. The platform data also contain useful details not in the administrative data, e.g., on funding rounds and whether a given company is a unicorn or scaleup[17]. We focus on matching Dealroom data to individual administrative company microdata, which we extensively cross-validate using Crunchbase, AngelList and Pitchbook.

Our matching process is briefly described as follows. The administrative dataset alphabetizes company records with an algorithmically generated normalized company name derived from each company's legally registered name. Normalized company names can be accessed through the public API, but the details of the algorithm are not publicly available. We thus reverse engineer the algorithm[18] and generate normalized company names in the same format from the platform data.

[17] A scaleup is a high-growth company that has reached approximately USD 500,000 revenue.
[18] The reverse engineered version has >99.9% accuracy with only minor differences in output in a minority of edge cases.

Comparing normalized company names allows us to decisively match over half of the fintech firms in the platform data to individual company records in the administrative data. Using a variety of natural language processing methods and heuristics, we measure concordances between other details including location data and company founders' details to resolve cases where there are multiple potential matches[19]. These additional information are also used to filter out irrelevant platform records, e.g., to detect companies that are inaccurately recorded as operating in the UK, or those that are inaccurately classified in the platform data as fintech firms. The matched records are semi-manually validated with the assistance of a purpose-written tool. In this way, approximately 75% of the fintech firms in the platform data can be successfully matched, with the remaining records being either obviously invalid or lacking sufficient information for a 1:1 match. To prevent double counting, any given matched fintech company is not simultaneously considered to be in finance or digital economy even if a given fintech firm lists an SIC code(s) in the administrative dataset that belongs to either of these antecedent industries.

4. The emerging geography of UK fintech

We explore high-level trends in the emerging fintech industry, focusing here on three salient concerns. First, we provide a substantive context for our discussion by briefly examining the evolving geography of UK fintech. Second, we examine simple associations between fintech growth and regional social structure. Assuming we are generally on the right track, then we should expect to find a positive relationship between initial network openness in finance and digital economy and subsequent fintech growth. Third, we examine whether the fintech industry really has technological antecedents in the finance and digital economy sectors. If it does not, then this suggests that popular understandings of fintech as a technology-driven

[19] We do this using various NLP methods and with manual validation if unavoidable.

disruption of traditional financial services might be unfounded. More cogently, this means that our initial premises are then be flawed, and it would be difficult to justify investigating how regional characteristics relating to the digital economy and finance sectors impact future fintech growth.

4.1 The evolving fintech landscape

Figure 16 presents the spatial distribution of fintech firms at the start and the end of our study period, alongside the digital economy and finance industries for comparison. All indicators are normalized by working population to facilitate comparability across years and sectors. The top row (A-C) depicts the initial distribution for the 218 study TTWAs at the start of our study period in 2010, while the bottom row (D-F) shows the corresponding regional distributions in 2019. There is obvious regional variation in all three industrial sectors, which is not unexpected considering the differences in regional histories and devolved governance across the UK.

The geography of fintech appears to be taking shape around distinct spatial clusters. Established fintech clusters in Scotland, Northern England, and around Birmingham have persisted amid growing fintech entrepreneurship across UK regions. Fintech is generally more spatially concentrated in 2010 (A) than in 2019 (D), most noticeably in and around London by 2019 (cf. HM Treasury, 2021). Fintech concentration increases modestly in the South West, Wales, and the East of England, while marginally decreasing in Scotland and the East Midlands. Fintech concentration in other NUTS1 macro-regions remains largely unchanged. There is also considerable turbulence in the leading fintech TTWAs over the study period. The relative concentration of fintech fell in several city-regions, including in Manchester, Glasgow, Edinburgh, and Leeds. It conversely increased for several others, including for London, Bath, Brighton, and Reading. The strongly agglomerated spatial distribution of fintech mirrors the findings from the empirical literature, which has consistently found that new work opportunities created in response to technological innovation tend to be spatially clustered in highly educated and skilled cities (Lin, 2011).

Both fintech and its antecedent industries – digital economy and finance – were concentrated around London and the South East in 2010, and in 2020. These industrial sectors also had relatively high concentrations in the South West, although the East of England has a considerably initial higher concentration of digital economy firms than it had for fintech. Digital economy is diffused more broadly across the UK than fintech, and likewise for finance. The regional distribution of both the digital economy and finance sectors at the NUTS1 macro-regional level is remarkably stable. While there is turbulence at the TTWA level, the relative ordering of industrial concentration at the more aggregated NUTS1 macro-regional level largely preserved over the study period in both of fintech's antecedent industries. These differences with fintech are not surprising considering that finance, and digital economy to a lesser extent, are more mature industrial sectors relative to fintech.

Figure 16 might be taken to suggest convergence in the spatial distribution of the three industrial sectors given that all three sectors had a marked increase in relative industrial concentration in London over 2010-2019. We might thus want to know the extent to which firms in each of these three industries collocate with each other. Based on our initial premises, we might expect that fintech firms would tend to coagglomerate with digital economy and finance firms, given that relative physical proximity appears to be a necessary condition for any of the benefits from regional diversity, specialization in antecedent industries, or being embedded on relatively open regional networks to obtain. It would thus be concerning if fintech firms did not tend to collocate with either digital economy or finance firms.

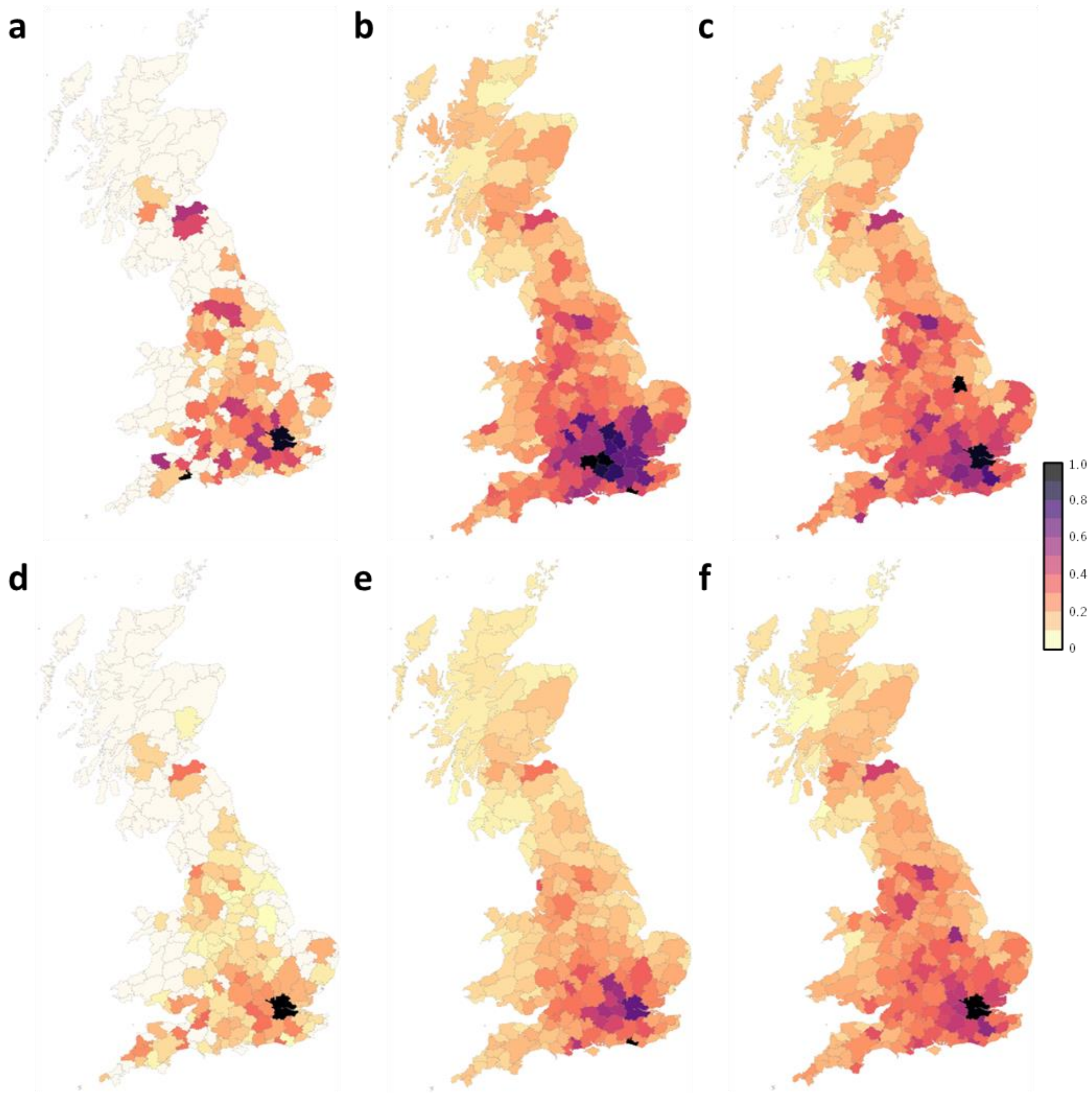

Figure 16. The distribution of firms in the fintech, digital economy, and finance industries in the UK. (A-C) Show the initial distribution in 2010 at the TTWA level for fintech, digital economy, and finance, respectively. (D-F) Show the corresponding regional distributions for 2019. All indicators are working population normalized to facilitate comparability. Higher regional values are mapped to darker colours, as shown in the colour bar.

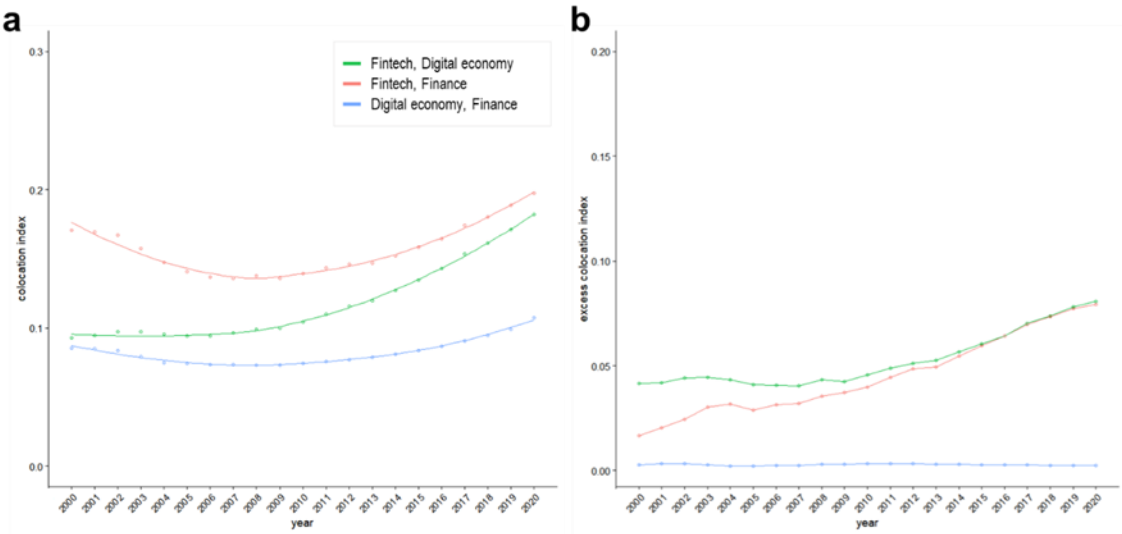

Figure 17. Colocation trends for firms in fintech, finance and digital tech, 2000-2020. The CL colocation index (A) and excess colocation index XCL (B) for active firms in each year is shown[20].

Figure 17 accordingly shows the longer-term evolution of colocation patterns between the three sectors from 2000-2020, with the colocation index (CL; Panel A) and the excess colocation index (XCL; Panel B), both measured as per Howard et al. (2016). We might be reassured that firms in fintech demonstrate a clear tendency to increasingly collocate with both finance and digital economy firms. Conversely, we do not find compelling evidence for coagglomeration effects between firms in the digital economy and finance sectors. Despite the initial impressions from Figure 16, Firms in digital economy and finance have a consistently smaller tendency to collocate than for fintech with either digital tech or with finance (Panel A) and has virtually no tendency to collocate once we control for the existing spatial distribution of firms (Panel B). This implies that the coagglomeration economies between fintech's antecedent industries are not economically significant. The implied lack of complementarities between finance and digital tech is unsurprising and indirectly indicates that both these industries are, at best, only modestly technologically related.

[20] Both CL and XCL are calculated for each firm as per Howard et al. (2016). The XCL index ($-1 \leq XCL \leq 1$) controls for the existing firm locations by comparing the CL index to a bootstrapped counterfactual random spatial distribution. Positive values indicate firms in both industries collocate higher than one would expect given the general tendency for economic activities to agglomerate, and vice versa for negative values.

4.2 Specialization, openness and fintech growth

Figure 18 shows the relationship between (A) initial network openness in finance and (B) initial network openness in digital economy and future fintech growth over the next decade. There is an unambiguously positive association between regional performance and initial network openness in both antecedent industries. This is the expected relationship as posited in Section 2. While these figures only depict direct correlations, the unmistakable association might nonetheless address concerns over the relevance of network openness to the ability of regions to foster emerging frontier industries.

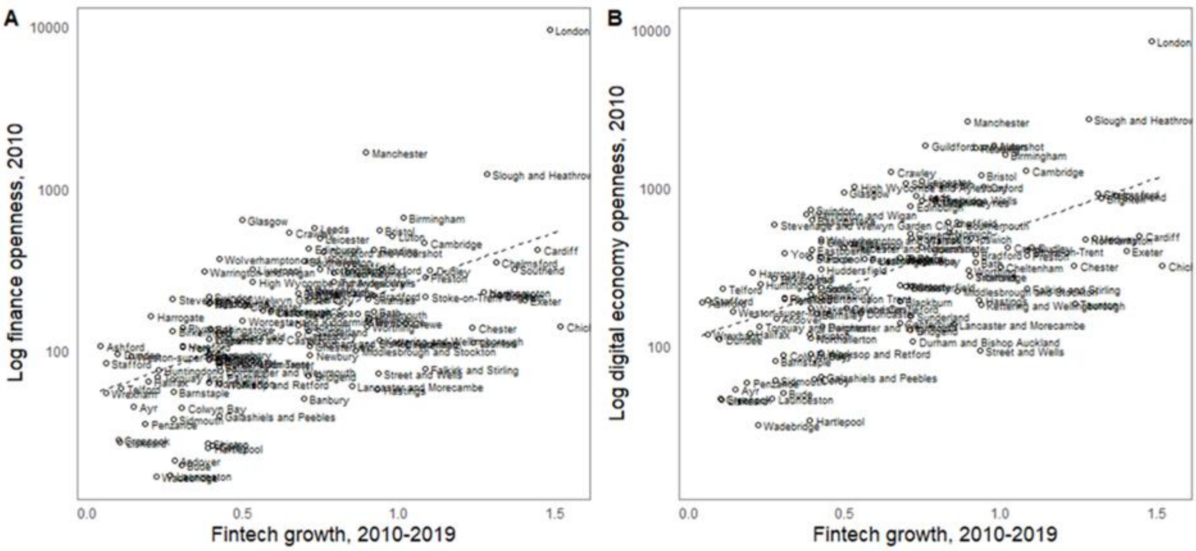

Figure 18. Initial regional network openness in (A) finance and (B) digital economy versus fintech firm growth from 2010-2019.

Figure 19 illustrates the simple correlations between (A) initial regional employment specialization in finance and (B) initial regional employment specialization in digital economy and future fintech growth over the next decade. There is a positive association between specialization and subsequent fintech growth. However, these correlations appear substantially weaker relatively to those seen in Figure 18, particularly for initial digital economy specialization in (B).

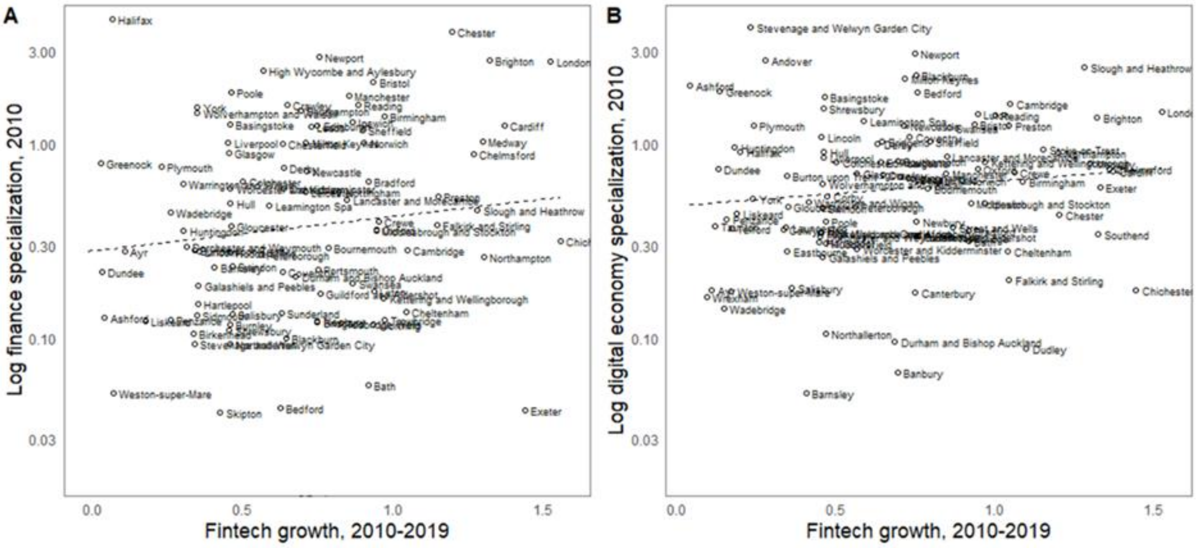

Figure 19. Initial regional specialization in (A) finance and (B) digital economy versus fintech firm growth from 2010-2019.

4.3 Is Fintech = Finance + Tech?

Fintech is widely reputed to emerge at intersection of the finance and ICT sectors. Given our present purposes, it is prudent here to assess whether this belief is grounded in the actual economic activities and industrial sectoral antecedents of firms in UK fintech. We do this by briefly examining the SIC information submitted by each firm characterizing their primary economic activities in the company register database. By inspection of the data, fintech firms are largely classified using SIC codes associated with digital economy, or with SICs related to financial services, though few report to be in both ICT and/or finance. This accords with popular intuitions about fintech's industrial and technological antecedents and a useful sanity check for our present objectives. While reassuring, this nonetheless also makes the task of identifying fintech firms harder as these overlaps imply that we cannot straightforwardly identify fintech firms based on SIC information alone.

Table 7. Frequently used SIC codes by UK fintech firms.

	SIC	%	Digital economy related	Finance related	SIC description
1	62012	16.3%	Y		Business and domestic software development
2	64999	10.4%		Y	Financial intermediation not elsewhere classified
3	62090	10.3%	Y		Other information technology service activities
4	82990	9.3%			Other business support service activities not elsewhere classified
5	62020	6.0%	Y		Information technology consultancy activities
6	58290	2.5%	Y		Other software publishing
7	70229	2.5%			Management consultancy activities other than financial management
8	96090	2.4%			Other service activities not elsewhere classified
9	63990	2.4%	Y		Other information service activities not elsewhere classified
10	63110	2.0%	Y		Data processing, hosting and related activities
11	66190	2.0%		Y	Activities auxiliary to financial intermediation not elsewhere classified
12	74909	1.9%			Other professional, scientific and technical activities not elsewhere classified
13	66220	1.6%		Y	Activities of insurance agents and brokers
14	64205	1.3%		Y	Activities of financial services holding companies
15	70100	1.3%			Activities of head offices
16	64921	1.2%		Y	Credit granting by non-deposit taking specialist consumer credit grantors
17	63120	1.2%	Y		Web portals
18	64209	1.1%			Activities of other holding companies not elsewhere classified
19	65120	1.0%		Y	Non-life insurance
20	64191	1.0%		Y	Banks

Table 6 reports the SIC codes that are most frequently associated with fintech firms in the company register data. UK fintech firms appear to engage in a relatively wide diversity of economic activities, considering that the SIC codes in Table 6 comprise less than 20 percent of the set of unique SIC codes in use by UK fintech firms. However, if we instead consider the relative proportions of SICs, the codes shown here constitute close to 80 percent of all SIC codes aggregated over all existing UK fintech firms.

The SICs used by fintech firms substantially overlap with those typically used to characterize industrial activities in the digital economy and finance sectors. Six of the SIC codes shown in Table 6 do not belong to either of fintech's antecedent sectors. These six codes largely pertain to miscellaneous activities such as 'Management consultancy activities other than financial management', 'Other business support service activities not elsewhere classified' and 'Other professional, scientific and technical activities not elsewhere classified'. The remaining 14 are evenly split between digital economy and finance. Fintech-related industrial activities appear to be biased towards a relatively small set of digital economy activities when we consider the relative share of each code relative to all SICs used in fintech. While approximately 65% of the SIC codes used by fintech firms are not used by firms in digital economy or finance, these only constitute around 30% of the SIC codes used by fintech companies when aggregated for all fintech firms in 2010. Finance-related SIC codes constitute around 30% of all SICs in fintech relative to both the unique set of SICs in use by fintech and the raw aggregated total. However, while only 10% of the SIC codes used by fintech firms are also used by digital economy firms, these same SIC codes comprise around 40% of the fintech SIC codes in aggregate.

We might also further assess the connections between fintech to digital economy and finance by making use of the comprehensive microdata on company locations and their economic activities to construct a network representation of the geography of economic activities, as measured through company-level SIC codes for all industrial sectors represented within our study regions. As such, we construct the network of relatedness between industrial activities using widely used techniques established by the empirical economic complexity literature (Hidalgo et al., 2017; Hidalgo, 2021). Doing so helps us to visualize the economy-wide structure of industrial activities across all UK regions and thus more easily explore the relationship between fintech and its antecedent industries.

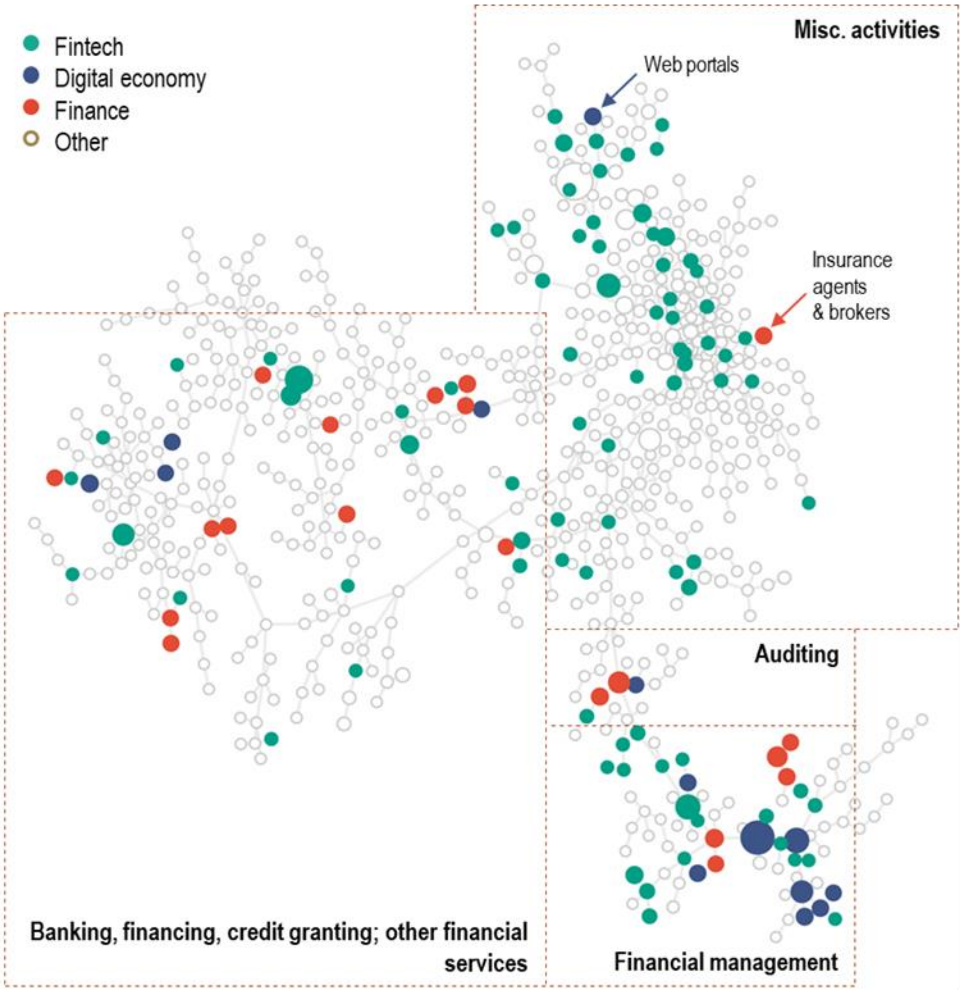

Figure 20. The industry space. The minimum spanning tree of the 'SIC' projection of the bipartite graph of TTWAs and the regional aggregates of the SICs used by their firms is illustrated here. Each node represents a 5-digit SIC industrial classification code used by UK firms and is scaled by the ubiquity of each industrial activity. Each node's colour denotes the industrial sector of interest the SIC code they represent belongs to, as per the legend. The bounding boxes summarize the general character of the fintech-related activities highlighted within them.

Figure 20 shows the industry space: the network connecting relatively similar industrial activities across UK TTWAs in the study period. Nodes that are closer together represent relatively more similar industrial activities. One might thus loosely interpret the relationships in Figure 6 as expressing relative coagglomeration tendencies between SIC activities. The nodes representing SICs in the industries of interest, i.e., fintech, digital economy, and finance, are highlighted in teal, blue and red, respectively[21].

We might make several pertinent observations from inspecting Figure 20: (1) The industrial activities relating to digital economy and finance appear to be highly clustered. (2) Digital economy activities are more highly clustered than those for finance. (3) Digital economy and finance activity clusters are largely distinct and relatively distantly connected on the industry space, which corroborates with our supposition that finance and digital economy have little relatedness. It also accords with the observed lack of collocational tendencies between digital economy and finance shown in Figure 17. (4) Fintech-related activities tend to be relatively closely connected to activities in its antecedent industries. (5) However, this connectivity is relatively uneven, and there is a distinct modularity to how fintech-related activities are clustered in relation digital economy and finance related activities (shown by the four bounding boxes in Figure 20).

In general, the patterns are consistent with the idea that fintech emerges at the intersection of finance and tech. The densely connected cluster related to 'Financial management' at the bottom-right shows fintech-related activities connected to activities in antecedent industries in two distinct ways: a fintech activity might bridge between finance and digital economy activities; or a fintech activity might be adjacent to pair of directly connected finance and digital economy activities. A few other smaller activity clusters in 'Auditing' and 'Banking and other financial services' also show fintech-related activities either being adjacent to or bridging between antecedent activities. This picture accords with our assumption that successful fintech outcomes depend on spillovers between substantively unrelated industries.

[21] Note that the teal-coloured nodes denote SIC codes that fintech firms specialize in, but not digital economy and finance firms. These SIC codes are not necessarily exclusive to fintech but may be also used by non-fintech firms in the broader economy. Fintech firms might also specialize in digital economy or finance-related activities.

Nonetheless, fintech-related activities are relatively widely distributed across the industry space compared to digital economy and finance. Fintech also observably comprises a considerably greater diversity of economic activities than are typically considered as belonging to a single industrial sector, particularly in 'Misc. activities', suggesting a high degree of experimentation and substantial heterogeneity underlying fintech. Considering that large distances between nodes in the industry space implies relative dissimilarity between activities, this also suggests an explanation for why network openness is important for fintech growth – because fintech is itself far from homogeneous. Fintech firms are thus more likely to benefit from being embedded in an open network than a given firm in finance or in digital economy.

5. Model and results

5.1 Empirical model

This paper explores the systemic impacts of a diverse mix of industries, specialization in antecedent industries, and the regional social network macrostructure on regional growth in the emerging fintech industry. Although we have detailed microdata at the firm and individual level, we focus on the regional level of analysis as we are primarily interested in examining systemic gains to fintech performance. Accordingly, we examine firm growth in the fintech industry using a commonly used empirical design from the urban-regional growth literature (Glaeser et al., 2015; Grillitsch et al., 2021)

$$ln\left(\frac{\text{Fintech firms}_{i,2010}}{\mathit{Fintech}\ \text{firms}_{i,2019}}\right) = \alpha + \beta_1 \mathrm{Z_i} + \gamma\ \text{Other Controls}_\mathrm{i} + \epsilon_i,$$

where *i* indexes TTWAs[22]. The dependent variable is the change in the log number of fintech firms over the decade from 2010 to 2019. The explanatory variables of interest

[22] We note here that these models are exploratory in purpose and do not control for simultaneity and selection issues. This accords with our general aim of making an exploratory first cut into understanding the emerging

are included in Z. The other controls account for initial TTWA characteristics which affect subsequent firm growth, and the stochastic error term is ϵ.

To account for the impact of initial regional social structure we include the log of initial network openness in fintech and the log of initial network openness in fintech's antecedent industrial sectors, i.e., in finance and digital economy. We first consider the log of network openness in finance and the log of network openness digital economy separately, and later include their interaction. The coefficient on these terms describes the correlation of initial network openness and future fintech industry growth. A positive coefficient indicates that initial network openness in fintech and its antecedent industries are associated with subsequent growth in the nascent fintech sector. This is the expected finding given the importance of open social macrostructure to innovation cluster growth, based on the motivating literature (Piore & Sabel, 1986; Saxenian 1994; Almeida & Kogut, 1999; Brown & Duguid, 2000; Storper 2013; Huggins & Thompson, 2021). We favour a cross-sectional design over a year-on-year or dynamic panel model because we expect these network-wide social gains to have cumulative systemic impacts on regional performance rather than acute benefits,

We also assess the impact of mainstay explanations in urban economics by considering initial diversity and initial specialization in fintech's antecedent industries for each TTWA i in 2010 with the log of specialization in digital economy, the log of specialization in finance, and the log initial absolute diversity. We measure regional specialization for a given industry as the region-industry share of employment relative to the industry's share of national employment (Glaeser et al., 1992). The coefficient on specialization is expected to be positive as regions that are relatively more specialized in fintech's antecedent industries might relatively stronger agglomeration economies that foster more effective cross-industry Jacobs spillovers. We also consider the interaction between initial specialization in antecedent industries in our

geography of UK fintech, a topic that has received much public and policymaking attention but remains little understood.

preferred specification. We measure regional diversity as the reverse Hirschman–Herfindahl index of the regional employment mix (Grillitsch et al., 2021), excluding employment in digital economy or finance. We use regional employment data from the Business Register and Employment Survey and the Annual Population Survey published by the UK Office of National Statistics (ONS) to calculate these measures.

We include a set of controls widely used in the empirical literature. Aside from the social network metrics, all the controls for regional observables are calculated using official statistics from the Business Register and Employment Survey and the Annual Population Survey published by the UK Office of National Statistics (ONS).

We include a variable for the size of the TTWA -- the log of the total working population – to control for the expectation that larger TTWAs positively correlate with growth in high innovation and knowledge-intensive industries due to scale and urban density effects (Duranton & Puga, 2004; Lee & Rodriguez-Pose, 2013). We also include initial fintech controls for the number of fintech firms and the number of top team members in 2010. These are expected to control for the bipartite structure of the corporate affiliation networks under examination. We account for the effect of high skills at the TTWA level with the share of the local population qualified with National Vocational Qualification (NVQ) level 4 and above — i.e., higher education qualifications — a commonly used proxy for human capital in the UK setting (Lee, 2017). High skills are especially relevant in this setting, as UK policymakers often cite high skill levels as driving the strong demand for fintech services from 'digitally savvy' UK consumers (DIT, 2019: 17). Finally, we include ten region dummies for location fixed effects at the NUTS 1 level to control for the role of unobserved regional characteristics and regional differences in devolved governance and policy regimes. These controls also help to account for unobserved initial differences in fintech industry characteristics across regions.

Table 8. OLS results for regional fintech growth, 2010-2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Sample	Full	Full	Full	Full	Full	Full	Full	No London	No London
Specialization (Digital tech)	0.046***	0.024**	0.016	0.009	0.003	0.004	0.019	0.004	0.019
	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.017)	(0.011)	(0.017)
Specialization (Finance)	0.012	-0.015	-0.014	-0.013	-0.013	-0.012	-0.003	-0.011	-0.003
	(0.013)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.013)	(0.010)	(0.013)
Specialization, Digital tech X Finance							0.004		0.004
							(0.004)		(0.004)
Diversity	0.007	0.013	0.011	0.012	0.011	0.011	0.016*	0.011	0.016*
	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)
Open networks (Fintech)			0.052***	0.051***	0.056***	0.059***	0.060***	0.061***	0.062***
			(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
Open networks (Digital tech)				0.051**	0.058***	0.118***	0.119***	0.118***	0.119***
				(0.023)	(0.022)	(0.037)	(0.037)	(0.037)	(0.037)
Open networks (Finance)				-0.000	-0.031**	-0.036**	-0.036**	-0.036**	-0.036**
				(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Open networks, Digital tech X Finance					0.013***	0.019***	0.019***	0.019***	0.019***
					(0.003)	(0.005)	(0.005)	(0.005)	(0.005)
Working population						-0.110*	-0.115**	-0.109*	-0.114*
						(0.057)	(0.058)	(0.058)	(0.058)
High skill share						-0.136	-0.152	-0.133	-0.149
						(0.094)	(0.095)	(0.094)	(0.095)
R2	0.387	0.578	0.645	0.659	0.686	0.692	0.694	0.683	0.685
R2 Adj.	0.351	0.549	0.618	0.63	0.657	0.661	0.662	0.650	0.651
Initial fintech industry controls		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	218	218	218	218	218	218	218	217	217

5.2 Results

Table 7 reports the OLS results for the impacts of specialization, diversity, and network openness on subsequent regional fintech firm growth. All estimations are unweighted and include region fixed effects. Robust standard errors are reported in parentheses. Columns 1-7 perform stepwise OLS regressions with all 218 UK TTWAs; Columns 8 and 9 repeat the analysis in Columns 6-7 while excluding London from the sample.

The first two columns reports the basic relationship between industrial diversity and specialization in fintech's antecedent sectors on fintech growth. Column 1 only includes the region dummies as controls, while Column 2 also includes initial fintech industry controls. The coefficient for diversity is positive but imprecisely estimated and is not close to statistical significance. The estimated coefficients for initial finance specialization also do not approach any conventional level of statistical significance here; and more generally also for all the models reported in Table 7 The estimated OLS coefficient for initial specialization in digital economy is positive and statistically significant at the 1% level in the first column, with a reduced magnitude and statistical significance at the 5% level in Column 2.

Column 3 extends the analysis to also consider the impact of initial network openness in fintech. The coefficient on digital economy specialization is no longer statistically significant from this point onwards. The coefficient for fintech network openness is significant at the 0.1% level and suggests that a one standard deviation increase in 2010 fintech network flatness is associated with a 0.05 standard-deviation increase in fintech job growth over the next decade. Column 4 also includes initial network openness in digital economy and in finance. The coefficient on fintech network openness is largely unchanged here. Initial finance network openness does not have a discernible effect, while the estimate for initial digital economy is statistically significant at the 5% level, with a similar in magnitude as with initial fintech openness.

Column 5 includes the interaction between initial digital economy network openness and initial finance network openness. Column 6 reports our preferred specification with additional controls for working population and high skill share. There is a modest increase in magnitude for the coefficient on initial fintech openness. The results for the other variables of interest are similar in both cases. The main effect of initial digital economy openness is positive and remains significant at the 0.1% level, while the main effect of initial finance openness is negative and significant at the 5% level. Both columns also show a positive and highly statistically significant interaction effect. We thus discuss these findings in further detail below.

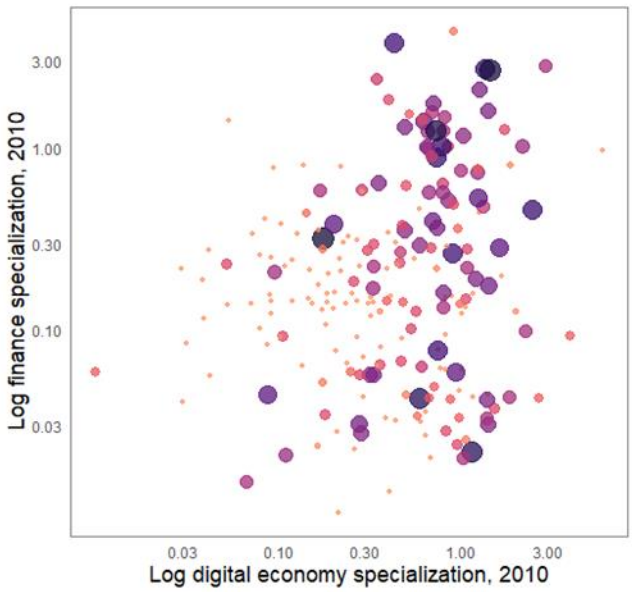

Figure 21. Regional distribution by log initial specialization in finance and digital economy. Each point represents a TTWA in 2010. The points are scaled by fintech growth over the study period. Darker coloured points likewise correspond to higher fintech growth.

We address the concern that the impacts of antecedent industry specialization might be observed only through their interaction in Column 7. Column 7 is also the only instance in which the estimates for diversity are significant (at the 10% level here) for all models using the full TTWA sample[23]. Neither the main effects of either of

[23] Replacing the diversity control with absolute diversity measured over all industrial sectors does not substantively change our findings.

fintech's antecedent industries, nor their interaction, come close to any conventional level of statistical significance[24]. The lack of statistical significance observed for both the independent effects from antecedent industry specialization and their interaction is unsurprising considering our descriptive findings from Section 4. The firm colocation trends (Figure 17) demonstrate a consistent and growing tendency for fintech firms to collocate with digital economy and finance firms. This might be taken to suggest a substantive connection between specialization in antecedent sectors and regional performance in subsequent fintech growth. On the other hand, the composition of SIC codes in fintech (Table) and the structure of the UK's industry space (Figure 20) suggest substantial underlying heterogeneity in the substantive relationship between fintech and finance and digital economy. The implication is that fintech might comprise of multiple industrial foci, instead of being coherently oriented around a small set of core economic activities with direct antecedents in either the digital economy or finance sectors. Assuming this is close to the ground truth, then it is unsurprising that specialization does not have a robust effect on fintech growth. The lack of clearly observable relationship between initial specialization in finance and digital economy shown in Figure 21 indicatively supports this interpretation.

Columns 8 and 9 repeat Column 6 and 7's analysis while omitting London from the sample. As shown in the foregoing, the largest agglomerations of fintech firms are found in UK's capital city in both 2010 and 2019. London is also a primate city, and we might be concerned that the results observed thus far could be potentially disproportionately driven by London. Nonetheless, the reported associations are essentially unchanged even when London is excluded, and the robustness of the results might reassure us that they are not a straightforward consequence of urban primacy effects.

[24] While not shown here, we find similar results when only controls for working population and high skill share are added to the model. Neither antecedent industry specialization nor their interaction are close to any conventional level of statistical significance even without including any network openness variables.

The OLS coefficient estimates (Columns 1-3) show the strong positive relationship between high-tech job growth over the decade 2010-2019 at the TTWA level and initial network openness in 2010. The empirical associations are economically and statistically significant, even when London is excluded from the sample, and suggest that network openness is positively associated with subsequent local high-tech job growth. Moreover, the estimated effect of initial open networks, in both fintech and in its antecedents industries is consistently economically and statistically significant. It is also robust to the inclusion of additional controls, and this might reassure us that our results are not simply explained by general factors as the size of urban-regional agglomerations or education levels

5.3 The role of open networks

The estimates for initial network openness in digital economy and initial finance openness are similar across both models that include the interaction between network openness in fintech's antecedent sectors (Columns 6 and 7 in Table 7). These results are also robust to the inclusion of London in the sample and are substantively unchanged in Columns 8 and 9. The coefficients for the main effect of initial digital economy network openness are positive and significant at the 1% level, while those for initial finance network openness are consistently negative and are statistically significant at the 5% level. The interaction effect is highly statistically significant at the 0.1% level. This indicates that it might be misleading to interpret the main effects in isolation, as they tell us little how the effect of initial network openness in either antecedent industry is conditional on regional social structure in the other antecedent industry.

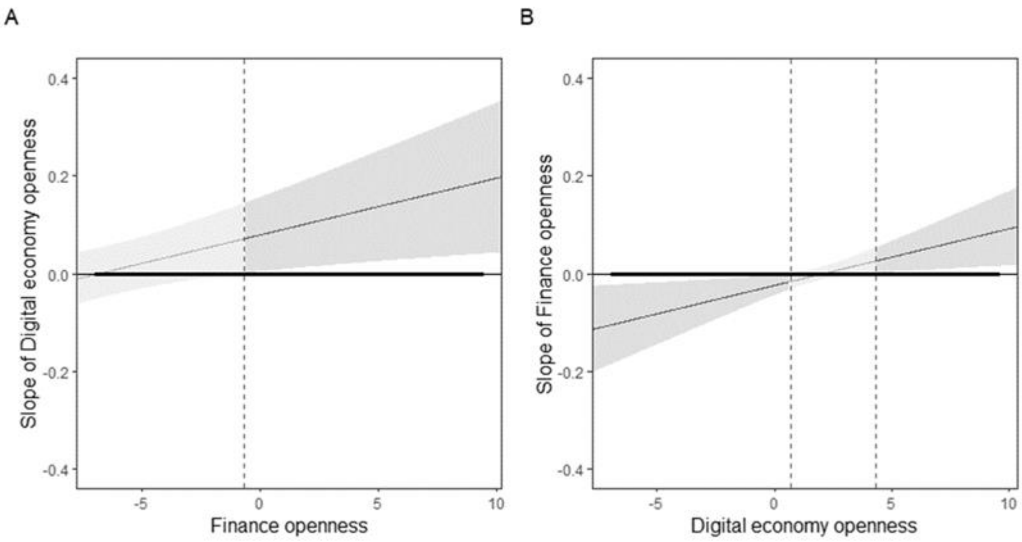

Figure 22. Johnson-Neyman plots for (A) the moderating effect of initial network openness in finance on the conditional slope of digital economy network openness and (B) the moderating effect of initial network openness in digital economy on the conditional slope of finance network openness. The outcome variable is fintech growth from 2010-2019. The false discovery rate is accounted for as per Esarey and Sumner (2017). The interval highlighted by the darker shared region indicates where the conditional slope differs significantly from zero at the 0.05 alpha level.

Figure 22 accordingly shows Johnson-Neyman plots for the moderating effect of initial finance network openness on the conditional slope of digital economy network openness (Panel A) and vice versa (Panel B). The panels illustrate the values at which the slope of network openness in either antecedent industry is likely to have a significant effect. It is immediately apparent that both antecedent industries have statistically significant moderating effects on each other within the range of the observed data. More specifically, initial digital economy network openness has a positive conditional effect for regions with sufficient initial finance network openness. The slope of initial network openness in digital economy increases with initial financial openness, with a statistically significant effect at the 5% level in regions with a minimum threshold of initial finance openness, as indicated by the highlighted region in Panel A of Figure 22

However, the conditional effect of initial finance openness is less straightforward. For regions with sufficiently open digital economy place-based networks, the conditional effect of initial finance network openness is positive and statistically different from zero (shown by the highlighted region on the right tail of Panel B). The impact of finance openness is complementary with digital economy openness in these regions as the slope of finance openness increases with digital economy openness. This relationship largely mirrors the conditional effects of initial digital economy openness seen above. The situation is markedly different for regions with relatively more closed digital economy digital economy networks (the highlighted region on the left tail of Panel B). The slope of finance openness is statistically different from zero but is increasingly negative with lower values of digital economy network openness. The relationship between digital economy openness and finance openness thus becomes increasingly antagonistic in regions with relatively closed digital economy networks, such that an increase in initial finance openness and a decrease in initial digital economy openness are both associated with greater disbenefits to regional performance[25].

The conditional effect of initial network openness in the finance and digital tech industries is thus asymmetric. But how does this translate to regional performance in fintech growth? Figure 23 provides a more intuitively accessible illustration of these moderating effects. The figure depicts the study regions by their initial network openness in finance and in digital economy, with more performant regions scaled larger and assigned a darker colour. The threshold for positive statistically significant effects from initial network openness for initial finance and digital network openness is shown by the horizontal dashed and vertical dotted lines, respectively. This divides the figure into four quadrants, which we number clockwise.

[25] Although the language used here might be taken to suggest causal relationships, we emphasize that we are discussing strictly descriptive associations, and not causal effects.

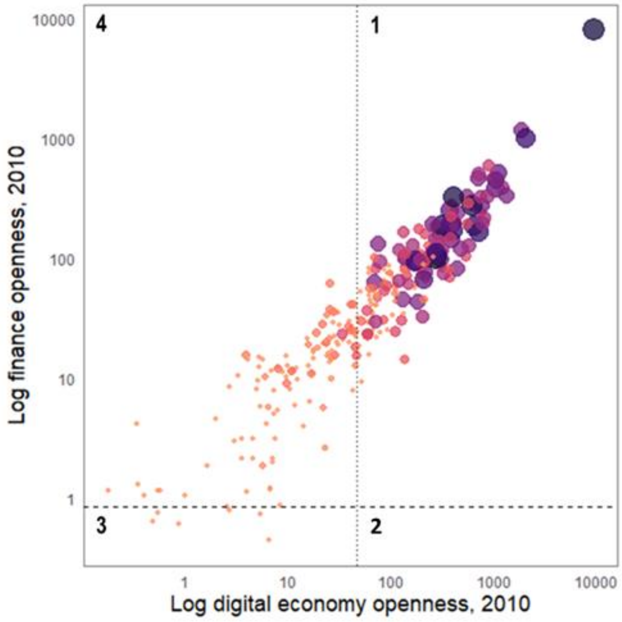

Figure 23. Regional distribution by network openness in finance and digital economy. Each point represents a TTWA. The points are scaled by fintech growth over the study period. Darker coloured points likewise correspond to higher fintech growth. The dashed horizontal line indicates the minimum value of finance network openness for statistically significant positive effects from digital economy openness. The dotted vertical line indicates the minimum value of digital economy network openness for positive statistically significant positive effects from finance network openness.

Quadrant 1 has relatively high initial levels of regional network openness in both digital economy and finance, and there is an observable tendency towards higher regional performance as one moves away from the dotted line. There are increasing returns to initial network openness from both finance and in digital economy, and as Figure 22 shows, the gains from initial network openness either antecedent sector are synergistic. Quadrant 2 has relatively high initial digital economy network openness and relatively low initial finance network openness. Although none of the regions in our data are in this quadrant, we might nonetheless extrapolate from Figure 22 that conjectural regions in this quadrant might experience modest gains from initial network openness in finance and digital economy. As in quadrant 1, the positive moderating effect of initial digital economy network openness translates into increasing returns to initial finance openness, but relatively low initial finance network openness means there are few gains to be realized. Moreover, unlike the first quadrant, potential gains from the relatively high initial digital economy network openness are not realized here due to the moderating effect of relatively low initial finance network openness.

Regions in quadrant 3 have relatively low initial network openness in both digital economy and finance. This is not a performant combination. Initial openness in digital economy has no statistically significant effect on regional fintech growth due to the low levels of finance openness. Relatively closed local digital economy networks also translates into negative impacts on regional performance from initial finance openness, though the comparatively low levels of finance openness in quadrant 3 helps to mitigates these negative impacts.

Quadrant 4 has relatively high initial levels of finance network openness but low initial digital economy openness. Like quadrant 1, relatively high levels of initial finance openness has an amplifying effect on initial digital economy openness, though the gains here are likely to be modest due to relatively low levels of digital economy openness. Like quadrant 3, low levels of digital economy openness translate into increasingly negative impacts on subsequent regional fintech growth. However, the negative impacts to fintech firm growth is likely substantially higher for regions in quadrant 4 than those in quadrant 3 due to relatively high levels of finance openness. This might help explain why fintech growth for TTWAs in quadrant 4 appears to decline precipitously with increasing distance from the dotted vertical line.

The findings relating to quadrants 1 and 3 are what we might expect given the motivating theory. The best outcomes are apparent when networks in both antecedent sectors are relatively open. This makes sense as openness in both antecedent industries might bolster fintech growth by providing a conducive regional environment that supports the effective mobilization of people and resources for flexible collaboration and recombinant innovation between two otherwise unrelated industrial sectors. The low performance of regions in quadrant 1 might be likewise understood as the undesirable outcome of relatively closed networks in both antecedent outcomes.

However, the finding that quadrant 4 is apparently the least performant combination is less easily understood. While we might expect that initial network openness in finance might substitute for that in digital economy, and vice versa, we saw that the high initial network openness in finance and low initial network openness in digital economy in quadrant 4 gives the worst possible combination of initial network openness. This suggests that the impacts of open networks are not necessarily always beneficial for regional performance. We might also observe that, unlike initial finance openness, having relatively closed networks in digital economy conversely appears to be universally bad, suggesting that having a high degree of openness in the disrupting sector is more important than in the incumbent sector for new industry growth.

Table 9. Share of SIC codes by general fintech-related activity (%)

General activity	**Share of activity (%)**		
	Unicorns & scaleups	Quadrant 1	Quadrant 4
Auditing	3.1	2.1	0
Financial management	73.4	72.3	48.5
Banking, financing, credit granting, other financial services	15.6	20.2	23.8
Misc. activities	7.8	5.3	27.7

The observed modularity of fintech activities in the industry space might offer potential explanatory clues. Table 8 summarizes the share of activities by SIC code by the four broad groups of fintech-related activities in the industry space (as indicated by the bounding boxes in Figure 20). There is already substantial divergence in evidence despite the nascence of the fintech industry and the fact that both quadrants have relatively high finance openness. Regions in quadrants 1 and 4 have substantively different specializations: quadrant 4 has relatively less ‘Financial management’-related activity, but has relatively more ‘Banking, financing, credit granting, other financial services’, and proportionately much more ‘Misc. activities’, compared to quadrant 1.

Firms in quadrant 1 have moreover specialized in similar general activities as the most successful fintech firms. The share of activity by fintech firms in quadrant 1 closely approximates those engaged in by fintech unicorns and scaleups. Unicorns and scaleups comprise a very small fraction of the entire industry, with less than 70 of them in our study period. Yet, quadrant 1's overall distribution of fintech-related activities closely tracks what the breakthrough successes specialize in. These observations imply that relatively low openness in the disrupting industry, digital economy, is associated with regions that specialize in less performant activities.

It is also worth noting that the average age of fintech unicorns and scaleups was only 6 years by the end of our study period. Although this is perhaps unsurprising given the youth of the fintech industry, this also means that many of these unicorns and scaleups must have been founded and achieved breakthrough success around the same time. It follows that the majority of fintech firms in quadrant 1 must also have chosen to specialize in similar activities as the most successful firms even before most of those firms achieved widely recognized success. The enhanced information flow in an open network might have facilitated the rapid and effective diffusion of cutting-edge ideas and fresh market intelligence implied here. Relatively more open networks in quadrant 1 might thus have fostered local 'buzz' that created a supportive local interactive environment for fintech growth by enhancing local collective learning and coordination processes (Storper, 2013). Unlike in quadrant 4, this in turn might enable start-ups and entrepreneurs in an emerging industry to respond more effectively to the opportunities, thus leveraging the social gains from open social structure. Similarly, this might also facilitate flexible collaborative arrangements between individuals and firms with digital economy and finance backgrounds.

We might speculate accordingly that the relatively high openness in quadrant 1 might therefore have enabled the rapid collective narrowing and refinement of the search space to isolate the most productive opportunities, thus allowing quadrant 1 firms and entrepreneurs to transition from exploration to commercial exploitation processes more efficiently than their counterparts in relatively more closed regions. These localized interactional dynamics might then create favourable conditions for circular causation, locking in sustained regional advantage of fintech clusters in quadrant 1. On the other hand, it is also plausible that specializing in the narrow set of economic activities as the most successful subset of firms might unexpectedly turn out to be counterproductive, and might thereby even inadvertently allow nascent fintech clusters outside of quadrant 1 to successfully go through previously inaccessible windows of locational opportunity (Scott & Storper, 1987). More sustained research efforts might investigate the extent to which these suppositions hold up as potential explanations of how relatively open localized networks in disruptive industries foster stronger regional performance, and future work might also unpack the generative processes that give rise the specialization pattern shown in Table 8.

6. Conclusions

How might we foster city-regional environments that support current economic vitality while also enabling future technological dynamism? Economic geographers and urban economists have long and extensively studied the sources of urban growth, but mainstay explanations often fall short of explaining how city-regions upgrade their economic base by attracting and supporting path-breaking innovative industries, despite its central importance for sustained long-run development (Glaeser, 1998; Storper, 2013; Feldman et al., 2016; Grillitsch et al., 2021). On the other hand, a distinct literature focuses on the role of social networks as the social infrastructure underpinning the performance of highly innovative clusters (Powell et al., 1996; Bathelt et al., 2004; Whittington et al., 2009; Kemeny et al., 2016; Spigel, 2017; Storper, 2018). This literature connects with a multidisciplinary body of work that emphasizes the importance of place-based open and decentralized networks in fostering the technological and entrepreneurial dynamism of city-regions (Saxenian, 1994; Almeida & Kogut, 1999; Brown & Duguid, 2000; Casper, 2009; Storper et al., 2015; Boey, 2022).

Fintech is a prominent new industry that is often seen as part of the so-called Fourth Industrial Revolution. Fintech has grown very rapidly since 2010, and the rise of fintech has been widely hailed by policymakers and pundits as the 'future of finance' and has been championed by UK policymakers as a strategic future growth industry (DIT, 2019: 11). However, despite widespread popular and policymaking attention, there has been little scholarly research on fintech (Goldstein, Wei & Karolyi, 2019; Lai & Samers, 2020). We know little about the localized capabilities that drive the local development of the new industry. More generally, notwithstanding the seminal work of Walter Powell and collaborators on organizational emergence, our understanding of how regions adapt to disruptive technological change remains underexplored (Padgett & Powell, 2012).

This exploratory study therefore focuses on the development of UK fintech over the decade 2010-2019, examining the importance of localized open social structure alongside mainstay explanations on diversity and specialization in fintech's antecedent industries. We do not find a consistently statistically significant effect from city-regional specialization in either the finance or digital economy industries on subsequent fintech growth, particularly once we account for regional social structure. Likewise, the effect of city-regional industrial diversity has a generally positive but inconsistent effect on regional performance. These findings suggest that being specialized in antecedent industries and having a diverse mix of industries are insufficient conditions for places attempting to capture a significant share of the emerging fintech industry, and are consistent with studies that do not find a central role of diversity or specialization for long-term regional performance (Kemeny & Storper, 2015; Storper, 2018).

By contrast, initial network openness in nascent regional fintech clusters have an unambiguously positive effect on fintech growth over the following decade. We also find that the effect of initial network openness in fintech's antecedents is asymmetric. High initial levels in both industrial sectors is complementary. However, contrary to initial expectations, the combination of high initial finance openness with low initial digital economy openness is the least performant combination, even more so than having low initial network openness in both antecedent sectors. These results are robust and are substantively unchanged when the primate city London is excluded from the sample.

These findings provide new evidence for understanding the development of new high-tech industries and suggest a central role for open network structures for the long-run success of highly innovative technology clusters. The stability of the findings suggests that the characteristics of local social networks might have a real and important effect in shaping the geography of disruptive and breakthrough innovation. We also develop a novel dataset that integrates administrative data with emerging data sources to reliably identify fintech firms and use this dataset to substantively contextualize our study by describing the emerging geography of fintech in the UK and provide indicative evidence for the relationship between fintech and its popularly assumed antecedent industries in the finance and digital economy sectors.

Overall, our findings suggest that the network openness of local social networks in antecedent industries are important factors for the development of disruptive new industries, particularly for social networks in the actively disrupting industry (i.e., digital economy). The unanticipated finding that the impact of relatively high initial levels of network openness in finance is asymmetrically moderated by network openness in digital economy industry implies that openness is not unambiguously beneficial, contrary to expectations from the motivating literature. While we can only draw preliminary conclusions from these empirical associations, future research might investigate the extent to which this finding reproduces in other settings and investigate underlying mechanisms and potential generative processes. Likewise, future work might analyse the coevolving relationship between the openness of regional social structures and patterns of fintech firm specialization.

There are also substantive policy implications. Policymakers and industry observers believe that 'the trajectory of UK fintech is at an inflection point of opportunity and risk' (HM Treasury, 2021: 7). If the apparent disjuncture in regional performance between the adjacent quadrants 1 and 4 shown in Figure 23 corresponds to the ground truth, then this suggests that relatively small policy interventions to augment regional ecosystems might nudge a majority of poorly performing regions into becoming high performing ones. However, these implied dynamics also suggest the possibility for substantial turbulence, as regions in quadrant 1 might quickly slip from being amongst the best to worst performers.

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Appendix

Table S1. Correlation matrix

	1	2	3	4	5	6	7	8	9	10
(1) Fintech growth										
(2) Specialization (Digital tech)	0.3***									
(3) Specialization (Finance)	0.36***	0.35***								
(4) Diversity	0.18**	0.34***	0.33***							
(5) Open networks (Fintech)	0.35***	0.19**	0.38***	0.2**						
(6) Open networks (Digital tech)	0.41***	0.24***	0.38***	0.19**	0.67***					
(7) Open networks (Finance)	0.3***	0.17*	0.32***	0.18**	0.53***	0.81***				
(8) Working population	0.26***	0.15*	0.31***	0.17*	0.86***	0.69***	0.54***			
(9) High skill share	0.24***	0.13	0.3***	0.17*	0.63***	0.5***	0.4***	0.79***		
(10) Initial fintech firms	0.44***	0.26***	0.41***	0.25***	0.7***	0.9***	0.8***	0.73***	0.55***	
(11) Initial fintech actors	0.22**	0.29***	0.18**	0.18**	0.28***	0.27***	0.14*	0.36***	0.25***	0.2**

* p < 0.1, ** p < 0.05, *** p < 0.01

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