Migrant Entrepreneurship, High-Growth Firms and Cities*

Tom Kemeny[1], Max Nathan[2,3,*], Ceren Ozgen[4], Guido Pialli[2,5], Anna Rosso[6], Mateo Seré[2], and Anna Valero[3,7]

[1]University of Toronto
[2]University College London
[3]Centre for Economic Performance
[4]University of Birmingham
[5]University of Turin
[6]University of Milan
[7]London School of Economics and Political Science
[*]Corresponding author: max.nathan@ucl.ac.uk

April 24, 2026

Abstract: This paper examines migrants' role in founding high-growth firms and the urban nature of high-growth entrepreneurship. Although high-growth firms represent a small share of businesses in OECD countries, they disproportionately drive national economic activity. Using novel founder- and firm-level data on over 12,000 UK companies and 15,000 founders, we establish five new facts. **First,** relative to the UK's migrant population, migrant entrepreneurs are substantially over-represented among founders of high-growth and high-growth-potential firms. **Second,** compared to UK-born founders, migrant founders are positively selected on human capital, but negatively selected on entrepreneurial experience. **Third,** high-growth potential firms are highly urbanised, and those with a migrant founder or co-founder display a distinctive urban geography different from migrants' underlying spatial distribution. **Fourth,** firms with all-migrant and mixed native-migrant founding teams follow faster employment and revenue growth trajectories than all-UK teams. We find suggestive evidence of a 'London bonus' in employment growth for all-migrant founded firms. **Fifth,** as compared with firms founded by natives, firms with mixed native-migrant founding teams have more distinctive strategic positioning, with fewer peers.

JEL classification: J61, L26, O31, R10, R12
Keywords: entrepreneurship, immigration, diversity, cities, high-growth firms

*Thanks to Sameera Siddiqui for outstanding research assistance. We thank the UKRI for funding under grant ES/W010232/1. The project was reviewed and approved by the UCL Research Ethics Board, application 22883/00. Thanks to Henry Whorwood at Beauhurst and Filipe Mesquita at Diffbot for guidance on data. Draft paper - final results may change. Please do not cite without permission. Other usual disclaimers apply.

Author contributions

Tom Kemeny: conceptualisation, methodology, formal analysis, writing - original draft; **Max Nathan:** conceptualisation, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, software, supervision, validation, writing - original draft; **Ceren Ozgen:** conceptualisation, methodology, writing - original draft; **Guido Pialli:** data curation, software, writing - reviewing and editing; **Anna Rosso:** data curation, software, writing - reviewing and editing; **Mateo Seré:** data curation, formal analysis, methodology, software, validation; **Anna Valero:** conceptualisation, methodology, writing - reviewing and editing. Authors are listed alphabetically.

1 Introduction

What role do migrants play in founding high-growth firms, and how does this shape the urban nature of high-growth entrepreneurship? In many countries, young, high-growth companies make a disproportionate contribution to national employment, innovation, and productivity (Calvino et al., 2018; Haltiwanger et al., 2013). These companies account for only a small share of all firms — around five percent in the UK.[1] In a recent review, Botelho et al. (2026) describe these firms as 'innovation-driven startups' whose founders bring novel business models, products and processes into the market, driving growth through Schumpetarian processes of entry, competition and knowledge spillovers (Aghion and Howitt, 1992; Klette and Kortum, 2004; Lentz and Mortensen, 2008). Channeling Jane Jacobs, Duranton and Puga (2001) argue that big cities are 'nurseries' for startups: high-growth-orientated firms are notably concentrated in high-tech clusters and urban cores (Guzman and Stern, 2015; Chatterji et al., 2014).

Understanding who founds these firms, which ventures succeed and why, is therefore central to understanding wider economic growth.[2] Migrants are over-represented in firm formation, including high-growth companies, and play prominent roles in high-tech clusters (Azoulay et al., 2022; Kerr and Robert-Nicoud, 2020). As we explain in Section 2, there are three intersecting explanations for these geographies of high-growth migrant entrepreneurship. A first line of argument emphasises migrants' positive selection on entrepreneurial skills and attitudes (Lee et al., 2025; Beine et al., 2024). But since both migrants and entrepreneurs differ from the average worker, migrant-native differences may disappear once other observables are controlled for (Manning, 2025). A second set of explanations emphasises co-founding team dynamics: innovative startups benefit from co-founders (Gans et al., 2019) and migrants may bring cognitive diversity to founding teams, gains from co-ethnic networks, or both (Kerr and Mandorff, 2023; Hong and Page, 2004). Conversely, team homophily might to suboptimal outcomes (via groupthink) and diversity might create frictions between team members. Migrant populations are highly urbanised, and a third suggestion is that concentrations of skilled migrants create high-end enclave effects, supporting innovation and entrepreneurship (Saxenian, 2006). Against this, urban-level concentrations of migrant entrepreneurs might simply reflect individual and team-level, rather than area-level processes.

What we do. We explore these issues using a rich, novel dataset covering over 12,000 UK companies and 15,000 founders. Our analysis focuses on a highly selected but economically important sample: UK companies identified as high-growth or high-growth-potential based on observable lifecycle triggers such as academic spinouts, winning large innovation-related grants, receiving external finance, or rapid employment or revenue growth. Combining geocoded

[1] `https://www.ons.gov.uk/explore-local-statistics/indicators/high-growth-enterprises`. Accessed 26 March 2026

[2] Our focus in this paper is entrepreneurship by choice, not necessity (Jones et al., 2018). we focus on high-growth and high-growth potential ventures, similarly to Botelho et al. (2026)'s notion of 'innovation-driven entrepreneurship'.

founder and company-level information with online profiles from a global knowledge graph, we build a novel linked founder–firm dataset, including detailed information on founders' education and career histories, dimensions that are remain rare in the entrepreneurship literature (Botelho et al., 2026). We describe our sources in detail in Section 3. We examine how the characteristics of migrant entrepreneurs, the composition of founding teams, and the spatial environments in which firms operate relate to the formation and trajectories of high-growth ventures in the UK. Our analysis is guided by four questions.

1. How do migrant founders differ from UK-born founders in terms of observable characteristics such as age, gender, education, and career histories?
2. How are high-growth firms and their founders distributed across space, and how urbanised are these patterns?
3. How does founding team composition vary across firms founded by UK-born entrepreneurs, migrant entrepreneurs, and mixed teams combining both groups?
4. How do firms with different founding team compositions compare across a range of outcomes, including novel market positioning, access to external finance, employment and revenue growth, and exit events?

Main results. We provide new evidence on high-growth migrant entrepreneurship and its geographies. In this version of the paper we establish five new facts. **First**, in line with international evidence, we show that migrant entrepreneurs are substantially overrepresented among founders of high-growth firms in the UK. **Second**, we find that while migrant founders are positively selected on higher-level qualifications compared to UK-born founders, they are negatively selected on entrepreneurial experience. **Third**, we document the strongly urban geography of these firms, with pronounced concentrations in London, major conurbations, and university cities, patterns that are even more marked for firms with migrant founders. **Fourth**, focusing on co-founded ventures, we examine how founding team composition varies across UK-born, migrant, and mixed teams. We find that mixed teams are more likely to obtain external finance, and that the employment and revenue growth trajectories of XXXXX are faster than all-UK founded teams. We also find suggestive evidence of a 'London bonus' in employment growth for all-migrant founding teams. **Fifth**, using novel measures derived from firm-level text data, we show that compared to firms founded by UK-born entrepreneurs, firms with mixed migrant-native founding teams have more distinctive strategic positioning, with fewer peers both in their 3-digit industry and across all industries. Given we find weak evidence for positive selection of migrant entrepreneurs, and no significant effects for solo migrant founders, our findings are consistent with migrant-driven team synergies and urban spillovers.

Our current findings are descriptive, not causal. One constraint is that we are unable to observe entrepreneurial entry, or co-founding decisions: these likely reflect factors that also influence firm outcomes, such as childhood exposure to entrepreneurship, parental wealth, attitudes or reputation (Akcigit et al., 2025; Bernstein et al., 2022; Hegde and Tumlinson, 2021; Lindquist et al., 2015). Conditional on founding, however, we observe a very rich array of individual characteristics, background and experience. Our focus on founders also means that we do not directly control for cross-firm differences in top team or wider workforce composition, which may also influence firm outcomes (Certo et al., 2006; Kenney and Patton, 2015; Triana et al., 2019; Mack et al., 2025). We use rich controls, detailed industry/area/time fixed effects and Oster/placebo test, to mitigate these endogeneity challenges. Finally, founders likely select into high-potential urban locations (Tareque et al., 2024; Bryan and Guzman, 2021). Our current analysis does not control for founder sorting, although future versions of the paper can exploit founder education and career history data to identify movers and variation in time spent in places where firms are founded.

Related literature. In documenting these findings, this paper contributes to several literatures. First, we add to the large literature on migrant entrepreneurs by providing new evidence from the UK on the characteristics and performance of migrant-founded high-growth firms. The closest papers to our own are Jin et al. (2025), who explore founding team synergies using broadly similar data for the US, and Lee et al. (2025), who link US survey and administrative data to explore migrant entrepreneurship and innovation. Our paper differs in its focus on high-growth entrepreneurship, on geographies of entrepreneurial activity, and in exploring firm value propositions alongside conventional measures of business performance. Given the distinctive role of skilled migrant entrepreneurs in the US innovation system, US-based findings may also not generalise. Second, we extend recent work on high-powered, innovation-driven firms (Akcigit et al., 2025; Botelho et al., 2026), by linking firm outcomes to unusually rich information on education and career histories. Third, we build on a large body of work on urban entrepreneurship (Duranton and Puga, 2001; Glaeser et al., 2010a; Guiso and Schivardi, 2011; Andersson and Larsson, 2014; Chatterji et al., 2014; Glaeser et al., 2015) by directly considering the role of migrant founders. Finally, from a methodological perspective, we contribute to a growing literature that combines online and firm-level microdata to explore an array of research questions (see Gray et al. (2026) and Dahlke et al. (2025) for reviews).

The remainder of the paper proceeds as follows. Section 2 provides a brief conceptual framework. Section 3 describes the data and build. TO UPDATE: Section 3 presents the founder descriptives. Section 4 focuses on empirical approach and presents evidence on founder characteristics and firm geography. Section 5 analyses founding team composition and firm outcomes // Section 7 concludes.

2 Framework

Seminal **models of entrepreneurship** (Knight, 1921; Schumpeter, 1962; Lucas, 1978; Rosen, 1982; Evans and Jovanovic, 1989) view entry and outcomes as primarily influenced by individual attitudes, such as high risk tolerance; resources, including family wealth; and entrepreneurial abilities. These latter 'skills' may include formal qualifications, years of experience, number of jobs held, previous entrepreneurial activity or management capabilities (Akcigit et al., 2025; Hegde and Tumlinson, 2021; Lazear, 2004); for innovation-driven founders, STEM qualifications also matter (Burton et al., 2002). More broadly, entry costs and learning opportunities influence both entrepreneurship decisions and venture performance. These vary across locations (Guiso and Schivardi, 2011; Andersson and Larsson, 2014; Guiso et al., 2015), with dense urban areas offering lower entry costs and greater learning opportunities (Glaeser et al., 2010a,b, 2015; Davis and Dingel, 2019; Duranton and Puga, 2023). Founders are therefore likely to sort into areas more promising for entrepreneurship. Entrepreneurs also decide whether to work alone or in teams, and this decision reflects both individuals' own assessment of their abilities, and the availability of co-founders. Developing distinctive ideas has high payoffs but is risky, complex and time-consuming, often requiring specialist skills and knowledge (Gans et al., 2019; Rajan, 2012; Luttmer, 2011). High-growth potential firms may therefore perform better with teams than solo-founders; however, poorly matched teams will damage the success of the venture (Botelho et al., 2026; Honoré, 2022; Calder-Wang et al., 2021; D'Acunto et al., 2020).

A large literature also documents the outsized role of **migrants in entrepreneurship**. Migrants are overrepresented among the self-employed, among founders of employer firms, and among founders of high-growth companies. They also play prominent roles in high-technology clusters such as Silicon Valley (for a review, see Chodavadia et al. (2024)). However, there is less agreement about the mechanisms underlying these patterns. Given existing theories of entrepreneurship, why might *migrant entrepreneurs* differ from other entrepreneurs in their propensity to start firms or in the trajectories of the ventures they create?

One set of explanations focuses on the **individual characteristics of entrepreneurs**. Migrants are often positively selected on human capital (Hunt and Gauthier-Loiselle, 2010; Lee et al., 2025; Beine et al., 2024), and migrant entrepreneurs may also differ in attitudes toward risk, ambition, or opportunity recognition (Kleinhempel et al., 2023). They may possess informational advantages, including knowledge of international markets or the ability to identify underserved niches in host economies. If migrants disproportionately possess such endowments, the firms they found may achieve outsize success (Azoulay et al., 2022). At the same time, apparent migrant advantages may reflect **compositional effects** rather than causal differences. Entrepreneurs themselves are not a random draw from the workforce: they tend to be disproportionately male, middle-aged, and relatively experienced. If migrants share similar demographic profiles, differences in entrepreneurial representation or venture outcomes may simply reflect these underlying characteristics. Recent work emphasises that once observable characteristics such as age, gender, and human capital are taken into account, migrants may not appear inherently more entrepreneurial or more successful than natives (Manning, 2025). Moreover, some scholars argue that migrants may enter entrepreneurship because barriers in mainstream labour markets limit alternative opportunities (Kloosterman and Rath, 2003; Jones et al., 2018). In such cases, entrepreneurship may reflect necessity rather than opportunity, and discrimination may constrain firm survival and growth (Ewens, 2022; Fairlie et al., 2022).

A second set of mechanisms emphasises the role of **founding teams and networks**. Many ventures are created by teams rather than individual founders, and as above, team composition may shape both the entry process and subsequent firm performance. Specifically, founder sameness and founder difference might affect firm positioning and performance. For instance, co-ethnic networks among migrant founders may lower entry costs by facilitating access to labour, finance, and market information. Shared ethnic and migrant backgrounds can support trust and knowledge exchange within entrepreneurial communities (Aldrich and Waldinger, 1990; Kerr, 2010; Kerr and Mandorff, 2023). On the other hand, diversity within founding teams may generate advantages. Given costs and complexity of entrepreneurial search, differences in experience and perspectives can enhance problem solving and idea generation (Hong and Page, 2004), potentially improving both innovation and firm management. Founding teams combining migrants and natives may therefore benefit from complementarities in knowledge and networks, and these might be reflected in firm positioning and firm outcomes. However, per the literature on suboptimal teams, diversity may also introduce coordination frictions, making the overall effect of team composition theoretically ambiguous.

These mechanisms operate within **spatial contexts**. A third strand of the literature highlights the role of **location characteristics**, particularly those associated with cities, in shaping entrepreneurial activity and firm performance. Complex economic activities tend to concentrate in urban areas where dense labour markets and localised knowledge spillovers facilitate learning and collaboration (Balland et al., 2020; Kemeny and Storper, 2020; Koster and Ozgen, 2021). Ethnic enclaves and migrant networks can influence economic outcomes by providing access to labour, customers, and information (Edin et al., 2003; Wahba and Zenou, 2012; Marinoni, 2023; Marinoni and Choudhury, 2024). In high-skill contexts, the spatial concentration of skilled migrants in locations such as London or Silicon Valley may create a high-end version of the enclave effect, supporting innovation and entrepreneurship (Saxenian, 2006; Kerr and Robert-Nicoud, 2020). If diversity operates as a production complementarity, urban agglomeration may amplify the firm-level effects of founder characteristics and team composition.

Taken together, these perspectives suggest that the formation and trajectories of migrant-founded firms may reflect the interaction between *individual founder characteristics, founding team composition, and spatial context*. Yet relatively little empirical work studies these mechanisms jointly, particularly for high-growth firms and outside the United States. The UK provides a particularly useful setting in which to examine these questions. While there is extensive evidence on migrant entrepreneurship in the United States, much less is known about the composition and performance of migrant-founded high-growth firms in the UK, despite the country's openness to skilled migration and the strong spatial concentration of innovative activity, especially in London and other large cities. Moreover, most existing work in the UK focuses either on individual founders or on firms as homogeneous units, paying less attention to the demographic composition of founding teams and the potential complementarities between migrant and native entrepreneurs [REFs].

3 Data

We develop rich, linked information on high-growth companies and their founders via two main data sources. Our company-level data come from Beauhurst, a commercial provider that tracks high-growth and high-growth-potential companies in the United Kingdom.[3] We link founders described in Beauhurst to individual founder profiles in Diffbot, a very large commercial knowledge graph database constructed from the public web.[4] Below we provide more details of these data:

1. **Beauhurst** is a dataset of 'high-growth' or 'high-growth-potential' UK companies, including company level characteristics (age, industry, headcount, etc), geolocated trading addresses, detailed rich-text descriptions and financial performance measures (external finance, revenues). Companies are selected on the basis of one or more lifecycle events, which Beauhurst treats as 'growth signals'. Some of these signals are early-stage (being an academic spin-out, attending an accelerator programme), others typically mid-stage (receiving angel or VC finance) and others later stage (high-revenue growth or employment growth episodes). Section 4.2 gives more detail of these signals. Beauhurst start with the UK's open companies registry, Companies House, the population of companies in the UK, then for tracked firms, enrich this through multiple, validated, other sources.[5] Our raw dataset covers 44,100 companies, of which 33,400 companies are founded 2000-2020 inclusive. The dataset also covers 257.9k 'key individuals', including firm founders, company officers, other top employees and investors/shareholders. For these individuals we have names, ages, gender, nationalities, and information on previous founder / employee / board roles. Beauhurst identifies 33.5k of these individuals as founders, based on their job titles.

2. **Diffbot** is a global knowledge graph database built from the public internet, using feature extraction and supervised learning (Mesquita et al., 2019). Graph databases link entities (such as firms, founders, workers and places) through meaningful relationships (such as founding activity, employment histories and trading addresses). As of January 2025, Diffbot's graph contained 231.3M individuals with employment histories globally, of which

[3] See www.beauhurst.com for more detail.

[4] See www.diffbot.com for more detail.

[5] Beauhurst's combination of structured sampling frame and validated data is an important advantage over crowd-sourced alternatives such as Crunchbase or Pitchbook, where the sampling frame is implicit, and where coverage across fields is variable (Botelho et al., 2026).

10.6M were in the UK. For these individuals, who will include company founders, Diffbot profiles include names, age, gender and detailed education and career histories, including details of job spells, roles and work locations. Diffbot also contains granular 'skills' for individuals, based on profiles, and leveraging a validated typology of 32,000 skills. Importantly, Diffbot's graph includes company identifiers from open company registers from around the world, including Companies House covering the UK. Building on methods developed in Gray et al. (2026), we use this feature to link organisations and people in Diffbot to companies and founders in Beauhurst. We detail our workflow below.

3.1 Defining founders

We consider company founders as entrepreneurs—individuals who set up companies which then employ others. 'Founder' has no legal definition, however, and so identifying company founders in data is not straightforward. Across the full timespan of the data, we identify 33,486 company founders and co-founders in Beauhurst by searching on validated roles and job titles. This is a conservative approach which precisely identifies a set of self-identified entrepreneurs. However, not all companies in our data have 'founders' or 'co-founders' listed.[6] We drop these companies from our analysis, reducing our sample of companies to 23,944. An alternative approach involves identifying the first appointed director of a company, which identifies founding board members and typically produces much higher counts. We run tests showing this approach generates inflated founder counts.[7] Overall, we deem the significant reduction in company sample size acceptable given the corresponding gain in precision.

3.2 Founder - company sample

Beauhurst person profiles contain limited information on individuals. For identified founders, we first gapfill missing data by scraping Companies House for updated profile information. We then search for founders on Diffbot and extract person profiles, providing us with much richer information. To accomplish this, we start by searching for companies in Diffbot; for matched companies we further search for founders. We initially keep only matches where companies are matched by identifier or name and UK location, and where founders are matched by name. A research assistant manually validated matches for a random 1% sample of founders.[8] Finally, we use an LLM-based workflow to adjudicate edge cases where founders are matched on first name

[6] For example, some entrepreneurs may not see themselves as 'founders', rather as 'someone who owns a business' (email exchange with Beauhurst, December 2025).

[7] Companies may be running for some while, including with employees, before they formalise governance arrangements; many companies appoint whole boards at single time points; some individual directors sit on many boards. Taken together these issues imply inflated counts. Applying the first director definition to our data generates 122.5k 'founders', around four times as many as using the self-identified basis. Further, the median firm now has six 'founders' and the largest 'founding team' has 143 members. These numbers are too big to be credible.

[8] The RA classified 160 Diffbot profiles and corresponding Beauhurst founders. 94.4% were confirmed matches.

or surname only, using contextual information to resolve underlying matches/non-matches.[9]

We then use cleaning routines detailed in Gray et al. (2026) to build detailed Diffbot founder profiles, which we match to Beauhurst founders and companies. Our final sample consists of Beauhurst companies founded in 2000 or later, which have identified founders, and whose founder/s are well-matched to Diffbot profiles. We further restrict our sample to companies where we can identify the founder(s) as either migrants or UK-born, using a rules-based approach we define below.

From our initial sample of 33,486 founders we match 31,767 to Diffbot profiles, and keep 26,379 matches, an overall match rate of 78.8%. Restricting to firms founded in 2000-2020 further reduces our sample to 23,641 founders. Restricting to founders where we can identify migrant/native status reduces our sample to 15,505 founders. Correspondingly, our starting sample of 23,944 companies with identified founders reduces to 22,689 where founders are matched to Diffbot, 19,739 with well-matched founders, and to 16,684 companies founded between 2000 and 2020. Taking out companies where any founder is non-identifiable as a migrant or native reduces the sample to 12,182 companies.

3.3 Defining migrant status

A fundamental constraint in migrant entrepreneurship research is that rich data on company founders often does not observe country of birth. Neither Beauhurst or Diffbot directly observes country of origin. Beauhurst—and the UK companies registry—contains nationality information, which is often used as a proxy for migrant status (Acosta and Marinoni, 2025). However, nationality is both endogenous and not perfectly overlapping with migrant status—in the UK in 2021 for instance, 43% of migrants held UK passports (Migration-Observatory, 2023). Using nationality as a noisy proxy for migrant status could simply lead to attenuation bias. However, the 2016 EU referendum result will also have led many EU migrants to apply for UK nationality, potentially introducing more structural bias into the measure.

Instead, and in line with Lee and Glennon (2023), Jin et al. (2025) and other recent studies, we proxy for migrant status by using founders' country of education, focusing on the lowest observed level of education in Diffbot profiles (typically undergraduate university education). In these studies, which use US data, country of education is viewed as giving a lower bound because US universities bring in large numbers of foreign students. Similarly, UK universities attract more foreign students than UK students study abroad—in 2022/3, 26% of all UK students were born abroad (HESA, 2024)—so overall, this proxy is likely to give a lower bound on migrant founders here too. We further validate our approach using a bespoke online survey

[9]Two examples illustrate the issue. Example 1: Edward E Johnson in Beauhurst / Woody Johnson in Diffbot. Both listed as a director of ABC Import Export, a company based in London with CRN GB123456. Our algorithm matches on the company and the surname. We accept the match: Woody is a known diminutive of Edward, and other contextual information checks out. Example 2: Luke Antonidis in Beauhurst / Diana Antonidis in Diffbot. Both listed as a director of XYS Strategies, a consultancy based in Manchester with CRN GN654321. Our algorithm matches on the company and the surname. We reject the match: Luke and Diana are very unlikely to be the same person; this is likely a family firm.

of UCL staff, finding nearly 99% correct attribution, as well as the predicted lower bound on true migrant status.[10]

Where missing, we fill in education location information by combining Diffbot text and UK / global place-name dictionaries (see Gray et al. (2026) for details). However, 20.7% of founders cannot be identified as migrants or UK-born, almost entirely because their Diffbot profiles contain no education information. Appendix Table A1 shows the results of balancing tests, where the dependent variable is either having identifiable migrant/native status, or having education information in Diffbot. Those included in our sample are younger, female, dual-nationals, or speak more than one language; they also have more jobs in their career history, are more likely to have management or tech experience; and are more likely to be current founders. However, the size of these differences is small: around 4-6 percent when controlling for founder location, slightly larger otherwise.

3.4 Outcome measures

As discussed in Section 1, theory and evidence on high-growth firms emphasises the importance of novel business models, processes and products: the resulting markups translate into higher revenue and employment. We therefore explore two types of company outcomes: business performance metrics, drawing on company accounts, and measures of company 'distinctiveness', which we build from company text data.

Business performance. Beauhurst contains an array of business performance data. Firms in Beauhurst have a range of potential growth paths, from sales and revenue-maximisation to VC-led scaling (building up user base / market share with or without revenue). To reflect this breadth, and as customary in the entrepreneurship literature, in this version of the paper we construct simple dummy variables covering whether the firm has any revenue post-incorporation, whether the firm has any employees, whether the firm has any external finance, and whether the firm has had a successful exit, through acquisition or IPO.

Distinctiveness. Here we follow a recent literature using natural language processing to explore company characteristics (Draca et al., 2023; Guzman and Li, 2022; Hoberg and Phillips, 2016). Specifically, we build measures of 'distinctiveness' based on companies' own descriptions of their strategies, products and services, taken by Beauhurst from firm websites.[11] Appendix Figure A1 gives an example of the text. Guzman and Li (2022), who use very similar data, refer to such text as describing firms' 'positioning' or 'value proposition'. Adapting the workflow from Draca et al. (2023), we clean the text from the Beauhurst 'description' field, build a TF-IDF matrix of the resulting text, and compute cosine similarities between each pair

[10] We surveyed a large UCL department, including senior, mid-career and early career researchers, PhD students and administrative staff. Respondents were asked to give their countries of school and (if any) university education, country of birth, nationality The overall response rate was 35 percent.

[11] We validate this interpretation of the text by sampling 100 company descriptions, then asking an RA and two different LLMs to classify the text as describing either 1) strategy 2) products and services 3) both 4) neither or 5) unable to classify. Both LLMs and the RA agree, classifying between 86 and 93 percent of the descriptions in classes 1)- 3).

of companies in our data. We define a data-driven global similarity threshold, which we set as the 95th percentile of all pairwise similarities (cosine similarity is scaled -1 to 1, and our threshold is 0.064). Because 'novelty' does straightforwardly translate to firm positioning, we then construct distinctiveness measures across several dimensions: a) the count of peers, defined as firms above the similarity threshold founded in any year, b) the count of peers for companies in the same SIC 3-digit industry in any year, and c) a dummy for companies with no peers in that industry bin and any year.[12] Following Draca et al. (2023), we also define two time-bound metrics: d) company 'originality', defined as (1 - maximum similarity of any company founded in earlier years), and e) company 'trendiness', defined as a company's mean similarity with all others founded in the same year.

More distinctive companies will have fewer peers, both overall and within nearby industry space. They are also likely to have more 'original' positioning and have less in common with peers founded in the same year. Per Section 1, pursuing such original business models, products and services has an *a priori* ambiguous link to subsequent firm outcomes. More novel companies are more likely to obtain external finance, especially from venture capital firms (Botelho et al., 2026; Kerr et al., 2014). Novelty may then innovative entrants to charge higher markups, building revenue and market share, raising headcount and raising the likelihood of successful exit (Klette and Kortum, 2004; Gans et al., 2019). Conversely, novel positioning is more complex and risky. 'Excess' novelty might be *less* likely to receive external finance, pick up market share and allow firms to scale (Rajan, 2012). Founders therefore have a choice about the level of novelty vs. adopting others' ideas. With this framework in mind, we validate our metrics by regressing measures of company distinctiveness to *company-level* performance measures, after controlling for founder and company characteristics, industry, location and cohort effects. Appendix Table A2 shows the extensive margin for linear probability models where the outcome is a dummy taking the value one if the firm achieves revenue, hires staff, attracts external finance, or achieve successful exits (IPO or acquisition). More novel companies are *more* likely to get some external finance after founding, but are *less* likely to add staff, achieve any revenue or exit. Appendix Figure A2 shows the intensive margin for employment and revenue, two outcomes we can track over time, across each distinctiveness measure. Conditional on receiving *any* employment or revenue, more novel firms have *higher* employment and revenue growth than their less distinctive counterparts.

4 Descriptives

4.1 Founders

Founder demographics. Table 1 summarises core demographic characteristics of the founders. Consistent with the wider literature on successful entrepreneurs, the average founder age for these high-growth companies is over 47. Over 80% of founders are male. In both cases, there

[12]Only one company in our sample has no peers in any industry or any year.

are modest raw difference between migrant and UK-born founders. We estimate that 26.5% of founders are migrants, measured by our country of education proxy. This is almost double the share of migrants in the UK working-age population and as explained above, is likely to be a lower bound. 32% of founders are non-UK nationals: however we estimate 20% of these are UK-born, highlighting the challenges in using nationality as a proxy for migrant status.

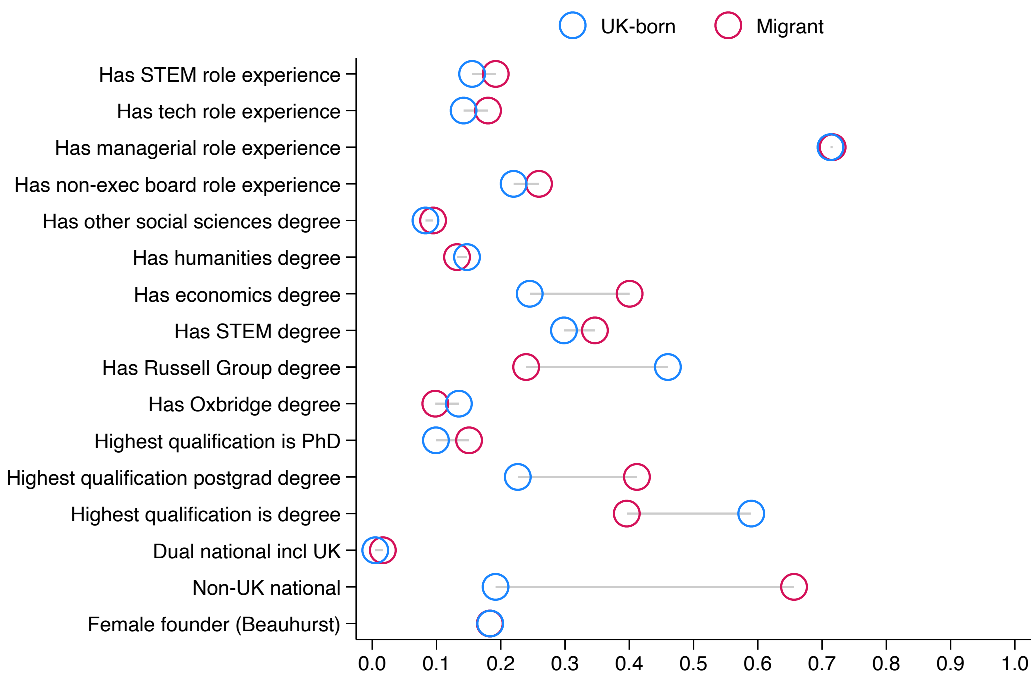
Table 1: Founder summary statistics by migrant status

	Founder type		
	UK-born	Migrants	All founders
Founder age	47.27 (11.07)	45.83 (10.01)	46.88 (10.82)
Founder age (Beauhurst)	43.43 (10.86)	42.08 (9.98)	43.09 (10.66)
Female founder	0.18 (0.38)	0.20 (0.40)	0.18 (0.39)
Female founder (Beauhurst)	0.18 (0.39)	0.18 (0.39)	0.18 (0.39)
Non-UK national	0.19 (0.39)	0.66 (0.47)	0.31 (0.46)
Dual national incl UK	0.00 (0.07)	0.02 (0.13)	0.01 (0.09)
Highest qualification is degree	0.59 (0.49)	0.40 (0.49)	0.54 (0.50)
Highest qualification postgrad degree	0.23 (0.42)	0.41 (0.49)	0.28 (0.45)
Highest qualification is PhD	0.10 (0.30)	0.15 (0.36)	0.11 (0.32)
Has Oxbridge degree	0.13 (0.34)	0.10 (0.30)	0.13 (0.33)
Has Russell Group degree	0.46 (0.50)	0.24 (0.43)	0.40 (0.49)
Has STEM degree	0.30 (0.46)	0.35 (0.48)	0.31 (0.46)
Has economics degree	0.25 (0.43)	0.40 (0.49)	0.29 (0.45)
Has humanities degree	0.15 (0.35)	0.13 (0.34)	0.14 (0.35)
Has other social sciences degree	0.08 (0.28)	0.09 (0.29)	0.09 (0.28)
Number of languages spoken	1.67 (1.21)	2.87 (2.01)	1.98 (1.55)
Years of experience	10.55 (8.18)	10.01 (7.55)	10.41 (8.02)
Number of jobs held	6.91 (4.76)	7.79 (5.07)	7.14 (4.86)
Has non-exec board role experience	0.22 (0.41)	0.26 (0.44)	0.23 (0.42)
Has managerial role experience	0.71 (0.45)	0.72 (0.45)	0.71 (0.45)
Has tech role experience	0.14 (0.35)	0.18 (0.38)	0.15 (0.36)
Has STEM role experience	0.16 (0.36)	0.19 (0.39)	0.17 (0.37)
Is currently a founder	0.75 (0.43)	0.77 (0.42)	0.75 (0.43)
Serial founder	0.06 (0.24)	0.05 (0.21)	0.06 (0.23)

Source: Beauhurst, Diffbot. Sample is 15,505 founders of Beauhurst companies founded 2000-2020 inclusive. Cells show means, with standard deviations in parentheses.

Founder characteristics. Figure 1 summarises mean characteristics for migrants and UK-born founders. As well as similar age, gender profiles, migrant founders have similar years of labour market experience to native founders. However, they differ on levels and types of qualifications, and types of professional experience. T-tests show that (virtually) all of these raw migrant-native differences are statistically significant: see Appendix Table A3. As Manning (2025) points out, such simple differences explain little if migrants and natives structurally differ on many dimensions (e.g. age, gender, qualifications). In section 5.1 we report regressions testing whether migrant status predicts specifically entrepreneurial capabilities (for example, management experience, years in the labour market or serial founding), controlling for other individual and company level characteristics.

Figure 1: Founder characteristics by origin



Source: Beauhurst, Diffbot. Sample is 15,505 founders of companies founded 2000-2020 inclusive.

Founder location. Table 2 shows founders' current location, derived using Diffbot profile information. Note that this field is missing for around 50% of founders, so this part of the results should be used with caution, although it is quite consistent with company location analysis which uses complete trading address information. Panel A shows all founders. Panel B shows migrant founders. Overall, founders are most likely located in London, big cities or university cities. Migrant founders have a somewhat different footprint, and are most concentrated in London, Oxbridge and Edinburgh. Notably, some migrant founders are not in the UK any more, with small groups in the US, India, Australia, South Africa, France, Italy, Germany, Switzerland and Russia. However, as we show below, while some migrant *founders* are now based outside the UK, their *companies* are more concentrated in London than the sample as a whole.

Table 2: Founder current location

All founders			Migrant founders		
N	Share (%)	City	N	Share (%)	City
3258	21.01	London	971	23.95	London
172	1.11	Manchester	54	1.33	Cambridge
168	1.08	Edinburgh	38	0.94	Edinburgh
150	0.97	Cambridge	27	0.67	Oxford
143	0.92	Bristol	23	0.57	Manchester
112	0.72	Glasgow	20	0.49	New York City
90	0.58	Leeds	19	0.47	Paris
82	0.53	Oxford	18	0.44	Sydney
79	0.51	Birmingham	17	0.42	Glasgow
67	0.43	Newcastle Upon Tyne	13	0.32	Birmingham
56	0.36	Hove	13	0.32	Bristol
54	0.35	Cardiff	12	0.30	Moscow
43	0.28	Southampton	11	0.27	Melbourne
40	0.26	Nottingham	10	0.25	Milan
39	0.25	Sheffield	10	0.25	Johannesburg
39	0.25	Aberdeen	8	0.20	Athens
36	0.23	Bath	7	0.17	Newcastle Upon Tyne
31	0.20	New York City	7	0.17	Hove
31	0.20	Liverpool	7	0.17	Bengaluru
29	0.19	Reading	7	0.17	Zurich

Source: Beauhurst, Diffbot. Sample is 15,505 founders of companies founded 2000-2020 inclusive. Location data comes from Diffbot, and includes founders of UK companies who are now no longer in the UK. Area units are cities (em_city in Diffbot).

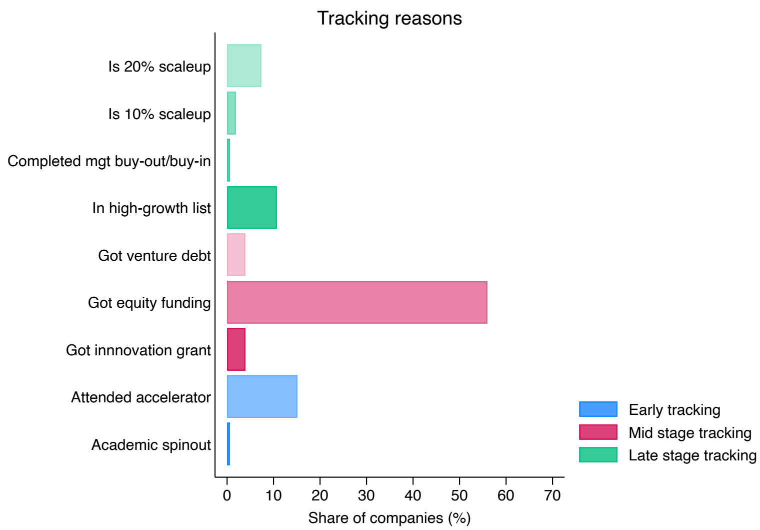
4.2 Companies

Company types. Table 3 breaks down the companies by Beauhurst 'growth signal'. Panel A gives frequencies and shares for individual signals. Panel B groups these into 'early', 'mid' and 'late' stage signals, based on mean company age for individual signals. Note that while the majority of signals refer to growth potential, over 11 percent of companies are tracked on the basis of being 'gazelles': exhibiting three years of 10 percent or 20 percent growth in employment or revenue. Figure 2 also summarises this info, see Panel A.

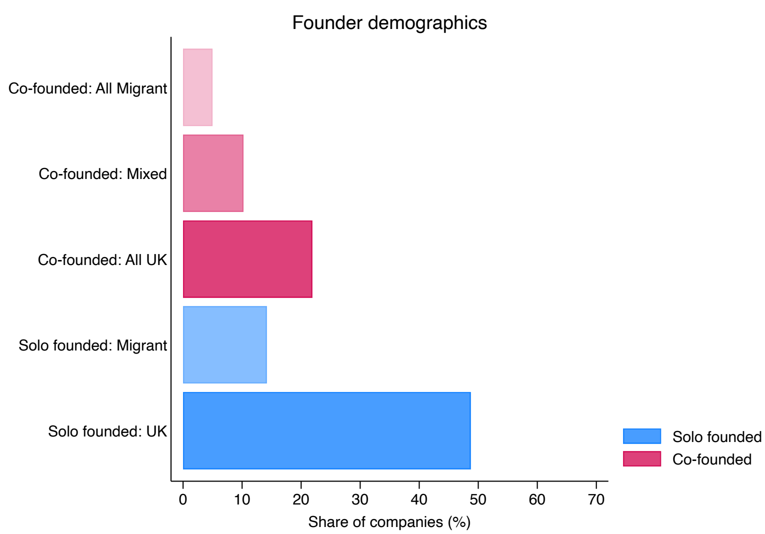
Founding team types. Table 4 decomposes the company sample by founding team types. 62.9% of companies are co-founded; 37.1% are solo founded. Only 22% of solo-founded firms have a migrant founder. By contrast, over 40% of co-founded firms have at least one migrant founder; of these just over 27% have a mix of migrant and native founders, and over 13% have all migrant founders. Figure 2 also summarises this info, see Panel B.

Company location. In-sample companies are present in almost all parts of the UK, but

Figure 2: Company tracking signals and founder demographics



(a)



(b)

Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive.

Table 3: Companies by reason for tracking

A. Tracking reason	Frequency	Percent
Academic spinout	73	0.60
Attended accelerator	1835	15.08
Got major innovation grant	479	3.94
Got equity funding	6804	55.92
Got venture debt	472	3.88
In high-growth list	1304	10.72
Completed managed buyout/in	73	0.60
Is 10% scaleup	233	1.92
Is 20% scaleup	894	7.35
N	12,167	100.00
B. Tracking stage	**Share**	**Avg. founding year**
Early stage trigger	0.157	2015
Mid stage trigger	0.637	2014
Late stage trigger	0.206	2009

Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive. Panel A shows companies in our sample by Beauhurst 'growth signal'. Panel B bins these into three growth stages based on company founding year. The intuition is the younger (older) a company is when it hits a growth signal, the earlier (later) is the corresponding growth stage. We define academic spinouts and companies attending accelerators as tracked at early stage. We define companies receiving major innovation grants, equity or debt finance, or cited in high-growth lists as tracked at mid stage. We define companies that have completed buyouts/buyins or are scale-ups as tracked at late stage. 41 companies have no tracking information.

are heavily concentrated in major cities, Oxford, Cambridge and Greater London. Figure 3 shows individual company trading locations, based on trading addresses postcode sectors. Postcode sectors contain an average of 3,000 individual addresses (building numbers plus full postcodes. Beauhurst provides full trading addresses; we aggregate to postcode sector level for speed. Figure 4 gives detail for the capital. Companies are very strongly concentrated in central London neighbourhoods (Panel A), with raw counts of firms dominated by a few central postcode sectors (Panel B).

Table 5 shows company counts and shares at the Travel to Work Area (TTWA) level. TTWAs are self-contained commuting zones, which we use here as proxies for local spatial economies. The table focuses on the top 20 TTWAs by company location counts. Panel A shows all companies. Panel B shows migrant-founded companies. Results are broadly consistent with the founder location analysis above. Nearly 40% of companies are in London, with other concentrations in contiguous 'mega-London' TTWAs such as Slough and Heathrow, Guildford and Aldershot, Luton and Reading. The next largest shares are in a mix of large conurbations (Manchester, Bristol, Birmingham, Leeds, Newcastle, Glasgow, Cardiff), and university cities

Table 4: Founding team composition

	Share (%)	N
At least one migrant founder	29.40	3,583
Sole founded company	62.90	7,661
Migrant founder	22.50	1,727
UK-born founder	77.50	5,934
Co-founded company	37.10	4,521
All migrant founders	13.50	609
All UK-born founders	58.90	2,665
Mixed founding team	27.60	1,247
N		12,182

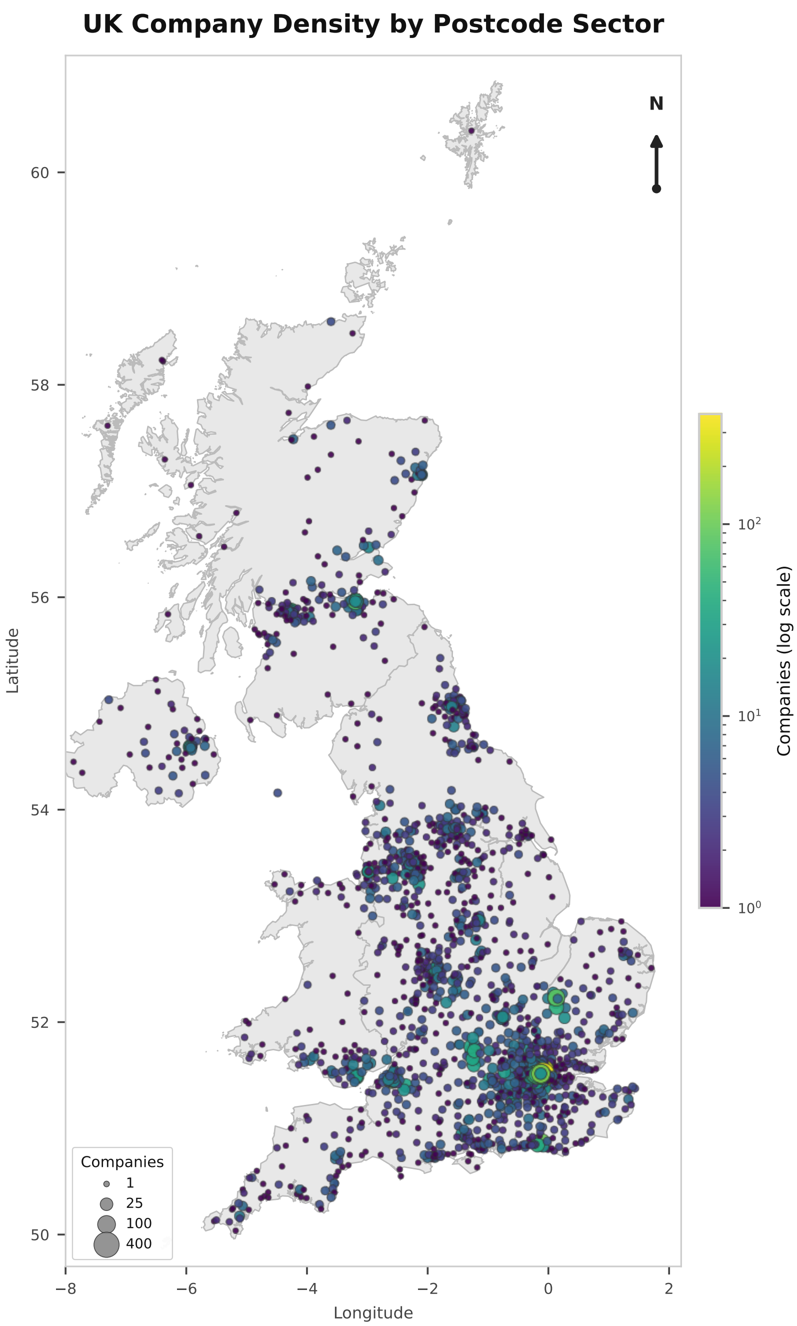
Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive and their founders.

(Cambridge, Edinburgh, Oxford, Aberdeen, Southampton). Migrant-founded companies show a much stronger London footprint, with nearly 60% in the capital, and rather higher shares in Cambridge and Oxford. Shares in other TTWAs are lower than for companies as a whole.

4.3 Company outcomes

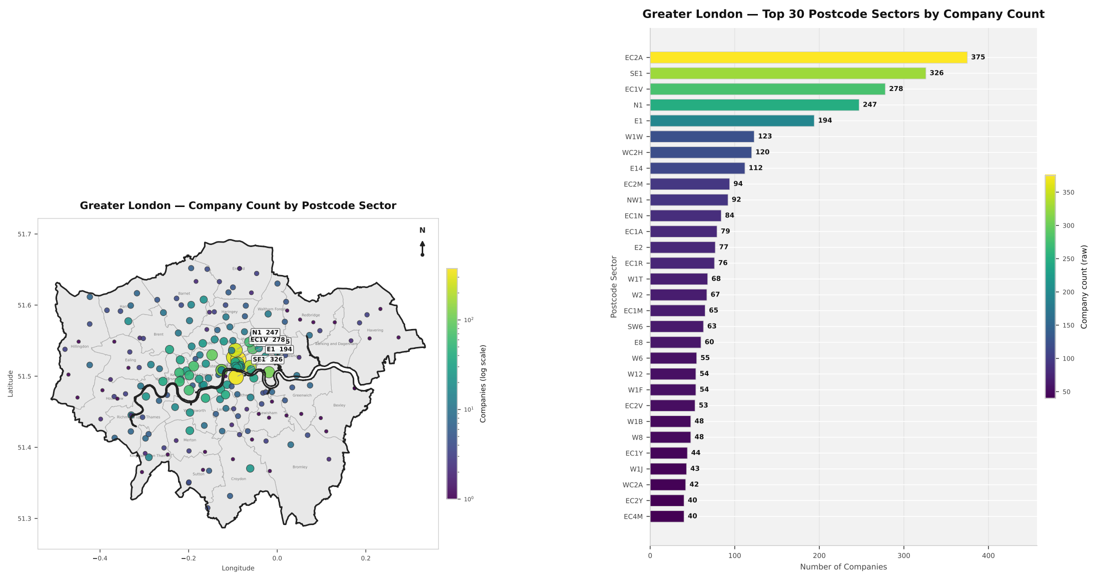
Table 6 reports summary statistics for the 12,182 companies in our sample, founded between 2000 and 2020. The upper panel shows outcome variables. Headcount data are available for 85% of firms, while revenue data are sparser, observed for around 18%. Nearly three-quarters of firms received some form of external finance over the sample period. Exit events are relatively rare: IPOs and acquisitions each occur for around six percent of firms. The lower panel describes firm-level measures of originality and peer similarity. The mean originality score—measuring textual distinctiveness relative to previously founded firms—is 0.71, with relatively low dispersion, suggesting most firms occupy moderately novel positions in idea space. Around 40% of firms are unique within their three-digit SIC industry bin, while the average similarity to the rest of the founding cohort is low (0.024), consistent with substantial heterogeneity across firms. Firms face on average around 1,358 peers in the full sample, but far fewer—around 5—within their narrower industry bin.

Figure 3: Company trading locations: UK



Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive. Company trading addresses aggregated to postcode sector.

Figure 4: Company trading locations: London



(a) (b)

Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive. Company trading addresses aggregated to postcode sector.

5 Migrant founders and firm performance

Our analysis proceeds in three parts. First, we look descriptively at differences between migrant and UK-born founders. Second, we explore linkages between founding team demography and company outcomes. Specifically, we look at whether all-migrant founding teams and mixed founding teams have different outcomes to all-UK-born founding teams, controlling for other founder and company-level characteristics. Third, consistent with our framework and given that firms and founders are highly clustered across space, we look at the role of area-level characteristics in shaping firm-level outcomes.

5.1 Migrant vs. UK-born founders

Are migrant and UK-born founders different? In our raw founder data (Section 4.1) the share of UK migrant entrepreneurs is at least twice that of the UK migrant population, and more informatively, when comparing migrant and UK-born *entrepreneurs*, we find some significant differences in individual characteristics and substantial clustering of founders and firms, especially in London, big cities and university cities.

As summarised in Section 1, migrants might be positively selected on entrepreneurial skills, such as years of experience, number of jobs held, qualifications, or previous experience in

Table 5: Company Locations: Top 20 TTWAs

A. All companies			B. Migrant-founded companies		
N	Share (%)	City	N	Share (%)	City
5374	44.22	London	2161	60.50	London
437	3.60	Manchester	126	3.53	Cambridge
359	2.95	Edinburgh	104	2.91	Oxford
344	2.83	Cambridge	80	2.24	Manchester
310	2.55	Bristol	78	2.18	Edinburgh
274	2.25	Oxford	76	2.13	Slough and Heathrow
257	2.11	Slough and Heathrow	55	1.54	Belfast
251	2.07	Birmingham	47	1.32	Bristol
207	1.70	Glasgow	46	1.29	Guildford and Aldershot
184	1.51	Cardiff	42	1.18	Birmingham
179	1.47	Leeds	41	1.15	Glasgow
178	1.46	Belfast	34	0.95	Brighton
177	1.46	Guildford and Aldershot	32	0.90	Newcastle
170	1.40	Newcastle	31	0.87	Milton Keynes
168	1.38	Brighton	24	0.67	Southampton
101	0.83	Luton	23	0.64	Luton
100	0.82	Reading	22	0.62	Cardiff
99	0.81	Aberdeen	20	0.56	Leeds
92	0.76	Southampton	18	0.50	Leamington Spa
90	0.74	Milton Keynes	14	0.39	Aberdeen

Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive. Trading address data. Area units are Travel to Work Areas. Panel A sample conditional on companies where trading address is known. Panel B sample conditional on trading address and founder demography known.

management or entrepreneurship. Conversely, these differences might be explained by other founder characteristics (age, gender) correlated with entrepreneurship. Migrant founders may also be negatively selected if entrepreneurship results from discrimination and/or inability to access other employment. Founders may also benefit from area-specific learning opportunities.

Because everyone in our data is a founder, we cannot directly test whether these characteristics affect entry into entrepreneurship. However, conditional on entry we can formally compare migrant and UK founders, and selection on observable entrepreneurial skills. To explore this we run two descriptive exercises. First, we look at correlates of migrant entrepreneurship. For founder i, company f, industry j and trading location a we estimate:

$$\text{Migrant}_{ifaj} = a + \mathbf{X}b_i + \mathbf{X}'c_f + A_a + J_j + e_{ifja} \tag{1}$$

Where **X** is a vector of individual level characteristics, **X'** is a vector of company level characteristics, J is a 3-digit industry dummy and A is a Travel To Work Area (TTWA) dummy. We estimate equation (1) in OLS for speed. Coefficients of $\hat{b}_i$ show the salience of individual characteristics on migrant founders, relative to UK-born founders, controlling for

Table 6: Company outcomes: summary statistics

	Mean	SD	Min	Max
Any headcount	0.854	0.353	0.000	1.000
Any revenue	0.177	0.382	0.000	1.000
Any external finance	0.721	0.449	0.000	1.000
Any IPO	0.057	0.232	0.000	1.000
Any acquisition	0.057	0.232	0.000	1.000
Originality vs. previous firms	0.709	0.091	-0.000	0.913
Unique in SIC3 bin	0.398	0.489	0.000	1.000
Similarity to rest of cohort	0.024	0.007	0.000	0.119
Number of peers	1357.972	1079.948	0.000	10597.000
Number of peers in SIC3 bin	5.040	10.354	0.000	111.000

Source: Beauhurst, Diffbot. Sample is 12,182 companies founded 2000-2020 inclusive.

company characteristics and location.

Challenges here include: first, that migrant founders may be selected on unobservable characteristics (such as being risk-loving); and second, that founding decisions may be influenced by the availability of co-founders, which may be correlated to industry and/or area-level conditions (milieux effects). To mitigate the first issue we run Oster Tests (Oster, 2019) to gauge the relative importance of unobservables. To handle other challenges, we estimate models with dummies for co-founded companies and the number of founders; alternate specifications with company fixed effects, and include industry and TTWA dummies.

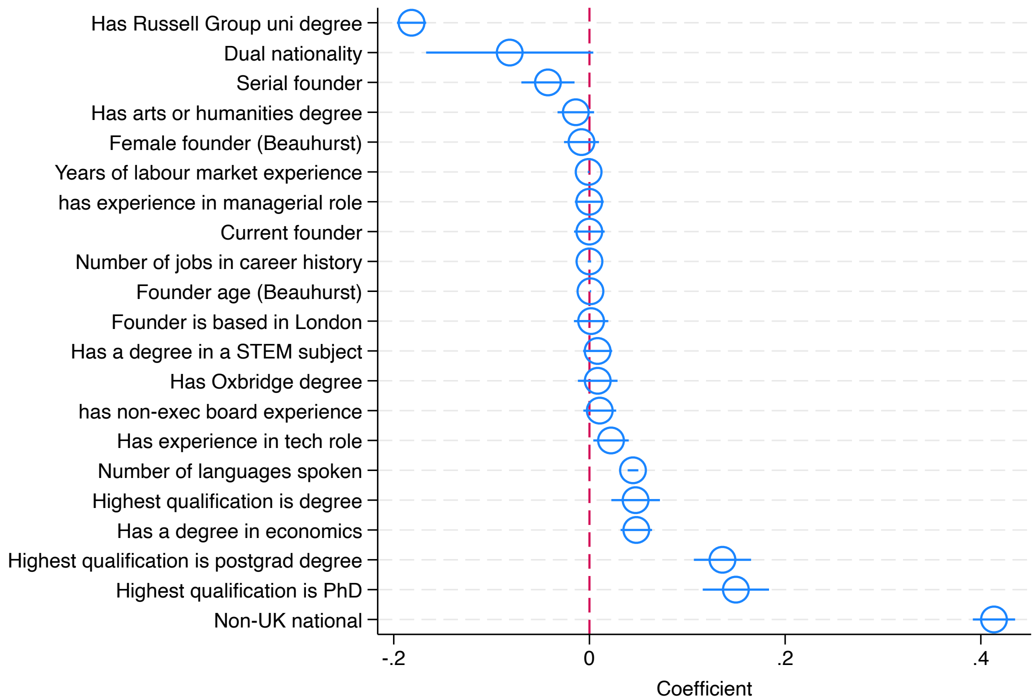
Individual covariates are summarised in Figure 5. Migrant entrepreneurship is positively correlated with founders having higher-level qualifications, especially post-graduate and PhD level; having an economics degree; number of languages spoken, and (as expected) being a non-UK-national. Appendix Table A4 gives full results including company controls.

Next, we look more precisely at potential migrant selection on observable entrepreneurial skills, which we define as as a vector **E** including: years of work experience; number of employments; qualifications; being a current founder; serial entrepreneurship; management experience; non-executive board member experience. For each variable E in **E** we estimate:

$$E_{ifja} = a + b_i \text{Migrant}_i + \mathbf{Z}b2_i + \mathbf{X}'c_f + J_j + A_a + u_{ifja} \tag{2}$$

We estimate equation (2) using OLS or a linear probability model (LPM) for binary outcomes. $\hat{b1}_i$ picks up the relative 'effect' of being a migrant on the level of experience or number of jobs, or on the probability of having management experience or being a serial entrepreneur, compared to UK-born founders, conditional on other individual level and company characteristics (**Z** and **X'** respectively), industry and location as before. **Z** consists of 'non-entrepreneurial' characteristics and **X'** is defined as before. Again, we run Oster tests and specifications with company, industry and location fixed effects.

Figure 5: Predictors of migrant entrepreneurship



Source: Beauhurst, Diffbot. Sample is 15,505 founders of companies founded 2000-2020 inclusive. Figure shows coefficients and 95 % confidence intervals of a linear probability model where the dependent variable is being a migrant founder, and individual-level predictors are shown above. Regression also includes controls for number of founders in the company, company incorporation year, Beauhurst tracking stage, 3-digit industry and Travel To Work Area location dummies.

Results are shown in Table 7. We find positive selection on qualifications, negative selection on experience and entrepreneurial experience, and no strong evidence of individual migrant founders' selection on other entrepreneurial skills. Specifically, migrant founders are significantly more likely to have higher-level qualifications than the UK-born, but less likely to be serial entrepreneurs compared to UK born; we also find they also have slightly fewer years of work experience. On other entrepreneurial skills, we find no evidence of significant migrant-native founder differences. However, many of these latter regressions are also underpowered, with Oster tests suggesting that unobservables—for example, differences in attitudes—explain much of the result.[13]

[13]We also run Seemingly Unrelated Regressions to explore migrant selection on all entrepreneurial skills simultaneously. Results, available on request, confirm negative selection on serial entrepreneurship and find no significant migrant-native differences on other characteristics.

Table 7: Entrepreneurial skill selection

Panel A			
	(1)	(2)	(3)
	Graduate	Postgrad	PhD
Migrant	-0.110***	0.097***	0.044***
	(0.012)	(0.011)	(0.008)
N	14680	14680	14680
R^2	0.145	0.186	0.242
F-statistic	71.746	105.187	41.839
Oster delta, Migrant	1.739	1.583	4.606
Panel B			
	(4)	(5)	(6)
	Experience	Number of jobs	Current founder
Migrant	-0.393**	-0.007	0.003
	(0.199)	(0.156)	(0.011)
N	14680	14680	14680
R^2	0.146	0.118	0.050
F-statistic	64.361	55.101	7.336
Oster delta, Migrant	1.996	0.021	0.233
Panel C			
	(7)	(8)	(9)
	Serial founder	Non-exec experience	Management experience
Migrant	-0.026***	0.013	-0.005
	(0.009)	(0.012)	(0.011)
N	14680	14680	14680
R^2	0.063	0.072	0.082
F-statistic	10.091	22.742	31.252
Oster delta, Migrant	7.284	1.006	0.823

: Source: Beauhurst, Diffbot. Sample is 12,182 founders of companies founded 2000-2020 inclusive. All regressions fit founder level controls (age, gender, non-UK national, dual nationality, highest qualification dummies [degree, post-graduate degree, PhD], degree type dummies [STEM, arts and humanities, economics, other social science], experience in tech role, based in London) and company controls (number of founders, company incorporation year, TTWA location, 3-digit industry and tracking stage). Standard errors clustered on founder. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2 Company scaling and exit

We now turn to company-level analysis. We start with simple cross-section models regressing 'anytime' company performance measures on founding team characteristics. For company f in 3-digit industry j, location a, founded in year t, we estimate:

$$Pr(Y)_{ifjta} = a + \mathbf{FOUNDERS}b1_f + \mathbf{Z}b2_i f + \mathbf{X}'c_f + JT_j t + A_a + u_{ifjta} \quad (3)$$

where Y is one of a set of dummies which take the value 1 if a firm has, at any point after founding: any employment, any revenue, has received any external finance, has exited or been acquired after incorporation. **FOUNDERS** is a set of dummies for founder demography: we include dummies for solo migrant founders, mixed migrant-native teams and all-migrant teams. Coefficients of these parameters pick up the relative 'effect' of these founder structures, relative to all UK-led firms. These models allow us to consider the association between founder demographics and a range of outcomes including rare events like external finance and acquisition, and can be considered an indication of the extensive margin for continuous measures like revenue and employment.

We flag two important design issues here. First, results are not causal because they do not fully control for individual unobservables influencing entry and outcomes, or driving the decision to co-found. Regressions comparing the entrepreneurial skills of migrant and UK-born founders suggest that unobservables are important influences on these differences. We mitigate these challenges by including rich founder-level controls in **Z**, 3-digit industry-by-founding year dummies to pick up sectoral trends, and TTWA dummies based on firms' trading location to cover milieu effects. Second, our regressions pool solo-founded and co-founded firms. To force a like-for-like comparison, **X'** includes a dummy for co-founded firms, and the count of the number of founders, alongside other company-level controls as before. (Appendix Table A5 shows results for co-founded firms only: the overall pattern of results is identical.)

Table 8: Founder demography and Firm Outcomes

	Firm Performance Outcomes				
	(1)	(2)	(3)	(4)	(5)
	Employ	Revenue	Ext. Fin	IPO	Acq
Solo migrant	0.013	0.003	-0.005	-0.008	-0.008
	(0.019)	(0.018)	(0.020)	(0.013)	(0.013)
Migrant-only team	-0.028*	0.002	0.055***	0.002	0.002
	(0.016)	(0.015)	(0.016)	(0.011)	(0.011)
Mixed team	-0.012	0.014	0.030**	0.007	0.007
	(0.011)	(0.013)	(0.014)	(0.009)	(0.009)
Mixed - Migrant	0.016	0.012	-0.025	0.006	0.006
Std. Error	0.017	0.017	0.018	0.011	0.011
p-value	0.363	0.479	0.157	0.629	0.629
Mean Dep. Var.	0.853	0.159	0.730	0.055	0.055
Observations	9,942	9,942	9,942	9,942	9,942
Adj. R^2	0.148	0.170	0.175	0.047	0.047

Source: Beauhurst, Diffbot. Linear probability models comparing future outcomes for migrant-founded companies and mixed / all-migrant founding teams, versus UK-founded companies. Sample is companies founded 2000-2020. Mixed - Migrant shows the difference in coefficients (H0: $b_{mixed} = b_{all-migrant}$). Controls: founder gender, founder age, education, serial founder, founder years of experience, founder managerial / tech / stem background, co-founded firm, team size, multisite firm. Fixed effects: 3-digit SIC Industry × Incorporation Year, Trading TTWA. Standard errors clustered at industry-year level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8 shows the results of linear probability models for equation (3). We find no performance advantages from solo migrant entrepreneurs compared to UK-founded firms, consistent with the minimal differences in entrepreneurial skills between individual migrant and UK-born founders. Conversely, all-migrant and mixed migrant-native founding teams demonstrate an advantage in accessing external finance. Relative to all-UK founded-firms, mixed teams are 3.3 percent more likely to receive external funding, compared to 4.5 percent for migrant-only teams, with both results significant at ($p < 0.001$). However, direct comparison shows no significant difference between these coefficients. Mixed teams also show a marginally significant disadvantage in achieving employment, although again this is not significant. We find no significant differences in future revenue realization, IPO or acquisition.

5.3 Founding team characteristics, growth and location

To more explicitly explore the association between founding team composition and firm growth, we shift to panel data, focusing on employment and revenue as outcomes. Our baseline specification regresses log outcomes on interactions between years since founding and team type, controlling for founder characteristics (gender, age, education, serial entrepreneurship, managerial and technical experience), team size, and calendar year and industry fixed effects. Standard errors are clustered at the firm level. The analytical sample is limited to firms with at least two founders, reflecting our focus on founding team composition as the central unit of analysis.Max: as agreed with Tom, here we pivot to just working with teams. Need to explain this pivot based on pattern of previous results - migrant founders are not selected, no positive effects on extensive margin for solo migrant founders

Max: check we don't have duplication of appendix tables with stuff in the descriptives

Observing the same firms evolving over time also allows us to consider a role for geography, exploring associations with urbanisation and, more specifically, with London. Appendix Tables A7 and A8 provide descriptive evidence on the spatial distribution of high-growth-firm founding teams and their outcomes across the urban hierarchy. Table A7 reports the composition of founding teams across Travel to Work Areas classified as major conurbations under the ONS 2011 Rural-Urban Classification. The sample is heavily concentrated in London, which accounts for over 80 percent of co-founded firms in the major conurbation category. This concentration is itself uneven across team types: all-migrant founding is overwhelmingly a London phenomenon, with 352 all-migrant firms in the capital compared to just 32 across all other major conurbations combined. London's all-migrant share (16.2 percent) substantially exceeds that of any other major conurbation, and several large cities, including Leeds, Liverpool, and Glasgow, record near-zero all-migrant high-growth-firm founding activity. Mixed-team founding is somewhat more geographically dispersed, with notable concentrations in Slough and Heathrow (47.8 percent) and Edinburgh (35.6 percent) alongside London (46.4 percent), though the absolute numbers outside London remain small. All-UK teams dominate the major regional cities of northern England and Scotland, with shares exceeding 70 percent in Manchester, Glasgow, Leeds, and Liverpool.

Table A8 reports mean outcomes by urban category and founding team type, using each firm's last observed year in the panel. Three patterns stand out. First, all-migrant firms show substantially lower employment and revenue outside major conurbations. In other urban areas, all-migrant firms average just 9.7 employees and £2.1 million in revenue, compared to 39.1 employees and £35.2 million for all-UK teams and 20.0 employees and £10.0 million for mixed teams. The revenue gap is particularly stark: all-migrant firms outside major conurbations generate less than one-tenth of the revenue of all-UK firms in the same category. In major conurbations these gaps narrow considerably: all-migrant firms average 31.4 employees and £24.6 million in revenue, much closer to the all-UK figures of 27.2 employees and £21.2 million, and the revenue gap reverses entirely for mixed teams, who average £37.5 million in major conurbations compared to £21.2 million for all-UK firms. This is consistent with all-migrant founding depending heavily on the networks, labour markets, and investor ecosystems concentrated in London and other major cities. Second, mixed teams exhibit greater resilience across the urban hierarchy: their employment levels hold up relatively well outside major conurbations and their revenue figures, while lower than all-UK outside cities, do not collapse in the way that all-migrant revenue does. This distinguishes mixed-team founding from the all-migrant model and suggests that the complementarities between migrant and UK-born founders are less geographically restricted than migrant-only founding. Third, measures of product distinctiveness — originality and trendiness — show essentially no variation across urban categories or team types, with both measures rounding to 0.71 and 0.02 respectively in almost every cell. This suggests that product innovation, as captured by these measures, is not systematically associated with either founding team composition or urban location.

The descriptive patterns motivate two extensions to the baseline specification. First, we ask whether the team-type effects identified in the panel regressions are robust to controlling for location — that is, whether they reflect genuine differences in firm behaviour rather than the sorting of migrant-involved teams into particular places. Second, we ask whether the team-type effects vary systematically across the urban hierarchy, and in particular whether London plays a distinctive role. To address these questions, we estimate three variants of the baseline: one adding TTWA fixed effects to absorb all location-level variation; one replacing TTWA fixed effects with urban category dummies to allow direct inference on the urban gradient; and one interacting team type with a London indicator to test whether the team-type effects differ inside and outside the capital. Tables A9 and A10 report results for employment and revenue respectively, and Figure 6 plots the underlying growth trajectories for both team types relative to the all-UK baseline.[14]

[14] One important caveat applies to the revenue results: revenue is observed for only around 16 percent of firm-year observations, reducing the revenue sample to approximately 1,840 observations and 554 firms compared to over 10,000 observations and 3,200 firms for employment. This reflects the fact that revenue reporting in Beauhurst and Companies House filings is far less systematic than employment data. Reassuringly, missingness is unrelated to team type — missing shares are 83.7 percent for all-UK, 84.1 percent for all-migrant, and 87.1 percent for mixed teams — and unrelated to urban category, suggesting the revenue sample is not systematically selected in ways that would bias the team-type comparisons. The revenue results should nonetheless be interpreted with appropriate caution given the smaller sample, and we place greater weight on the employment

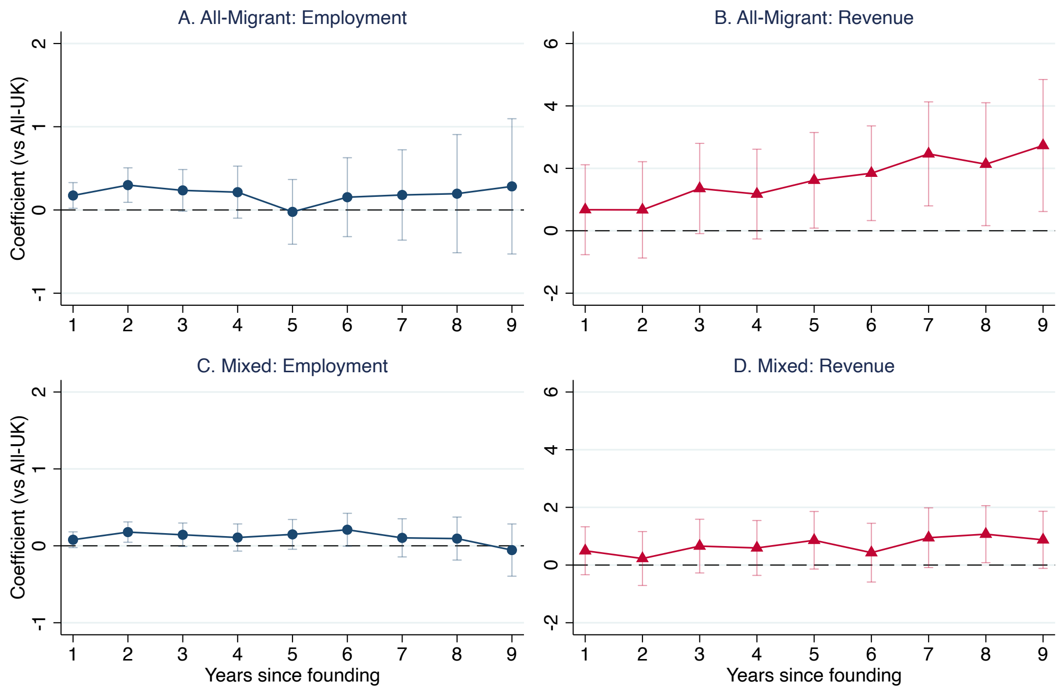


Figure 6: Growth trajectories by team type relative to All-UK founding teams
Note: Coefficients from years-since-founding × team type interactions, estimated via reghdfe with year and industry fixed effects and founder-level controls (any female founder, any STEM background, any serial founder, max experience, mean age, any Oxbridge, any managerial background, any tech background, number of founders). Baseline category is All-UK Founders at founding (years since founding = 0). Negative baseline coefficients for both all-migrant and mixed teams — reported in Table X — indicate that migrant-involved firms start with lower employment and revenue than all-UK teams; the interaction terms plotted here capture differential growth rates relative to this baseline. 95% confidence intervals shown. Results are robust to the inclusion of TTWA fixed effects and London × team type interactions. Standard errors clustered at firm level. Source: Beauhurst, Companies House.

Two findings emerge. First, both all-migrant and mixed founding teams begin with significantly lower employment and revenue than comparable all-UK teams. At founding, all-migrant firms employ around 26 percent less than all-UK firms (coefficient -0.265, significant at the 1 percent level), and generate revenue approximately 1.7 log points lower. Mixed teams also start smaller, with an employment gap of around 10 percent and a revenue gap of just over 1 log point. These starting gaps are not explained by location sorting — if anything, the gaps widen modestly when TTWA fixed effects are added, consistent with migrant-involved firms locating in areas that would otherwise predict higher performance.

Second, and more strikingly, both team types exhibit faster growth trajectories than all-UK firms in the years following founding, and this convergence is more pronounced and sustained for revenue than for employment. For all-migrant firms, the employment gap narrows signifi-

findings as our primary evidence on growth dynamics.

cantly within the first two to three years — the year 2 interaction coefficient of 0.299 offsets a substantial portion of the -0.265 baseline — but then stabilises, leaving a persistent though diminished gap at longer horizons. The revenue trajectory tells a different story: all-migrant firms show sustained and growing catch-up throughout the panel, with the year 9 interaction coefficient of 2.73 far exceeding the baseline gap of -1.73, implying that all-migrant firms that survive to later years substantially outperform all-UK firms on revenue. Mixed teams follow a qualitatively similar but more muted pattern, with revenue convergence emerging from around year 5 and sustained through year 9.

These patterns are robust across all four specifications. The interaction coefficients are stable when TTWA fixed effects are added (column 2), when urban category dummies replace TTWA fixed effects (column 3), and when London $\times$ team type interactions are included (column 4). The London interaction results — reported in Panel B of each table — reveal an important asymmetry: all-migrant firms do relatively better on employment inside London than outside (interaction coefficient +0.275, significant at 10 percent), but show no corresponding London premium on revenue. This suggests that the employment gains for London-based all-migrant firms may reflect access to co-ethnic labour markets or investor networks concentrated in the capital, rather than higher underlying productivity. Mixed teams show no significant London differential on either outcome, consistent with the descriptive evidence that mixed-team founding is less geographically concentrated and less dependent on London-specific ecosystems.

6 Migrant founders and firm distinctiveness

Over and above links between founding team composition and standard metrics of firm performance, we now explore other ways that migrant-led firms may differ. Per our framework in Section 1, we focus on founder strategy (Botelho et al., 2026; Guzman and Li, 2022; Gans et al., 2019; Rajan, 2012), in particular the way founders position firms and their products and services. Recall that in validation tests, more novel firms are more likely to attract external finance, and conditional on having some revenue or headcount, grow faster on both dimensions than less novel firms (3.4). We now look at the cross-sectional association between founder demography and text-based measures of firm distinctiveness detailed in Section 3.4. Per Section 1, teams with complementary skills and backgrounds may be more likely to develop distinctive propositions. If migrant and UK-born founders bring different qualities to a team, these migrant-native synergies may increase firm distinctiveness. Against this, more homogenous teams (all-migrant and/or all-UK) may work effectively together, with fewer frictions.

As in 5.2 for our initial exploration we run linear probability models regressing company distinctiveness measures on founding team characteristics. Each regression compares outcomes for migrant-only and mixed founding teams relative to all UK-born founding teams. Table 9 gives results for co-founded firms. Compared to all-UK teams, mixed migrant-native founding teams are just over 3.1 percent more likely to be unique in their 3-digit industry (column 2), and

Table 9: Founder demography and Firm Distinctiveness: teams

	Firm Performance Outcomes				
	(1)	(2)	(3)	(4)	(5)
	Originality	Unique in SIC3	Trendiness	# Peers	# Peers in SIC3
Migrant-only team	-0.000	0.008	0.000	-53.358	1.141**
	(0.006)	(0.021)	(0.000)	(51.117)	(0.499)
Mixed team	0.004	0.031*	-0.000	-102.221***	0.260
	(0.004)	(0.016)	(0.000)	(35.267)	(0.493)
Mixed - Migrant	-0.004	-0.023	0.001	48.864	0.881
Std. Error	0.006	0.021	0.000	48.761	0.500
p-value	0.480	0.266	0.100	0.317	0.079
Mean Dep. Var.	0.709	0.270	0.024	1322.938	7.160
Observations	3,253	3,254	3,254	3,254	3,254
Adj. R^2	0.053	0.422	0.131	0.162	0.382

Source: Beauhurst, Diffbot. Linear probability models comparing future outcomes for migrant-founded companies and mixed / all-migrant founding teams, versus UK-founded companies. Sample is companies founded 2000-2020. Mixed - Migrant shows the difference in coefficients (H0: $b_{mixed} = b_{all-migrant}$). Controls: founder gender, founder age, education, serial founder, founder years of experience, founder managerial / tech / stem background, co-founded firm, team size, multisite firm. Fixed effects: 3-digit SIC Industry × Incorporation Year, Trading TTWA. Standard errors clustered at industry-year level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

have over 102 fewer peers across all industries (column 4), a difference of almost eight percent on the average firm. Conversely, migrant-only teams have slightly more peers in their 3-digit industry (column 5). In general, we find no difference in outcomes for all-migrant versus mixed teams, except for the count of SIC3 peers (column 5), where the test statistic is significant at 10 %. Appendix Table ?? shows outcomes for an alternate sample pooling solo and co-founded firms. Results are very similar, and show no links from solo migrant founders to firm distinctiveness.

Overall, our results are consistent with migrant-native synergies, similar to (Jin et al., 2025), producing firms with more distinctive business models, products and services. We do not find evidence that more homogenous teams, either with all-migrant or all-UK founders, develop more distinctive propositions.

7 Conclusion - preliminary

In this preliminary paper, we use novel founder- and firm-level data on over 12,000 UK companies and 15,000 company founders to establish five new facts about migrant entrepreneurship, high-growth firms and cities. **First,** relative to the UK's migrant population, migrant entrepreneurs are substantially over-represented among founders of high-growth and high-growth-potential firms. **Second,** compared to UK-born founders, migrant founders are positively selected on human capital, but negatively selected on entrepreneurial experience. We find no evidence of selection on other entrepreneurial skills. **Third,** high-growth potential firms are highly urbanised, and those with a migrant founder or co-founder display a distinctive urban geography different from migrants' underlying spatial distribution. **Fourth,** firms with all-migrant and mixed native-migrant founding teams follow faster employment and revenue growth trajectories than all-UK teams. We find suggestive evidence of a 'London bonus' in employment growth for all-migrant founded firms. **Fifth,** as compared with firms founded by natives, firms with mixed native-migrant founding teams have more distinctive strategic positioning, with fewer peers.

Overall, the analysis shows that founding team composition is systematically related to both firm outcomes and product characteristics. Mixed migrant–native teams stand out in their ability to access external finance and, to a lesser extent, achieve exits, suggesting complementarities in skills or networks that are valued by investors. These advantages do not translate into stronger short-run operational outcomes such as employment or revenue, indicating that the mixed-team premium operates primarily through capital markets rather than day-to-day performance. We also find that mixed teams produce more original products, while migrant-only teams do not differ significantly from all-UK teams in distinctiveness. Taken together, the results point to the importance of founder diversity in shaping innovation and investor perceptions, even when immediate firm growth outcomes remain similar across team types.

Future versions of the paper will explore how founder, firm, and area characteristics may interact to explain these relationships.

References

Acosta, C. and Marinoni, A. (2025). Uncertainty and immigrant entrepreneurship: Evidence from brexit. *Organization Science*, 36(3):1072–1087.

Aghion, P. and Howitt, P. (1992). A model of growth through creative destruction. *Econometrica*, 60(2):323–351.

Akcigit, U., Alp, H., Pearce, J., and Prato, M. (2025). Transformative and subsistence entrepreneurs: Origins and impacts on economic growth. Report, NBER.

Aldrich, H. E. and Waldinger, R. (1990). Ethnicity and entrepreneurship. *Annual Review of Sociology*, 16:111–135.

Andersson, M. and Larsson, J. P. (2014). Local entrepreneurship clusters in cities. *Journal of Economic Geography*, 16(1):39–66.

Azoulay, P., Jones, B. F., Kim, J. D., and Miranda, J. (2022). Immigration and entrepreneurship in the united states. *American Economic Review: Insights*, 4(1):71–88.

Balland, P.-A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P. A., Rigby, D. L., and Hidalgo, C. A. (2020). Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4(3):248–254.

Beine, M., Peri, G., and Raux, M. (2024). The contribution of foreign master's students to us start-ups. Report, NBER.

Bernstein, S., Mehta, K., Townsend, R. R., and Xu, T. (2022). Do startups benefit from their investors' reputation? evidence from a randomized field experiment. Report, NBER.

Botelho, T. L., Fehder, D. C., and Hochberg, Y. V. (2026). Innovation-driven entrepreneurship. *Journal of Economic Literature*, 64(1):89–140.

Bryan, K. and Guzman, J. (2021). Entrepreneurial migration. Report.

Burton, M., Sørensen, J. B., and Beckman, C. M. (2002). *7. Coming from good stock: Career histories and new venture formation*, volume 19, page 0. Emerald Group Publishing Limited.

Calder-Wang, S., Gompers, P. A., and Huang, K. (2021). Diversity and performance in entrepreneurial teams. *National Bureau of Economic Research Working Paper Series*, No. 28684.

Calvino, F., Criscuolo, C., and Menon, C. (2018). A cross-country analysis of start-up employment dynamics. *Industrial and Corporate Change*, 27(4):677–698.

Certo, S. T., Lester, R. H., Dalton, C. M., and Dalton, D. R. (2006). Top management teams, strategy and financial performance: A meta-analytic examination. *Journal of Management Studies*, 43(4):813–839.

Chatterji, A., Glaeser, E., and Kerr, W. (2014). Clusters of entrepreneurship and innovation. *Innovation Policy and the Economy*, 14(1):129–166.

Chodavadia, S. A., Pekkala Kerr, S., Kerr, W. R., and Maiden, L. J. (2024). Immigrant entrepreneurship: New estimates and a research agenda. *National Bureau of Economic Research Working Paper Series*, No. 32400.

D'Acunto, F., Tate, G. A., and Yang, L. A. (2020). Entrepreneurial teams: Diversity of skills and early-stage growth. Report.

Dahlke, J., Schmidt, S., Lenz, D., Kinne, J., Dehghan, R., Abbasiharofteh, M., Schütz, M., Kriesch, L., Hottenrott, H., Kanilmaz, U. N., Grashof, N., Hajikhani, A., Liu, L., Riccaboni, M., Balland, P.-A., Wörter, M., and Rammer, C. (2025). The webai paradigm of innovation research: Extracting insight from organizational web data through ai. Report, ZEW.

Davis, D. R. and Dingel, J. I. (2019). A spatial knowledge economy. *American Economic Review*, 109(1):153–70.

Draca, M., Nathan, M., Nguyen, V., Oliviera-Cunha, J., Rosso, A., and Valero, A. (2023). Economic growth goes fractal.

Duranton, G. and Puga, D. (2001). Nursery cities: Urban diversity, process innovation and the life cycle of products. *American Economic Review*, 91(5):1454–1477.

Duranton, G. and Puga, D. (2023). Urban growth and its aggregate implications. *Econometrica*, 91(6):2219–2259.

Edin, P.-A., Frederiksson, P., and Åslund, O. (2003). Ethnic enclaves and the economic success of immigrants: Evidence from a natural experiment. *Quarterly Journal of Economics*, 118(1):329–357.

Evans, D. S. and Jovanovic, B. (1989). An estimated model of entrepreneurial choice under liquidity constraints. *Journal of Political Economy*, 97(4):808–827.

Ewens, M. (2022). Race and gender in entrepreneurial finance. Report, NBER.

Fairlie, R., Robb, A., and Robinson, D. T. (2022). Black and white: Access to capital among minority-owned start-ups. *Management Science*, 68(4):2377–2400.

Gans, J. S., Stern, S., and Wu, J. (2019). Foundations of entrepreneurial strategy. *Strategic Management Journal*, 40(5):736–756.

Glaeser, E. L., Kerr, S. P., and Kerr, W. R. (2015). Entrepreneurship and urban growth: An empirical assessment with historical mines. *Review of Economics and Statistics*, 97(2):498–520.

Glaeser, E. L., Kerr, W., and Ponzetto, G. A. M. (2010a). Clusters of entrepreneurship. *Journal of Urban Economics*, 67(1):150–168.

Glaeser, E. L., Kerr, W. R., and Ponzetto, G. A. M. (2010b). Clusters of entrepreneurship. *Journal of Urban Economics*, 67(1):150–168.

Gray, S., Kemeny, T., Nathan, M., Ozgen, C., Pialli, G., Rosso, A. C., Reades, J., Seré, M., Siddiqui, S., and Valero, A. (2026). Graph-ee: Building employer - employee panels from a knowledge graph and company microdata. *CEP Discussion Paper CEPDP2156.*

Guiso, L., Pistaferri, L., and Schivardi, F. (2015). Learning entrepreneurship from other entrepreneurs? *National Bureau of Economic Research Working Paper Series*, No. 21775.

Guiso, L. and Schivardi, F. (2011). What determines entrepreneurial clusters? *Journal of the European Economic Association*, 9(1):61–86.

Guzman, J. and Li, A. (2022). Measuring founding strategy. *Management Science*, 0(0):null.

Guzman, J. and Stern, S. (2015). Where is Silicon Valley? *Science*, 347(6222):606–609.

Haltiwanger, J., Jarmin, Ron, S., and Miranda, J. (2013). Who creates jobs? small versus large versus young. *The Review of Economics and Statistics*, 95(2):347–361.

Hegde, D. and Tumlinson, J. (2021). Information frictions and entrepreneurship. *Strategic Management Journal*, 42(3):491–528.

HESA (2024). Higher education student statistics: Uk, 2022/23 - where students come from and go to study. Report, HESA.

Hoberg, G. and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465.

Hong, L. and Page, S. E. (2004). Groups of diverse problem solvers can outperform groups of high-ability problem solvers. *Proceedings of the National Academy of Sciences*, 101(46):16385–16389.

Honoré, F. (2022). Joining forces: How can founding members' prior experience variety and shared experience increase startup survival? *Academy of Management Journal*, 65(1):248–272.

Hunt, J. and Gauthier-Loiselle, M. (2010). How much does immigration boost innovation? *American Economic Journal: Macroeconomics*, 2(2):31–56.

Jin, Z., Kermani, A., and McQuade, T. (2025). Native-immigrant entrepreneurial synergies. NBER Working Paper 33804.

Jones, T., Ram, M., and Villares-Varela, M. (2018). Diversity, economic development and new migrant entrepreneurs. *Urban Studies*, 56(5):960–976.

Kemeny, T. and Storper, M. (2020). Superstar cities and left-behind places: disruptive innovation, labor demand, and interregional inequality. LSE International Inequalities Institute Working Paper 41.

Kenney, M. and Patton, D. (2015). Gender, ethnicity and entrepreneurship in initial public offerings: illustrations from an open database*. *Research Policy*, 44(9):1773–1784.

Kerr, William, R. and Mandorff, M. (2023). Social networks, ethnicity, and entrepreneurship. *Journal of Human Resources*, 58(1):183.

Kerr, W. (2010). Breakthrough inventions and migrating clusters of innovation. *Journal of Urban Economics*, 67(1):46–60.

Kerr, W. R., Nanda, R., and Rhodes-Kropf, M. (2014). Entrepreneurship as experimentation. *Journal of Economic Perspectives*, 28(3):25–48.

Kerr, W. R. and Robert-Nicoud, F. (2020). Tech clusters. *Journal of Economic Perspectives*, 34(3):50–76.

Kleinhempel, J., Klasing, M. J., and Beugelsdijk, S. (2023). Cultural roots of entrepreneurship: Evidence from second-generation immigrants. *Organization Science*, 34(5):1800–1819.

Klette, T. and Kortum, S. (2004). Innovating firms and aggregate innovation. *Journal of Political Economy*, 112(5):986–1018.

Kloosterman, R. and Rath, J. (2003). *Immigrant Entrepreneurs: Venturing Abroad in the Age of Globalisation*. Berg, Oxford.

Knight, F. (1921). *Risk, Uncertainty and Profit*. Houghton Mifflin, Boston.

Koster, H. R. A. and Ozgen, C. (2021). Cities and tasks. *Journal of Urban Economics*, 126:103386.

Lazear, E. P. (2004). Balanced skills and entrepreneurship. *American Economic Review*, 94(2):208–211.

Lee, K. M., Kim, M. J., Brown, J. D., Earle, J. S., and Liu, Z. (2025). Are immigrants more innovative? evidence from entrepreneurs. *Journal of Economics Management Strategy*, n/a(n/a).

Lee, S. and Glennon, B. (2023). The effect of immigration policy on founding location choice: Evidence from Canada's Start-up Visa program. NBER Working Paper 31634.

Lentz, R. and Mortensen, D. T. (2008). An empirical model of growth through product innovation. *Econometrica*, 76(6):1317–1373.

Lindquist, M. J., Sol, J., and Van Praag, M. (2015). Why do entrepreneurial parents have entrepreneurial children? *Journal of Labor Economics*, 33(2):269–296.

Lucas, R. E. (1978). On the size distribution of business firms. *The Bell Journal of Economics*, 9(2):508–523.

Luttmer, E. G. J. (2011). On the mechanics of firm growth. *The Review of Economic Studies*, 78(3):1042–1068.

Mack, D. Z., Chen, G., Hsu, P.-H., Lee, Y. T., and George, G. (2025). Interfaces, social information processing, and diversity cascades: How board diversity influences invention output. *Research Policy*, 54(1):105148.

Manning, A. (2025). *Why Immigration Policy is Hard: And How To Make It Better.* Polity, Cambridge.

Marinoni, A. (2023). Immigration and entrepreneurship: The role of enclaves. *Management Science*, 69(12):7266–7284.

Marinoni, A. and Choudhury, P. (2024). Bounded solidarity: the role of migrants in shaping entrepreneurial ventures. Report, Harvard Business School.

Mesquita, F., Cannaviccio, M., Schmidek, J., Mirza, P., and Barbosa, D. (2019). Knowledgenet: A benchmark dataset for knowledge base population. Report, Association for Computational Linguistics.

Migration-Observatory (2023). Citizenship and naturalisation for migrants in the uk. Report, Migration Observatory.

Oster, E. (2019). Unobservable selection and coefficient stability: Theory and evidence. *Journal of Business & Economic Statistics*, 37(2):187–204.

Rajan, R. G. (2012). Presidential address: The corporation in finance. *The Journal of Finance*, 67(4):1173–1217.

Rosen, S. (1982). Authority, control, and the distribution of earnings. *The Bell Journal of Economics*, 13(2):311–323.

Saxenian, A.-L. (2006). *The New Argonauts: Regional Advantage in a Global Economy.* Harvard University Press, Cambridge, MA.

Schumpeter, J. (1962). *The Theory of Economic Development*. Springer, Berlin.

Tareque, I. S., Guzman, J., and Wang, D. (2024). High-skilled immigration enhances regional entrepreneurship. *Proceedings of the National Academy of Sciences*, 121(37):e2402001121.

Triana, M. d. C., Richard, O. C., and Su, W. (2019). Gender diversity in senior management, strategic change, and firm performance: Examining the mediating nature of strategic change in high tech firms. *Research Policy*, 48(7):1681–1693.

Wahba, J. and Zenou, Y. (2012). Out of sight, out of mind: Migration, entrepreneurship and social capital. *Regional Science and Urban Economics*, 42(5):890–903.

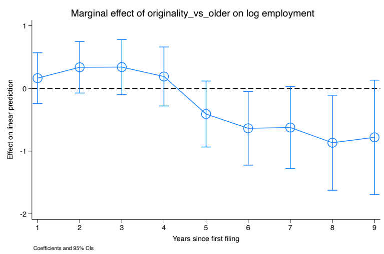
A Appendix

Figure A1: Example company description text provided by Beauhurst

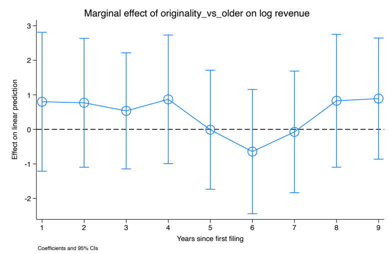
Company	**Company description text**	**Beauhurst analyst text**
Deliveroo	Deliveroo is on a mission to transform the way the world thinks about food delivery. It's not a chicken chow mein and a night on the sofa anymore, it's your favourite local restaurant, it's a dinner party, a date. We are five years in, and along the way our team have taken hundreds of ideas from brainstorms to global roll-outs, like Deliveroo Editions – bespoke kitchens designed to host a locally-curated selection of restaurants. Editions are our solution to ensuring that our customers have access to the best of the food-scene, no matter where they live. And that's just what we're like at Deliveroo, no compromise allowed and lots of food-inspired challenges to get your teeth into. Out-of-the-box thinking is actively encouraged and we move quickly to make great ideas happen. We're energetic, fast-paced and blow off steam with free-for-all Friday lunches. It's a formula that's working too – we're bringing great food to customers in 12 countries and over 800 cities.	Deliveroo provides delivery services for restaurants, using technology to predict the time taken to prepare meals and efficient ways of delivering orders using the location of restaurants, customers and riders.

Source: Beauhurst. *Note:* Example text for Deliveroo, a leading UK food delivery service. The figure shows the company's own description of its positioning - strategy, products and services - and Beauhurst's own summary. In our analysis we use companies' own words rather than Beauhurst's, because we are interested in how companies seek to position and differentiate themselves versus competitors.

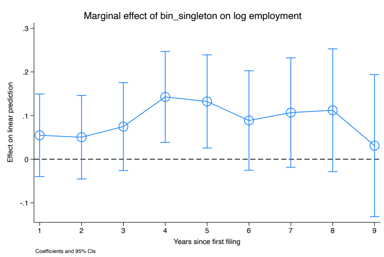
Figure A2: Validation: Company distinctiveness and employment / revenue dynamics



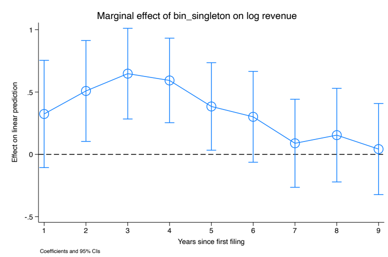
(a)



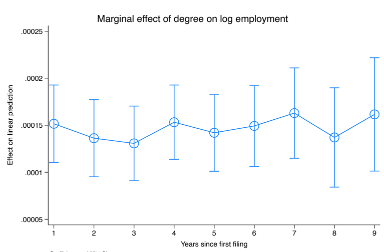
(b)



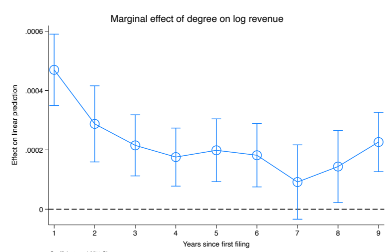
(c)



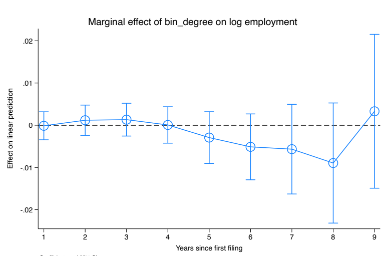
(d)



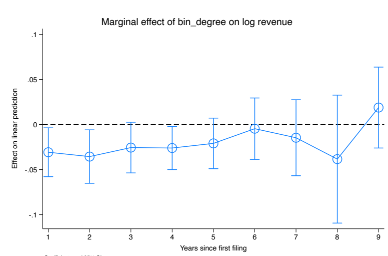
(e)



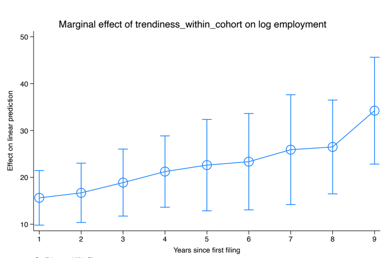
(f)



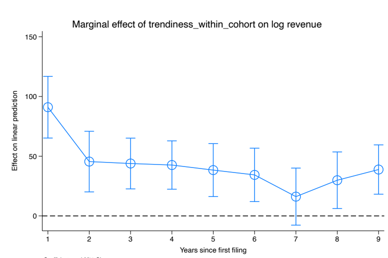
(g)



(h)



(i)



(j)

Source: Beauhurst, Diffbot. *Note:* Figures show marginal effects from regressions of firm novelty metrics on employment and revenue growth for 9,264 firms reporting headcount and 1,811 firms reporting revenue. Graphs show change from the first reported filing. Controls, fixed effects and standard errors as in Table A2.

Table A1: Founder balancing test. Dependent variable = Pr(founder in sample)

	(1) Status	(2) + city FE	(3) Education	(4) + city FE
Founder age (Beauhurst)	-0.006***	-0.005***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)
Female founder (Beauhurst)	0.015**	0.012	0.014**	0.014
	(0.007)	(0.011)	(0.006)	(0.009)
Non-UK national	0.028***	0.014	0.021***	0.006
	(0.006)	(0.010)	(0.006)	(0.009)
Dual nationality	0.054**	0.064***	0.031	0.040*
	(0.021)	(0.023)	(0.020)	(0.022)
Speaks more than 1 language	0.079***	0.051***	0.080***	0.060***
	(0.006)	(0.008)	(0.005)	(0.007)
Years of labour market experience	0.002***	0.001**	0.002***	0.002***
	(0.000)	(0.001)	(0.000)	(0.001)
Number of jobs in career history	0.013***	0.009***	0.013***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Current founder	0.046***	0.033***	0.043***	0.030***
	(0.007)	(0.011)	(0.006)	(0.010)
Serial founder	0.008	0.007	0.009	0.015
	(0.012)	(0.017)	(0.010)	(0.015)
Has board experience	0.003	-0.010	-0.003	-0.013
	(0.007)	(0.011)	(0.006)	(0.010)
Has management experience	0.019***	0.013	0.028***	0.013
	(0.006)	(0.010)	(0.006)	(0.009)
Has experience in tech role	0.021***	0.013	0.020***	0.010
	(0.007)	(0.011)	(0.006)	(0.009)
Observations	19112	7070	19112	7070
R^2	0.084	0.114	0.092	0.113
F-statistic	128.109	24.150	132.853	27.530
Oster delta	2.803	2.404	2.936	2.404

Notes: Source: Beauhurst, Diffbot. Sample is 23640 founders of companies founded 2000-2020. Models with city FE run on 8685 founders where current location is known. *** = significant at 1%, ** = 5%, * = 10%.

Table A2: Validation: Product Distinctiveness Measures and Firm Outcomes

	(1) Employ	(2) Revenue	(3) Ext Fin	(4) IPO	(5) Acq
Panel A: Originality vs older firms					
Originality	0.000	-0.004	-0.016	-0.032	-0.032
	(0.038)	(0.039)	(0.045)	(0.027)	(0.027)
N	9941	9941	9941	9941	9941
R^2	0.148	0.170	0.173	0.047	0.047
F-statistic	4.328	4.260	29.966	4.548	4.548
Panel B: Uniqueness in SIC3 bin					
Bin singleton	-0.034***	-0.007	0.036***	-0.016**	-0.016**
	(0.009)	(0.010)	(0.012)	(0.006)	(0.006)
N	9942	9942	9942	9942	9942
R^2	0.149	0.170	0.174	0.047	0.047
F-statistic	5.141	4.248	31.105	4.774	4.774
Panel C: Number of peers					
Degree	0.000***	0.000***	-0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	9942	9942	9942	9942	9942
R^2	0.149	0.171	0.178	0.048	0.048
F-statistic	5.610	4.796	33.358	4.612	4.612
Panel D: Number of peers in SIC3 bin					
Bin degree	0.001***	0.001*	-0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	9942	9942	9942	9942	9942
R^2	0.149	0.170	0.173	0.047	0.047
F-statistic	10.693	4.235	32.052	4.587	4.587
Panel E: Similarity within cohort					
Trendiness within cohort	1.511**	1.165**	-3.825***	0.525	0.525
	(0.632)	(0.588)	(0.742)	(0.377)	(0.377)
N	9942	9942	9942	9942	9942
R^2	0.149	0.170	0.176	0.047	0.047
F-statistic	4.637	4.302	31.514	4.522	4.522

Source: Beauhurst, Diffbot. Linear probability models. Originality measures distinctiveness relative to all previously founded companies (higher = more original). Bin singleton is a dummy = 1 if the firm has no peers (= similar firms based on cosine similarity) in its own SIC3 industry. Degree is a count of a firm's peers in any industry. Bin degree is a count of a firm's peers in its own SIC3 industry. Trendiness measures similarity to firms founded in the same year (higher = more similar to cohort). Controls: founder gender, founder age, education, serial founders, founder years of experience, founder managerial/tech/stem background, co-founded firm, team size, multisite firm. Fixed effects: 3-digit SIC Industry × Incorporation Year, trading TTWA. Standard errors clustered at industry-year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Migrant vs UK-born founders: t-tests

Variable	Significance
Founder age	***
Founder age (Beauhurst)	***
Female founder	**
Female founder (Beauhurst)	.
Non-UK national	***
Dual national incl UK	***
Highest qualification is degree	***
Highest qualification is postgrad degree	***
Highest qualification is PhD	***
Has Oxbridge degree	***
Has Russell Group degree	***
Has STEM degree	***
Has economics degree	***
Has humanities degree	**
Has other social sciences degree	**
Number of languages spoken	***
Years of experience	***
Number of jobs held	***
Has non-exec board role experience	***
Has managerial experience	.
Has tech role experience	***
Has STEM role experience	***
Is currently a founder	***
Serial founder	***

Source: Beauhurst, Diffbot.
*** = significant at 1%, ** = 5%, * = 10%.

Table A4: Predictors of migrant founders

	All companies	Co-founded firms only
	(1)	(2)
Years of labour market experience	-0.001^{*} (0.000)	-0.001 (0.001)
Number of jobs in career history	0.000 (0.001)	-0.001 (0.002)
Current founder	-0.000 (0.008)	0.006 (0.016)
Serial founder	-0.042^{***} (0.014)	-0.051^{*} (0.026)
Has non-exec board experience	0.011 (0.009)	0.026 (0.017)
Has experience in managerial role	-0.000 (0.008)	-0.018 (0.015)
Highest qualification is degree	0.047^{***} (0.013)	0.033 (0.030)
Highest qualification is postgrad degree	0.136^{***} (0.015)	0.116^{***} (0.033)
Highest qualification is PhD	0.150^{***} (0.017)	0.150^{***} (0.038)
Founder age (Beauhurst)	0.001^{***} (0.000)	-0.001 (0.001)
Female founder (Beauhurst)	-0.008 (0.009)	-0.032 (0.021)
Non-UK national	0.413^{***} (0.011)	0.115^{***} (0.026)
Dual nationality	-0.081^{*} (0.044)	-0.009 (0.084)
Has a degree in a STEM subject	0.008 (0.008)	0.002 (0.015)
Has a degree in economics	0.048^{***} (0.008)	0.055^{***} (0.016)
Has arts or humanities degree	-0.014 (0.010)	-0.043^{**} (0.019)
Has Oxbridge degree	0.008 (0.010)	-0.003 (0.022)
Has Russell Group uni degree	-0.182^{***} (0.008)	-0.220^{***} (0.017)
Number of languages spoken	0.045^{***} (0.003)	0.044^{***} (0.005)
Founder is based in London	0.002 (0.009)	0.011 (0.017)
Has experience in tech role	0.022^{**} (0.009)	-0.002 (0.018)
Observations	14680	6521
R^2	0.368	0.667
F-statistic	221.453	19.017
Oster delta, PhD	4.162	
Company controls	Yes	No
Company FE	No	Yes

Source: Beauhurst, Diffbot. *Notes:* Company controls include incorporation year, dummy for tracking at mid stage, dummy for late stage tracking, co-founded company dummy, number of founders. All regressions include 3-digit industry dummies and TTWA dummies. Standard errors in parentheses, clustered on founder. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Founder demography and Firm Outcomes: teams sample

	Firm Performance Outcomes				
	(1)	(2)	(3)	(4)	(5)
	Employ	Revenue	Ext. Fin	IPO	Acq
Migrant-only tean	-0.032	-0.013	0.070***	0.003	0.003
	(0.020)	(0.017)	(0.021)	(0.013)	(0.013)
Mixed team	-0.003	0.016	0.040**	0.006	0.006
	(0.011)	(0.015)	(0.016)	(0.009)	(0.009)
Mixed - Migrant	0.029	0.028	-0.030	0.003	0.003
Std. Error	0.020	0.016	0.020	0.012	0.012
p-value	0.150	0.081	0.127	0.800	0.800
Mean Dep. Var.	0.868	0.142	0.825	0.061	0.061
Observations	3,254	3,254	3,254	3,254	3,254
Adj. R^2	0.182	0.135	0.113	0.067	0.067

Source: Beauhurst, Diffbot. Linear probability models comparing future outcomes for migrant-founded companies and mixed / all-migrant founding teams, versus UK-founded companies. Sample is companies founded 2000-2020. Mixed - Migrant shows the difference in coefficients (H0: $b_{mixed} = b_{all-migrant}$). Controls: founder gender, founder age, education, serial founder, founder years of experience, founder managerial / tech / stem background, co-founded firm, team size, multisite firm. Fixed effects: 3-digit SIC Industry × Incorporation Year, Trading TTWA. Standard errors clustered at industry-year level.* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Employment and revenue growth trajectories by founding team type

	ln(Employment)		ln(Revenue)	
	(1)	(2)	(3)	(4)
	Baseline	Extended	Baseline	Extended
All-migrant founders	-0.137^{***}	-0.109^{**}	-0.264	-0.235
	(0.051)	(0.052)	(0.251)	(0.252)
Mixed founding team	0.017	-0.180^{***}	-0.620^{*}	-0.825^{**}
	(0.048)	(0.053)	(0.336)	(0.351)
Year × All-migrant				
Year 1	0.094^{**} (0.039)	0.080^{**} (0.039)	-0.255 (0.231)	-0.263 (0.231)
Year 2	0.097^{*} (0.053)	0.090 (0.053)	-0.096 (0.232)	-0.102 (0.232)
Year 3	0.039 (0.062)	0.033 (0.062)	0.129 (0.240)	0.116 (0.240)
Year 4	-0.020 (0.072)	-0.024 (0.071)	0.086 (0.243)	0.078 (0.243)
Year 5	-0.060 (0.079)	-0.063 (0.079)	0.205 (0.261)	0.201 (0.260)
Year 6	0.031 (0.087)	0.027 (0.087)	0.470^{*} (0.260)	0.463 (0.260)
Year 7	0.068 (0.094)	0.065 (0.094)	0.473^{*} (0.267)	0.466 (0.266)
Year 8	0.033 (0.107)	0.033 (0.107)	0.761^{***} (0.257)	0.758^{***} (0.257)
Year 9	0.087 (0.121)	0.086 (0.122)	0.596^{**} (0.272)	0.601^{**} (0.272)
Year × Mixed				
Year 1	0.151^{***} (0.041)	0.147^{***} (0.041)	0.381 (0.281)	0.359 (0.280)
Year 2	0.257^{***} (0.053)	0.253^{***} (0.053)	0.318 (0.328)	0.293 (0.328)
Year 3	0.296^{***} (0.062)	0.289^{***} (0.062)	0.941^{***} (0.329)	0.902^{***} (0.329)
Year 4	0.268^{***} (0.073)	0.252^{***} (0.073)	0.716^{**} (0.337)	0.690^{**} (0.336)
Year 5	0.281^{***} (0.078)	0.272^{***} (0.078)	0.964^{***} (0.341)	0.925^{***} (0.341)
Year 6	0.277^{***} (0.087)	0.266^{***} (0.087)	0.772^{**} (0.354)	0.738^{**} (0.353)
Year 7	0.198^{*} (0.103)	0.195 (0.102)	0.993^{***} (0.362)	0.945^{***} (0.361)
Year 8	0.170 (0.112)	0.174 (0.110)	1.328^{***} (0.346)	1.297^{***} (0.345)
Year 9	0.127 (0.134)	0.138 (0.133)	1.283^{***} (0.360)	1.260^{***} (0.359)
Female founder	-0.314^{***}	-0.347^{***}	-0.742^{***}	-0.786^{***}
Mean age	0.007^{***}	0.009^{***}	0.024^{***}	0.026^{***}
Oxbridge		0.085^{**}		-0.021
Number of founders		0.211^{***}		0.202^{*}
Observations	33,141	33,141	8,872	8,872
R-squared	0.413	0.417	0.410	0.412

Notes: Dependent variable is ln(employment). Reference category for founding team types is all UK. Calendar year and industry fixed effects included. Standard errors clustered by firm. Model 2 additionally includes the following founding team controls: mean age, dummies for serial entrepreneurship, managerial and technical experience, and STEM education. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Spatial Descriptives: Founding Team Composition by Travel to Work Area: Major Conurbations

	All-UK		All-Migrant		Mixed		Total	
TTWA	*N*	%	*N*	%	*N*	%	*N*	%
London	814	37.4	352	16.2	1,008	46.4	2,174	100
Manchester	63	71.6	5	5.7	20	22.7	88	100
Edinburgh	51	58.6	5	5.7	31	35.6	87	100
Slough and Heathrow	28	40.6	8	11.6	33	47.8	69	100
Glasgow	30	71.4	2	4.8	10	23.8	42	100
Newcastle	24	60.0	2	5.0	14	35.0	40	100
Birmingham	32	66.7	3	6.3	13	27.1	48	100
Leeds	21	75.0	1	3.6	6	21.4	28	100
Aberdeen	12	60.0	2	10.0	6	30.0	20	100
Liverpool	13	81.3	1	6.3	2	12.5	16	100
All conurbations	*1,130*	*42.1*	*384*	*14.3*	*1,171*	*43.6*	*2,685*	*100*

Notes: Sample restricted to co-founded firms incorporated 2000–2020, observed at last year in panel. TTWAs classified as major conurbations under the ONS 2011 Rural-Urban Classification (category A1). TTWAs with fewer than 15 firms are excluded from listed rows but included in "All conurbations" totals. All-UK: all founders UK-born. All-Migrant: all founders born outside UK. Mixed: at least one founder UK-born and at least one born outside UK. Source: Beauhurst, Companies House, ONS Postcode Directory.

Table A8: Spatial Descriptives: Firm Outcomes by Urban Category and Founding Team Type

		Team type			
Urban category	Outcome	All-UK	All-Migrant	Mixed	Total
Major conurbation	Employment (mean)	27.24	31.41	24.49	26.63
	Revenue, £m (mean)	21.17	24.62	37.51	29.45
	Originality	0.71	0.71	0.71	0.71
	Trendiness	0.02	0.02	0.02	0.02
	N (employment)	995	312	980	2,287
Other urban	Employment (mean)	39.08	9.68	19.96	30.30
	Revenue, £m (mean)	35.22	2.10	10.03	26.32
	Originality	0.71	0.71	0.70	0.71
	Trendiness	0.02	0.02	0.02	0.02
	N (employment)	453	53	279	785
Rural town/fringe	Employment (mean)	38.83	—	18.94	30.03
	Revenue, £m (mean)	109.69	—	30.70	73.23
	Originality	0.72	—	0.71	0.71
	Trendiness	0.02	—	0.02	0.02
	N (employment)	52	5	31	88
Rural	Employment (mean)	24.90	—	32.82	27.34
	Revenue, £m (mean)	13.51	—	9.00	11.05
	Originality	0.70	—	0.70	0.70
	Trendiness	0.02	—	0.02	0.02
	N (employment)	92	6	66	164
Total	Employment (mean)	30.85	27.60	23.84	27.62
	Revenue, £m (mean)	28.28	22.27	31.75	29.15
	Originality	0.71	0.71	0.71	0.71
	Trendiness	0.02	0.02	0.02	0.02
	N (employment)	1,592	376	1,356	3,324

Notes: Sample restricted to co-founded firms (2+ founders) incorporated 2000–2020, at their last observation in the panel. Urban categories based on ONS 2011 Rural-Urban Classification. Employment is mean number of employees. Revenue is mean annual revenue expressed in £ millions. Originality measures product distinctiveness relative to older firms; trendiness measures distinctiveness within founding cohort (both derived from TF-IDF cosine similarity of company descriptions). N reports number of non-missing employment observations. — indicates suppressed cells with fewer than 10 observations. * indicates cells with fewer than 10 observations; interpret with caution. Source: Beauhurst, Companies House, ONS Postcode Directory.

Table A9: Employment Growth, Founding Team Type and Location

	(1) Baseline	(2) TTWA FEs	(3) Urban category	(4) London interaction
Panel A: Team type (baseline = All-UK Founders)				
All-Migrant Founders	-0.265^{***}	-0.355^{***}	-0.265^{***}	-0.506^{***}
	(0.082)	(0.086)	(0.083)	(0.148)
Mixed Founding Team	-0.100^{*}	-0.140^{**}	-0.102^{*}	-0.113
	(0.059)	(0.061)	(0.059)	(0.084)
Panel B: Location controls				
Other urban			-0.055	
			(0.058)	
Rural town/fringe			-0.016	
			(0.179)	
Rural			0.039	
			(0.133)	
London				0.086
				(0.069)
All-Migrant × London				0.275^{*}
				(0.162)
Mixed × London				-0.002
				(0.100)
Panel C: Years since founding × team type interactions (selected)				
Year 1 × All-Migrant	0.174^{**}	0.187^{**}	0.169^{**}	0.179^{**}
	(0.079)	(0.080)	(0.079)	(0.080)
Year 1 × Mixed	0.079	0.087	0.079	0.081
	(0.052)	(0.054)	(0.053)	(0.052)
Year 2 × All-Migrant	0.299^{***}	0.321^{***}	0.295^{***}	0.307^{***}
	(0.106)	(0.106)	(0.106)	(0.106)
Year 2 × Mixed	0.178^{***}	0.174^{**}	0.174^{**}	0.181^{***}
	(0.067)	(0.068)	(0.068)	(0.067)
Year 3 × All-Migrant	0.235^{*}	0.255^{**}	0.241^{*}	0.252^{*}
	(0.128)	(0.128)	(0.129)	(0.128)
Year 3 × Mixed	0.144^{*}	0.149^{*}	0.139^{*}	0.146^{*}
	(0.078)	(0.078)	(0.079)	(0.078)
Year 6 × All-Migrant	0.154	0.217	0.134	0.169
	(0.242)	(0.240)	(0.241)	(0.241)
Year 6 × Mixed	0.209^{*}	0.217^{**}	0.197^{*}	0.212^{*}
	(0.109)	(0.108)	(0.110)	(0.109)
Founder controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
TTWA FEs	No	Yes	No	No
London interaction	No	No	No	Yes
Observations	10,295	10,290	10,191	10,295
Clusters	3,262	3,257	3,221	3,262
R^2	0.357	0.395	0.360	0.358

Notes: Dependent variable is ln(employment). Sample restricted to co-founded firms (2+ founders) incorporated 2000–2020, observed through 2020, with non-missing employment and valid UK trading postcode. Baseline team type is All-UK Founders. Panel A reports team type baseline coefficients, interpreted as the effect at founding (years since founding = 0). In column (4), team type coefficients are identified off non-London firms; London interaction terms report the differential effect for London-based firms. Panel C reports selected years-since-founding × team type interactions; full results available on request. Founder controls include: any female founder, any STEM background, any serial founder, max experience, mean age, any Oxbridge, any managerial background, any tech background, number of founders. Standard errors clustered at firm level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: Beauhurst, Companies House, ONS Postcode Directory.

Table A10: Revenue Growth, Founding Team Type and Location

	(1) Baseline	(2) TTWA FEs	(3) Urban category	(4) London interaction
Panel A: Team type (baseline = All-UK Founders)				
All-Migrant Founders	−1.732**	−1.939**	−1.673**	−2.168***
	(0.722)	(0.788)	(0.776)	(0.819)
Mixed Founding Team	−1.046**	−1.146**	−1.105**	−0.866
	(0.478)	(0.498)	(0.483)	(0.533)
Panel B: Location controls				
Other urban			−0.200	
			(0.272)	
Rural town/fringe			−0.009	
			(0.767)	
Rural			0.236	
			(0.462)	
London				0.059
				(0.365)
All-Migrant × London				0.523
				(0.758)
Mixed × London				−0.299
				(0.469)
Panel C: Years since founding × team type interactions (selected)				
Year 3 × All-Migrant	1.355*	1.535**	1.372*	1.281*
	(0.737)	(0.777)	(0.787)	(0.767)
Year 3 × Mixed	0.657	0.793*	0.755	0.664
	(0.475)	(0.478)	(0.477)	(0.473)
Year 5 × All-Migrant	1.617**	1.617*	1.531*	1.509*
	(0.782)	(0.831)	(0.805)	(0.801)
Year 5 × Mixed	0.859*	0.666	0.873*	0.856*
	(0.509)	(0.511)	(0.511)	(0.511)
Year 7 × All-Migrant	2.464***	2.649***	2.374***	2.392***
	(0.850)	(0.901)	(0.886)	(0.884)
Year 7 × Mixed	0.948*	0.915*	0.964*	0.948*
	(0.529)	(0.527)	(0.532)	(0.529)
Year 9 × All-Migrant	2.732**	2.973***	2.677**	2.625**
	(1.079)	(1.121)	(1.105)	(1.097)
Year 9 × Mixed	0.874*	0.948*	0.867*	0.850*
	(0.505)	(0.529)	(0.506)	(0.504)
Founder controls	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes
TTWA FEs	No	Yes	No	No
London interaction	No	No	No	Yes
Observations	1,840	1,832	1,823	1,840
Clusters	554	546	549	554
R^2	0.508	0.581	0.514	0.509

Notes: Dependent variable is ln(revenue). Sample restricted to co-founded firms (2+ founders) incorporated 2000–2020, observed through 2020, with non-missing revenue and valid UK trading postcode. Revenue is missing for approximately 84% of firm-year observations; missingness is unrelated to team type and urban category. Baseline team type is All-UK Founders. In column (4), team type coefficients are identified off non-London firms; London interaction terms report the differential effect for London-based firms. Panel C reports years-since-founding × team type interactions at odd years to capture the convergence trajectory; full results available on request. Founder controls include: any female founder, any STEM background, any serial founder, max experience, mean age, any Oxbridge, any managerial background, any tech background, number of founders. Standard errors clustered at firm level in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Source: Beauhurst, Companies House, ONS Postcode Directory.