

Do start-ups follow their industry? Sectoral bases and start-up location in southern Brazil

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Abstract

Policies that seek to anchor start-ups in regional strengths assume that new ventures locate where the productive and knowledge assets of their own sector are concentrated. This paper tests that assumption for 483 health, agricultural and information and communication technology (ICT) start-ups registered in Rio Grande do Sul, Brazil, observed across the state's 497 municipalities. Official data were used to measure, for each sector, a productive base (hospital beds, the agricultural share of gross value added and ICT establishments) and a knowledge base (enrolment in on-campus degree programmes in the corresponding field). A stacked municipality-by-sector Poisson pseudo-maximum likelihood model with municipality and sector fixed effects absorbs population, income, schooling and every other attribute that attracts start-ups irrespective of sector, so identification rests on the sectoral composition of start-ups within each municipality. A one-standard-deviation stronger productive base was associated with 42% more start-ups of the same sector (incidence rate ratio 1.42; 95% CI 1.21 to 1.67), a result that held without the state capital, with broader sector definitions, with alternative measures of each base and under a negative binomial specification. The knowledge base showed no independent association (1.02; 0.84 to 1.25). The productive-base association lost precision once region-by-sector fixed effects were added, which suggests that municipal and regional specialisation overlap. Start-ups appear to follow the industries they serve more closely than the campuses that train their founders, a pattern that favours place-based support built on existing sectoral capabilities.

JEL classification: R12; R30; L26; O18

Highlights

- Start-ups are more numerous where the productive base of their own sector is stronger.
- A one-standard-deviation stronger productive base is associated with 42% more same-sector start-ups.
- Sector-specific higher education shows no independent association with start-up location.
- Municipality fixed effects remove general urban attraction from the comparison.
- The association overlaps with regional specialisation and loses precision within regions.

1 Introduction

Start-ups are unevenly distributed across space, and most of that unevenness follows the familiar gradient of city size, income and education. Large and diversified cities concentrate founders, capital and customers, and they attract new ventures in almost every activity (Glaeser et al. 2010; Fritsch and Storey 2014). A second, sector-specific geography sits beneath this general gradient. Entrepreneurs often start firms in the industries where they previously worked, close to the organisations that trained them and to the customers they already know (Klepper 2007; Dahl and Sorenson 2012). Knowledge generated by universities and incumbents also spills over most readily to nearby firms that share its

technological domain (Jaffe et al. 1993; Audretsch et al. 2005). If these mechanisms operate, start-ups should be relatively more numerous where the productive and knowledge assets of their own sector are concentrated, and not merely where cities are large.

This proposition underpins a generation of place-based innovation policies. Smart specialisation strategies, entrepreneurial ecosystem programmes and regional innovation networks all ask territories to build on the sectors in which they already hold capabilities (McCann and Ortega-Argilés 2015; Stam 2015; Balland et al. 2019). In Brazil, the state of Rio Grande do Sul organised its innovation policy around eight regional innovation ecosystems, each with declared thematic priorities, and maintains a public registry of start-ups to monitor them. Whether start-ups actually locate where their sector's base is strong, however, is rarely tested directly, and the evidence available has three limitations.

First, most studies of start-up location estimate the effect of generic regional attributes, such as population, density, human capital or university presence, on the total number of new firms (Arauzo-Carod et al. 2010; Bonaccorsi et al. 2014). Generic attributes cannot tell whether a city attracts health start-ups because it has hospitals or simply because it is large, and cities with many hospitals also tend to have large universities, high incomes and dense labour markets. Second, when sectoral assets are examined, they are usually studied one industry at a time, which leaves open whether the same mechanism holds across sectors with different knowledge bases and market structures (Malerba 2002; Asheim and Coenen 2005; Celebioglu and Brenner 2026). Third, the evidence comes overwhelmingly from Europe, North America and East Asia (Hellwig 2024; Gao et al. 2026). Emerging economies, where productive capabilities are more territorially concentrated and higher education expanded rapidly, remain underexplored, and Brazilian studies of start-ups have focused on firm characteristics and survival rather than on location (Couto et al. 2022; Gonçalves et al. 2024).

This paper examines whether health, agricultural and information and communication technology (ICT) start-ups in Rio Grande do Sul locate where the productive base and the knowledge base of their own sector are stronger. I combine the state registry of start-ups with official municipal data on hospital beds, agricultural value added, ICT establishments and enrolment in on-campus higher education by field. The unit of analysis is the municipality, and the empirical strategy stacks the three sectors within each municipality and estimates a Poisson pseudo-maximum likelihood (PPML) model with municipality and sector fixed effects.

The paper makes three contributions. First, the within-municipality design separates sector-specific location factors from general urban attraction. Because the fixed effects absorb population, income, schooling and any other attribute that draws start-ups of every kind, the estimates answer a sharper question: within the same municipality, is the sector with the relatively stronger base also the sector with relatively more start-ups? Second, the paper compares two channels, industrial heritage and proximity to the productive base on one side and academic knowledge spillovers on the other, using parallel measures for three sectors with contrasting knowledge bases. Third, it provides evidence from a

Brazilian state with a public start-up registry and a regionalised innovation policy, which allows the results to speak to the assumptions of place-based policy in an emerging economy.

The results indicate that a one-standard-deviation stronger productive base is associated with 42% more start-ups of the same sector. The association is robust to the exclusion of the state capital, to broader sector definitions, to alternative measures of each base and to a negative binomial specification. Sector-specific higher education shows no independent association. The productive-base association, however, loses precision once region-by-sector fixed effects are introduced, which indicates that municipal and regional specialisation are closely intertwined.

The remainder of the paper is organised as follows. Section 2 reviews the mechanisms that link start-up location to sectoral assets and states the hypotheses. Section 3 describes the setting, the data and the empirical strategy. Section 4 presents the results, Section 5 discusses them and Section 6 concludes.

2 Background and hypotheses

2.1 Industrial heritage and the productive base

A long line of research shows that new firms are rarely footloose. Founders tend to start ventures in the region where they live and work, and ventures located in the founder's home region survive longer and perform better, largely because founders draw on local networks of customers, suppliers and collaborators (Dahl and Sorenson 2012). The industry-level counterpart of this regularity is industrial heritage. Spin-offs from incumbent firms inherit routines, technologies and market knowledge from their parents and locate close to them, which reproduces and deepens existing clusters (Klepper 2007; Buenstorf and Klepper 2009). In the medical device industry, for example, ventures founded by former employees of incumbents outperform other entrants, a sign that industry experience transfers valuable knowledge (Chatterji 2009).

Proximity to the productive base also matters for reasons unrelated to founders' origins. Start-ups that sell to hospitals, farms or software buyers benefit from access to users who test prototypes, provide feedback and become early customers. Industry-specific agglomeration generates input sharing, labour pooling and localised learning, and new firm births respond to nearby employment in the same industry and to the strength of related clusters (Rosenthal and Strange 2003; Delgado et al. 2010). Evolutionary economic geography frames these regularities as relatedness: regions diversify into activities that are technologically and cognitively close to those they already perform (Neffke et al. 2011; Boschma 2017). Start-ups are one of the channels through which such branching occurs.

These mechanisms may be particularly strong in emerging economies. Where venture capital, specialised intermediaries and dense professional networks are scarce outside a few metropolitan areas, founders depend more heavily on the organisations they know and on the customers within reach. In health, the hospital is simultaneously a source of clinical problems, a test site and the main buyer of many technologies. In agriculture, producers and cooperatives define the problems that agtechs address

and provide the first contracts. In ICT, local firms supply both experienced founders and early corporate clients. In each case the productive base offers the tacit, user-side knowledge that is hardest to acquire at a distance. These arguments lead to the first hypothesis.

H1. Within a municipality, the sector with a relatively stronger productive base has relatively more start-ups.

2.2 Knowledge bases and academic spillovers

The knowledge spillover theory of entrepreneurship offers a second channel. Knowledge created by universities and incumbents is only partially appropriated by the organisations that produce it, and entrepreneurship converts the remainder into new ventures (Acs et al. 2009). Because tacit knowledge travels poorly, the resulting firms tend to locate near its sources. Knowledge-based start-ups in Germany cluster near universities, and their number increases with the region's knowledge capacity and graduate output (Audretsch and Lehmann 2005; Audretsch et al. 2005). Italian evidence indicates that local university knowledge fosters the creation of knowledge-intensive firms, particularly in services (Bonaccorsi et al. 2014). In Brazil, the university environment is associated with students' entrepreneurial behaviour, although the association differs across regions (Rocha et al. 2021), and universities have been reorganising to support venture creation (Dalmarco et al. 2018). Recent regional research also portrays higher education as an infrastructure for innovation whose effects spread across space (Gao et al. 2026).

If academic spillovers are field-specific, start-ups should be relatively more numerous where higher education in their own field is stronger, over and above the productive base.

H2. Within a municipality, the sector with a relatively stronger knowledge base has relatively more start-ups.

H3. The productive base and the knowledge base remain associated with start-up location when considered jointly.

2.3 Sectoral heterogeneity

The two channels need not operate with equal strength in every sector. Sectoral systems of innovation differ in their knowledge bases, the actors involved and the importance of proximity to users (Malerba 2002). Analytical knowledge bases, typical of life sciences, rely on scientific research and codified knowledge, whereas synthetic knowledge bases, typical of engineering and much of ICT, rely on applied problem solving and interaction with customers (Asheim and Coenen 2005). Health start-ups depend on hospitals and clinical settings for validation and adoption. Agricultural technology ventures, often called agtechs, emerge from rural production systems but also from urban technology centres that serve them (Mikhailov et al. 2021; Ramos and Pedroso 2021). ICT start-ups can locate with fewer physical constraints but draw on pools of skilled labour and on digital clusters (Hellwig 2024). Recent evidence confirms that relationships between start-ups, specialisation and qualification vary substantially across

industries (Celebioglu and Brenner 2026). The pooled model therefore estimates average within-municipality associations, and sector-specific models describe how they vary.

The spatial scale at which these channels operate is a further source of heterogeneity. Heritage and user proximity may act within commuting distance of hospitals, farms or firms, while academic spillovers can travel further through graduate mobility and research collaboration. Estimates obtained at one administrative scale may therefore understate channels that operate at another, a concern that recent regional studies address by aggregating local data over functional areas (Celebioglu and Brenner 2026; Gao et al. 2026). The present analysis uses the municipality as its unit and examines the regional scale in a sensitivity analysis.

3 Setting, data and empirical strategy

3.1 Setting and start-up data

Rio Grande do Sul is Brazil's southernmost state, with 11.2 million inhabitants distributed across 497 municipalities. Its economy combines a diversified metropolitan region around Porto Alegre, an industrial corridor in the northeast and extensive agricultural areas in the west and north. Since 2019 the state innovation programme has organised policy around eight regional innovation ecosystems, and the state's start-up network maintains a public registry of start-ups associated with these ecosystems (SICT-RS 2026).

The registry contains 1,514 start-up records located in 101 municipalities, each with its municipality, a sector classification, target customers and a self-declared stage of development. The registry is not a census, and the date of each record is not reported, so the analysis describes the geography of registered start-ups rather than of all new firms. I retained start-ups classified as HealthTech (165), AgTech (123) and ICT (195), for a total of 483 start-ups in 61 municipalities. The stage of development is irrelevant to the outcome and records without it were kept. Records were linked to municipalities through the seven-digit code of the Brazilian Institute of Geography and Statistics (IBGE), and all 101 codes matched the official list without loss.

3.2 Productive and knowledge bases

For each sector, I constructed one measure of the productive base and one measure of the knowledge base from official sources (Table 1). The productive base of health is the number of inpatient hospital beds per 10,000 inhabitants in December 2025, from the National Registry of Health Establishments (CNES). The productive base of agriculture is the share of agriculture in municipal gross value added, averaged over 2019 to 2021 to smooth harvest shocks, from the IBGE municipal accounts. The sectoral breakdown of municipal value added is not available after 2021 because of the ongoing revision of the national accounts. The productive base of ICT is the number of local units in information technology and information services (divisions 62 and 63 of the Brazilian activity classification) per 10,000 inhabitants in 2024, from the IBGE Central Register of Enterprises (CEMPRE). The knowledge base of each sector is

enrolment in on-campus undergraduate programmes of the corresponding broad field of the International Standard Classification of Education (health and welfare; agriculture, forestry, fisheries and veterinary; ICT) per 10,000 inhabitants, from the 2024 Higher Education Census (INEP). Population estimates for 2025 serve as denominators.

Table 1
Start-ups and sectoral bases by sector, Rio Grande do Sul

Start-ups	HealthTech	AgTech	ICT
	165	123	195
Municipalities with at least one start-up	27	36	37
Share in Porto Alegre (%)	61.8	23.6	35.4
Herfindahl-Hirschman index	0.391	0.098	0.153
Effective number of municipalities	2.6	10.2	6.5
Productive base	Hospital beds per 10,000 inh. (Dec 2025)	Agricultural share of GVA, 2019–2021 (%)	ICT local units per 10,000 inh. (2024)
Municipalities with base > 0	237	497	312
Median (IQR) among municipalities > 0	35.0 (22.9–53.5)	36.0 (16.3–48.8)	4.0 (2.5–6.8)
Knowledge base	On-campus enrolment, health and welfare, per 10,000 inh.	On-campus enrolment, agriculture and veterinary, per 10,000 inh.	On-campus enrolment, ICT, per 10,000 inh.
Municipalities with base > 0	37	44	47
Median (IQR) among municipalities > 0	68.9 (30.8–95.0)	45.0 (23.3–79.8)	20.4 (13.4–35.1)
Sources: state start-up registry; CNES; IBGE (municipal accounts, CEMPRE, population estimates); INEP Higher Education Census 2024. GVA, gross value added; IQR, interquartile range.			

Because the three sectors are measured in different units and most distributions are strongly skewed with many zeros, each intensity was transformed with the inverse hyperbolic sine, which behaves like a logarithm for large values and accommodates zeros (Bellemare and Wichman 2020), and then standardised across the 497 municipalities within each sector. The resulting variables, P and K, express how strong a municipality’s base is relative to other municipalities in the same sector, in standard deviations.

3.3 Empirical strategy

The dataset stacks the 497 municipalities and the three sectors. Let n_{ms} be the number of start-ups of sector s in municipality m . The main specification is

$$\log E(n_{ms}) = \alpha_m + \gamma_s + \beta_P P_{ms} + \beta_K K_{ms} \quad (1)$$

where α_m are municipality fixed effects and γ_s are sector fixed effects. The model is estimated by PPML, which is consistent for count outcomes with many zeros under the sole assumption that the conditional mean is correctly specified (Santos Silva and Tenreiro 2006; Wooldridge 1999), and it is equivalent to a conditional logit model of location choice across municipality-sector alternatives (Guimarães et al. 2003). The municipality fixed effects absorb population, income, schooling, centrality, the presence of universities and any other attribute that attracts start-ups irrespective of sector. Identification therefore comes from differences in the sectoral composition of start-ups within municipalities. Municipalities without any start-up in the three sectors do not contribute to the likelihood and drop out (Correia et al. 2020), leaving 61 municipalities and 183 observations. Standard errors are clustered by municipality (Cameron and Miller 2015). Coefficients are reported as incidence rate ratios (IRR) per standard deviation with 95% confidence intervals. H1 and H2 were tested in separate models and H3 in the joint model.

The design rests on a simple comparison. Consider two municipalities of similar size and income, one with a regional hospital complex and few ICT firms and the other with the reverse profile. A model of total start-up counts would treat them as equivalent. The stacked model asks instead whether the first has relatively more health start-ups and the second relatively more ICT start-ups than their overall start-up activity would predict. Standardising each base within its sector makes this comparison meaningful across sectors measured in different units. The fixed effects do not remove sector-specific unobservables, such as regional programmes targeted at one sector, nor do they rule out reverse causality, and the estimates are interpreted as conditional associations.

As a complement, I estimated separate PPML models for each sector across all 497 municipalities, with log population, log mean household income per capita and the share of adults with a university degree (2022 Census) as controls, and heteroskedasticity-robust standard errors. Because health start-ups occur in only 27 municipalities, these models include no further covariates, and p values for the six coefficients of interest were adjusted with the Benjamini and Hochberg (1995) procedure. A secondary question compared the distribution of target customers across the three sectors with a chi-square test evaluated by 10,000 Monte Carlo permutations. The analysis plan, including all sensitivity analyses below, was registered in a dated protocol before any model linked start-up counts to municipal variables.

3.4 Sensitivity analyses

The main model was re-estimated (i) without Porto Alegre; (ii) with broader sector families that add biotechnology and medical technology to health, food technology to agriculture and deep tech, security and related digital verticals to ICT (620 start-ups in 73 municipalities); (iii) with region-by-sector fixed effects for the eight regional innovation ecosystems, which absorb regional sectoral specialisation; (iv)

with alternative bases, namely crop and livestock output per capita, beds in teaching hospitals, health-care establishments, ICT employment, enrolment including distance learning at the municipality of the learning centre and graduates instead of enrolment; (v) with percentile ranks instead of standardised values; (vi) without six possible duplicate records; and (vii) with a negative binomial model. Influence was assessed by re-estimating the joint model 61 times, omitting one municipality at a time.

4 Results

4.1 The sectoral geography of start-ups

The three sectors differ sharply in spatial concentration (Table 1). Health start-ups are the most concentrated: 61.8% are located in Porto Alegre, and the effective number of municipalities, the inverse of the Herfindahl-Hirschman index, is only 2.6. Agricultural start-ups are the most dispersed, with 23.6% in the capital and an effective number of 10.2 municipalities, while ICT start-ups occupy an intermediate position (35.4% and 6.5). The bases are equally uneven. Hospital beds exist in 237 municipalities, ICT establishments in 312 and on-campus programmes in each field in fewer than 50, whereas agriculture contributes to value added everywhere. Porto Alegre illustrates why a within-municipality comparison is needed: it has the largest stock of hospital beds, ICT establishments and on-campus enrolment in all three fields, yet an agricultural share of value added close to zero.

4.2 Within-municipality associations

The productive base was consistently associated with the sectoral composition of start-ups (Table 2). When entered alone, a one-standard-deviation stronger productive base was associated with 43% more start-ups of the same sector (IRR 1.43; 95% CI 1.21 to 1.69), which supports H1. The knowledge base, entered alone, showed a positive but imprecise association (IRR 1.16; 0.88 to 1.52), and H2 was not supported. In the joint model the productive-base estimate remained practically unchanged (IRR 1.42; 1.21 to 1.67), whereas the knowledge-base estimate fell to 1.02 (0.84 to 1.25). H3 was therefore supported only for the productive base. Omitting one municipality at a time produced productive-base IRRs between 1.39 and 1.63 and knowledge-base IRRs between 0.98 and 1.06. The largest productive-base estimate occurred when Porto Alegre was omitted.

Table 2
Within-municipality associations between sectoral bases and start-up counts (PPML)

Productive base (P)	Model 1	Model 2	Model 3
	1.43 (1.21–1.69)		1.42 (1.21–1.67)
Knowledge base (K)		1.16 (0.88–1.52)	1.02 (0.84–1.25)
Municipality fixed effects	Yes	Yes	Yes
Sector fixed effects	Yes	Yes	Yes
Observations (municipalities)	183 (61)	183 (61)	183 (61)
Incidence rate ratios per within-sector standard deviation, with 95% confidence intervals based on standard errors clustered by municipality. Municipalities without start-ups in the three sectors do not contribute to the likelihood.			

4.3 Robustness

Figure 1 summarises the sensitivity analyses. The productive-base association remained positive, with confidence intervals above one, when Porto Alegre was excluded (IRR 1.63; 1.31 to 2.03), with the broader sector families (1.36; 1.17 to 1.59), with crop and livestock output as the agricultural base (1.33; 1.18 to 1.50), with health-care establishments (1.47; 1.25 to 1.72) or ICT employment (1.45; 1.22 to 1.72), with alternative knowledge measures, without possible duplicates and under the negative binomial specification (1.57; 1.29 to 1.91). The estimate was weaker, though still positive, when the health base was restricted to teaching-hospital beds (1.15; 1.02 to 1.30). The percentile-rank specification yielded the same conclusion on a different scale (IRR for the full range 20.2; 2.9 to 140.3). The knowledge base never departed meaningfully from one.

The only specification that changed the inference was the one with region-by-sector fixed effects. The productive-base IRR fell to 1.18 (0.80 to 1.75) and the knowledge-base IRR was 1.10 (0.87 to 1.39). This specification adds 14 parameters to a model identified by 61 municipalities, and the wider interval partly reflects lost precision. The drop in the point estimate, nevertheless, shows that much of the municipal association coincides with differences in sectoral specialisation between regions.

4.4 Sector-specific models and market orientation

The sector-specific models, which compare municipalities rather than sectors within municipalities, were less informative (Table 3). After adjustment for population, income and schooling, the productive base showed positive but imprecise associations for ICT (IRR 1.87; 0.94 to 3.71) and agriculture (1.29; 0.94 to 1.78) and no association for health (0.86; 0.40 to 1.85), a sector in which the capital dominates the distribution. The knowledge base was associated with the location of ICT start-ups (IRR 1.45; 1.19 to 1.77; adjusted $q = 0.002$) but not with the other two sectors.

Table 3
Sector-specific associations across the 497 municipalities (PPML)

Sector	Productive base (P)	Knowledge base (K)	Municipalities with start-ups
HealthTech	0.86 (0.40–1.85); q = 0.70	1.09 (0.86–1.38); q = 0.59	27
AgTech	1.29 (0.94–1.78); q = 0.23	1.08 (0.87–1.35); q = 0.59	36
ICT	1.87 (0.94–3.71); q = 0.22	1.45 (1.19–1.77); q = 0.002	37
Incidence rate ratios per standard deviation with 95% confidence intervals based on heteroskedasticity-robust standard errors. All models control for log population (2025), log mean household income per capita and the share of adults aged 25 or older with a university degree (2022 Census). q, p value adjusted by the Benjamini and Hochberg procedure across the six coefficients.			

The distribution of target customers also differed across sectors ($\chi^2 = 47.8$, 6 degrees of freedom, Monte Carlo $p < 0.001$; Cramér's $V = 0.22$; $n = 474$). Business-to-business models predominated in ICT (74%), whereas business-to-business-to-consumer models were most common in health (34%). The odds of a consumer-oriented model, adjusted for region and location in the capital, did not differ precisely across sectors (health versus ICT, odds ratio 1.93; 0.94 to 3.94).

5 Discussion

Health, agricultural and ICT start-ups in Rio Grande do Sul tend to be relatively more numerous where the productive base of their own sector is stronger, and this regularity holds after every attribute that attracts start-ups in general has been absorbed. The magnitude is substantial. Moving from the median municipality to one a standard deviation above it in the sector's own base corresponds to roughly two-fifths more start-ups of that sector, holding the municipality's overall attractiveness fixed. The finding is consistent with the view that new ventures emerge from and near the industries they serve, through spin-offs, founders' prior experience and proximity to early users (Klepper 2007; Buenstorf and Klepper 2009; Dahl and Sorenson 2012; Chatterji 2009). It also echoes evidence that new firm formation responds to industry-specific agglomeration and cluster strength (Rosenthal and Strange 2003; Delgado et al. 2010).

The absence of an independent association for the knowledge base deserves careful interpretation. It does not show that universities are irrelevant for start-ups. On-campus programmes in any of the three fields exist in only 65 municipalities, and 42 of them offer programmes in at least two fields, so the knowledge measures largely capture whether a municipality hosts a higher education centre at all. The municipality fixed effects absorb that common component, and what remains is the relative weight of each field, which may be too weak a signal to detect a field-specific spillover. Knowledge spillovers may also operate at a scale larger than the municipality, as students and graduates move between cities (Gao et al. 2026), or through the productive base itself, since teaching hospitals and agricultural research centres are both productive and academic institutions. The sector-specific result for ICT, where the

knowledge base was associated with location across municipalities, fits the view that synthetic, skills-based knowledge bases depend closely on local pools of graduates (Asheim and Coenen 2005). Overall, the results are more consistent with heritage and user proximity than with field-specific academic spillovers as the channel linking sectoral assets to start-up location in this setting (Acs et al. 2009; Audretsch et al. 2005; Bonaccorsi et al. 2014).

This pattern is not unique to Brazil. In German cities, the presence of research institutes and universities had mixed associations with the birth of digital firms, whereas proximity to similar firms was consistently associated with it (Hellwig 2024). The Brazilian setting may nonetheless sharpen the contrast. In Rio Grande do Sul, private institutions held 82% of undergraduate enrolment in 2024 and distance learning accounted for 58%, according to the census data used here, and links between universities and firms remain uneven despite recent efforts to build entrepreneurial universities (Dalmarco et al. 2018). Under these conditions, the number of students enrolled in a field is a weak proxy for the flow of commercially relevant knowledge, while hospitals, agricultural producers and ICT firms are direct sources of problems, experience and demand.

The sectoral differences in concentration are also informative. Health start-ups are concentrated in Porto Alegre, where the state's largest hospital complexes and teaching hospitals are located, and agricultural start-ups are the most dispersed, in line with a productive base that spreads across the interior. The spatial distribution of each sector therefore mirrors the distribution of its own users. The within-municipality estimates show that this correspondence is not an artefact of city size, since the capital's attraction is absorbed by its fixed effect and the association strengthened when it was excluded.

The loss of precision under region-by-sector fixed effects qualifies the main result. Sectoral bases are spatially autocorrelated: agricultural value added is high across entire regions, and health and ICT infrastructure concentrate around a few regional centres. Once each region's sectoral specialisation is absorbed, little independent municipal variation remains. Two readings are compatible with the data. Start-ups may respond to sectoral assets at the scale of the regional economy rather than the municipality, or the regional innovation ecosystems may have partly shaped where start-ups of each sector register. Distinguishing these readings requires longitudinal data on entry and on exposure to regional programmes, which the registry does not yet provide.

These findings bear on place-based policy. Programmes that aim to seed start-ups in sectors where a territory has no productive base face an uphill task, whereas programmes that connect ventures with existing hospitals, agricultural producers and technology firms work with the grain of observed location patterns (Barca et al. 2012; McCann and Ortega-Argilés 2015). The evidence also cautions against equating a strong university presence with a sectoral entrepreneurial advantage. Ecosystem policies may gain from involving incumbent firms and service providers as sources of founders and first customers, in addition to universities (Stam 2015; Brown and Mason 2017). In Brazil, where health and agricultural capabilities are unevenly distributed and start-up support has multiplied at the state and municipal

levels, aligning support with the productive base appears more consistent with the observed geography than dispersing it evenly across sectors.

6 Conclusions

This paper tested whether start-ups locate where the productive and knowledge bases of their own sector are stronger, using a within-municipality design that separates sectoral assets from general urban attraction. In southern Brazil, health, agricultural and ICT start-ups follow the productive base of their sector, whereas field-specific higher education shows no independent association. The municipal association overlaps with regional specialisation and loses precision once regional sectoral patterns are absorbed.

The study has limitations. The registry is a cross-sectional list of registered start-ups rather than a census of new firms, and its records carry no date, so the estimates describe associations in the stock of registered ventures and cannot establish that sectoral bases cause start-up formation. Reverse causality is possible, as successful ventures may expand the local base, although the size of hospitals, farms and ICT employment relative to the start-ups makes this channel unlikely to dominate. The measures of each base are proxies, the knowledge measures are sparse, and only 61 municipalities contribute to the within-municipality estimates. The results refer to one Brazilian state and three sectors. Future research should follow start-ups over time with dated entries, link founders to their previous employers and universities to observe heritage and spillovers directly, extend the analysis to functional regions and other states, and assess whether regional innovation programmes have altered the sectoral geography of new ventures.

Declarations

Author Contribution

RRB conceived and designed the study, defined the research questions and the analysis protocol, was responsible for data acquisition, directed and supervised the statistical analysis, interpreted the results, critically revised the manuscript for important intellectual content, approved the final version and agrees to be accountable for all aspects of the work.

Data Availability

The data are available upon request.

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Figures

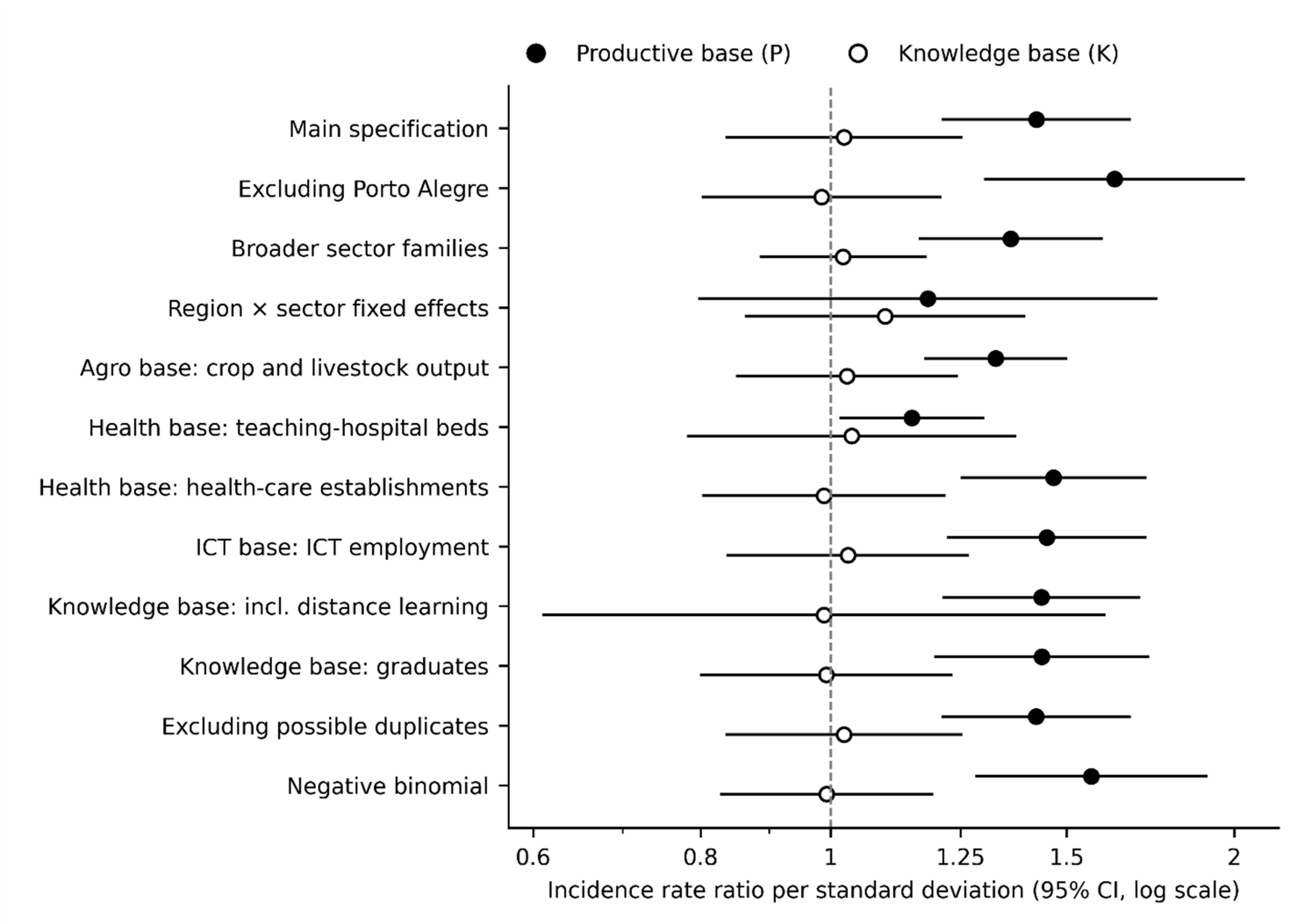


Figure 1

Sensitivity of the within-municipality associations. Incidence rate ratios per within-sector standard deviation and 95% confidence intervals for the productive base (filled circles) and the knowledge base (open circles) under alternative specifications. All models include municipality and sector fixed effects; the region-by-sector specification adds fixed effects for each of the eight regional innovation ecosystems interacted with sector. The percentile-rank specification is reported in the text because its scale differs.