ADAPTIVE LANDSCAPES: A CONFIGURATIONAL ASSESSMENT OF SECTORAL PATTERNS IN US ENTREPRENEURIAL ECOSYSTEMS

-EXTENDED ABSTRACT-

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1. INTRODUCTION

Entrepreneurial Ecosystems (EE) emerged as an analytical lens that dedicate attention to the contextual embeddedness of entrepreneurial activity across the geographical space (Cohen, 2006; Isenberg, 2011; Mason & Brown, 2014; Stam, 2015). Its influence has gone beyond academia and has garnered the interest of policymakers worldwide concerning ways of shaping place-based initiatives targeting the promotion of productive entrepreneurship as a conduit for regional development (Leendertse et al., 2022; Stam & van de Ven, 2021). In this vein, EE are understood as regional "bundles" of institutional arrangements, resource endowments, and their respective interactions as a way to nurture the emergence of new firms. Such background offered a framework that comprehends key parameters from economic geography with some coarse-grained causation mechanisms (Fischer et al., 2024). Yet, as literature in the field evolved, a growing number of

criticisms emerged concerning the static nature of typical EE models and their incapacity of explaining the dynamics of places outside the reality of some highly eminent examples (Brown & Mason, 2017; Harrison, 2025; Kuckertz, 2019). From an analytical standpoint, these criticisms were echoed by several empirical assessments dealing with the causal complexity of EE in the sense that "ideal" configurations are the exception rather than the rule across the most successful EE (Bennett et al., 2025; Cherubini Alves et al., 2021; Komlósi et al., 2024; Schrijvers et al., 2024; Torres & Godinho, 2022).

In addition to this configurational debate – or *complementary* to it – we ought to highlight that EE literature has established a tradition of sectoral agnosticism (Spigel, 2022). The underlying idea is one of not ascribing the role of contextual elements any specific industrial orientation. This has caused a departure from principles of complexity economics typically addressed in Evolutionary Economic Geography through elements of related and unrelated variety of industrial structures (e.g. Neffke et al., 2011; Rigby, 2015; Xiao et al., 2018). By not focusing on any specific factors, EE scholars have remained mostly unable to identify how specific dimensions can coalesce (or fail to) in driving new firms in different sectors – a feature that might be particularly relevant to understand how to enable place-based initiatives targeting the most promising economic activities in terms of spurring regional development (Fischer et al., 2026). In this vein, we derive our overarching research question: How are EE elements configured in order to generate entrepreneurial activity across different industries? Our expectation in this regard is to find different configurational patterns associated with levels of entrepreneurial activity in different sectors, thus shedding new light on the interplay between regional economic structures and dynamics of new firm emergence.

From an empirical perspective, we examine a sample of 872 Core-Based Statistical Areas (CBSAs) in the United States across three five-year panels (2009–2013, 2014–2018, 2019–2023). Entrepreneurial growth is measured using new establishment counts from the Business Dynamics Survey, overall and by industry, and also by normalized counts of each region's awards from the Small Business Innovation Research (SBIR) program. EE dimensions are measured through seven conditions that approximate typical EE models (e.g. Stam & van de Ven, 2021; Stam, 2015). We analyze the relationship between the seven conditions and regional entrepreneurship to derive an *Ecosystem Readiness Score*, a novel technique to estimate the stability of EE configurational components underpinning entrepreneurial success in different industries.

Here, it is important to highlight that our panel-based assessment allows a pioneering effort in the EE field to build a *longitudinal appraisal of configurations* in these regional productive structures. Thus, we tackle the issue of looking at EE as static phenomena. Rather, we rely on the view that EE are manifestations of *Complex Adaptive Systems (CAS)*, thus likely demonstrating structural shifts as a response to endogenous and exogenous factors (Napoli et al., 2026; Haarhaus et al., 2020). This will allow our empirical exercise to observe not only the configurations that emerge and affect new business formation rates in the United States, but also how they adapt over time as a function of their complex and evolutionary nature. From these empirical insights, we derive a synthetic index of Ecosystem Readiness that represents the consistency of EE elements to nurture entrepreneurship across industries over time.

2. ENTREPRENEURIAL ECOSYSTEMS: A STRUCTURALIST PERSPECTIVE

Entrepreneurial Ecosystems can be understood as "*a set of interconnected entrepreneurial actors […], entrepreneurial organisations […], institutions […]and entrepreneurial processes […]which formally and informally coalesce to connect, mediate and govern the performance within the local entrepreneurial environment*" (Mason & Brown, 2014; p. 5). The variety of agents, resources and institutions who "*formally and informally coalesce*" is essential to define the systemic nature of EE. It is also important to highlight that EE consist of a "*local entrepreneurial environment*". In this respect, literature has long recognized the existence of a highly concentrated geography of

entrepreneurship, thus mirroring other socioeconomic processes (Brown & Mason, 2017). This is attached to the notion that spatial proximity enables easier access to tangible and intangible resources that are necessary for new businesses to emerge (Acs et al., 2017), a situation that has not been significantly altered by increasing levels of digitalization (Sternberg, 2022; Audretsch et al., 2019; Sussan & Acs, 2017).

Because of its analytical focus on the role of regional context, the trajectory of the EE literature has been intertwined with structuralist approaches dealing with the quest for identifying the most relevant and consistent set of influential dimensions leading to high rates of productive entrepreneurship (following the flexible notion of "desirable" entrepreneurship proposed by Baumol, 1996). Although competing frameworks exist (e.g. Spigel, 2017), the dominant model for structural appreciation of EE is that of Stam (2015), later refined in (Stam & van de Ven, 2021). In essence, the model (Stam, 2015) builds on two pillars: Framework and Systemic conditions. Framework conditions comprehend elements associated with Formal Institutions, Culture, Physical Infrastructure, and Demand. Systemic conditions include Networks, Leadership, Finance, Talent, Knowledge, and Support Services (intermediaries).

Notwithstanding its role in providing a clear roadmap for empirical research, this model has faced increasing criticism due to its lack of adherence to empirical data. In this respect, the use of methods aligned with principles of causal complexity has generated results that suggest equifinal patterns in terms of entrepreneurial output in regions demonstrating variegated structural profiles (e.g. Bennett et al., 2025; Cherubini Alves et al., 2021; Komlósi et al., 2024; Schrijvers et al., 2024; Torres & Godinho, 2022). In other words, this means that regions can reach similar levels of entrepreneurial output (new firm formation) while displaying different patterns of availability of specific elements associated with Stam's (2015) Framework and Systemic Conditions. Hence, it appears that EE structural features are not a regularity. In addition to that, scholars have raised concerns about the static nature of these models (Alvedalen & Boschma, 2017; Audretsch et al., 2022; Cao & Shi, 2021; Theodoraki et al., 2022), which implicitly assumes temporal isomorphism or the existence of predictable life-cycle stages along evolutionary trajectories. While some studies have taken up the challenge of looking into EE as Complex Adaptive Systems (Napoli et al., 2026; Haarhaus et al., 2020), to the best of our knowledge, no structural appraisal of EE has made a similar effort. In this respect, we remain mostly restricted to inductive insights which do not appear to be transferable to broad sample of regions (e.g. Mack & Mayer, 2016).

2.1 Sectoral Agnosticism and the Configuration of Entrepreneurial Ecosystems

EE literature has traditionally adopted a sector-agnostic perspective about the definition of productive entrepreneurship (Spigel, 2022). This is justified by an interest in establishing a view of entrepreneurial activity that is not restricted to individual industries. Yet this lax appraisal of the interplay between EE structural features and their respective levels of entrepreneurial output neglects that intrinsic connection between these two properties of regions (Fischer et al., 2024). In other words, specific structural traits of EE can likely be more (less) relevant for specific industries. This has emerged from observations from the case of ecosystems that appear to operate as "nested" structures within the same region, with little integration between them and sustaining multiple social clusters (Spigel, 2022; Neumeyer & Santos, 2018).

These features appear to be engrained in the evolutionary dynamics of regions. Fischer et al. (2026), for example, identify the existence of different patterns of growth, stagnation, and decline across regions and sectors in the United States, outlining the existence of highly heterogeneous trends. This is a feature typical of the complex co-evolutionary interconnectedness of natural ecosystems and the species that inhabit them – a metaphor also valid for the sector-region association as demonstrated in Yang et al. (2026). Hence, drawing from this background, our argument is that the existence of specific sets of configurational elements in a given region will affect all types of productive

entrepreneurship in a similar manner. Bennet et al. (2025) have illustrated this for a comparison between high-growth new firms and rates of new venture creation in general – there is a very marginal overlap when looking at possible configurational structures among these two definitions. This situation creates the expectation that upon a higher level of sectoral granularity, larger differences may emerge and help us understand the regional capacity of sustaining diversified or specialized industries (O'Connor & Audretsch, 2022; Auerswald & Dani, 2022; Boschma, 2021). These are critical issues when looking at the evolutionary trajectory of EE as such sectoral elements shape the adaptive capacity of regions to nurture the emergence of new industries due to the necessary "packages" of capabilities and resources available (Cho et al., 2022; Ortega-Argilés, 2022; Fotopoulos, 2023; Fritsch & Kublina, 2018).

3. METHOD

To address our research question, our spatial analytical scope analyzes data for regions of the U.S. using Core-Based Statistical Areas (CBSAs). The sample encompasses 872 CBSAs — Metropolitan Statistical Areas (MSAs, urban core ≥ 50,000) and Micropolitan Statistical Areas (μSAs, 10,000–49,999) — across three five-year panels (2009–2013, 2014–2018, 2019–2023). Including μSAs is methodologically consequential: it tests whether configurations identified in large metropolitan areas generalize to resource-constrained contexts, a question invisible in MSA-only samples. Outcomes are per-capita new establishment counts across 19 industries (by two-digit NAICS code) and two aggregate proxies of entrepreneurial activity manifested at the regional level (SBIR awards and New Business Starts). Seven conditions operationalize regional structural dimensions that, theoretically, facilitate entrepreneurial activity. Specifically, we build proxies based on Stam and van de Ven (2021) and Fischer et al. (2024) that allow a comprehensive coverage of EE components while retaining parsimony in estimations. In order to keep some degree of comparability with previous research on the topic dealing with the US case, we have made an effort to generate data based on similar specifications for the US case (Bennett et al., 2025; Vedula & Fitza, 2019). These variables are described in Table 1.

EE Dimensions	Variable	Description	Source
EE output	SBIR	SBIR Award Count (all awards in Phase 1 and 2) per capita	Small Business Administration
	New Business Starts	New Business Starts per capita	Census
	BDS Establishments by Sector (19 sectors)	Establishment count per 100,000 inhabitants across 19 NAICS sectors: Logging (11), Mining (21), Utilities (22), Construction (23), Manufacturing (31–33), Wholesale Trade (42), Retail Trade (44–45), Transportation (48–49), Information (51), Finance & Insurance (52), Real Estate (53), Professional Services (54), Management (55), Administrative Services (56), Education (61), Health Care (62), Arts & Entertainment (71), Accommodation & Food (72), and Other Services (81)	U.S. Census Bureau – Business Dynamics Statistics (BDS)
Culture (entrepreneurship)	Self-employment	Self-employment and employment income per household in firms under 10 years of age or under 10 employees.	American Community Survey
Leadership	Advanced Industries	Knowledge and Technology Intensive (KTI) Industry Establishments as a Percentage of All Establishments[1].	Bureau of Labor Statistics - Quarterly Census of Employment and Wages
Finance	Funding rounds	Total number of deals per capita involving risk capital investment in early-stage companies within the MSA.	Crunchbase
New knowledge	Patents	Patents Filed per capita (Fractional Count).	USPTO
Talent	Stem PhDs	PhDs per capita in STEM fields.	Integrated Postsecondary Data System

[1] The definition of advanced industries is based on the National Center for Science and Engineering Statistics' classification of Knowledge- and Technology-Intensive (KTI) Industries.

Demand	Income level	Income per capita.	Bureau of Economic Analysis
Infrastructure	Population density	Population per square mile.	National Computational Infrastructure

Table 1. Analytical variables and corresponding EE dimensions. All data available for the 2009-2023 period.

Within an ecosystemic paradigm (Yang et al., 2026), no single condition drives outcomes independently; rather, the simultaneous presence and absence of multiple structural attributes jointly produce entrepreneurial activity, and multiple distinct combinations can lead to the same outcome (Stam & van de Ven, 2021; Fischer et al., 2024). This theoretical architecture is fundamentally incompatible with regression-based methods, which decompose outcomes into additive, symmetric net effects and assume that the contribution of one variable is independent of the values of all others[2]. Fuzzy-set Qualitative Comparative Analysis (fsQCA; Ragin, 1987, 2008) is purpose-built for this logic: it identifies which combinations of conditions are sufficient or necessary for an outcome, accommodates equifinality — multiple pathways leading to the same result — and treats causal asymmetry as a structural feature rather than a nuisance.

In fsQCA, conditions and outcomes are calibrated onto the [0, 1] interval as fuzzy sets, where a score of 0.95 denotes full membership, 0.50 maximum ambiguity (the crossover point), and 0.05 full non-membership. We calibrate all seven conditions via the direct method (Ragin, 2008) using within-period empirical percentiles — the 10th, 50th, and 90th — as anchors. This choice is imposed by the sample's heterogeneity: the distribution of structural attributes spans rural μSAs with thin labor markets and dense metropolitan innovation hubs. Fixed external thresholds would collapse meaningful variation across this range, incorrectly assigning full non-membership to entire strata of the distribution (Krogslund et al., 2017). Recalibrating within each five-year period further prevents the artificial inflation of consistency scores that would arise from pooling across periods with different marginal distributions. Sufficient configurations are identified by Boolean minimization of the truth table (Quine-McCluskey algorithm; Dusa, 2019) with inclusion threshold 0.70, PRI $\geq$ 0.50, and minimum case frequency of 5; necessary conditions require inclusion $\geq$ 0.90 (Schneider & Wagemann, 2012).

Despite these strengths, fsQCA faces well-documented limitations that, left unaddressed, compromise the validity of any configurational claim. Arel-Bundock (2022) demonstrates a 'double bind' of researcher degrees of freedom: the same flexibility that makes fsQCA powerful — in calibration, truth table construction, and minimization — renders its outputs sensitive to a cascade of analytic choices that are rarely made transparent or tested. Baumgartner and Thiem (2020) show that the standard treatment of logical remainders systematically introduces spurious configurations into parsimonious solutions, particularly in large truth tables where simplifying assumptions are empirically unverifiable. Krogslund et al. (2017) document how small perturbations to calibration anchors generate substantively different solutions, making confirmation bias a structural risk. Most consequentially for this field, Rönkkö et al. (2025), reviewing fsQCA, find that the overwhelming majority fail to adequately test robustness — a conclusion that places the evidential base of configurational entrepreneurship research in a precarious position. Our methodological design responds to each of these critiques.

3.1 Sample-Replication Robustness

To address the sensitivity concerns raised in literature (Arel-Bundock,2022; Baumgartner and Thiem, 2020; Krogslund et al. 2017), we implement a resampling protocol grounded in a principle well-established in statistical inference: that a finding which is genuine should be recoverable from

[2] Although the introduction of moderating effects can partially solve this issue, it still falls short of offering a conjunctural picture based on the emergence of configurations of elements.

repeated subsamples of the data (Efron, 1979; Efron & Tibshirani, 1993). In econometrics, this logic underlies both the nonparametric bootstrap — which repeatedly resamples the observed data to approximate the sampling distribution of an estimator (Horowitz, 2001) — and the deletion diagnostics of influential-observation analysis (Cook & Weisberg, 1982), where the stability of parameter estimates under case removal serves as a diagnostic for their reliability. Cross-validation, a closely related tradition in predictive modeling (Arlot & Celisse, 2010), extends this logic by testing whether model structure identified on one partition of the data generalizes to held-out partitions. The common thread is that analytic outputs that collapse under moderate, random perturbation of the sample cannot be trusted as genuine data-generating features.

We operationalize this principle as follows. Across 1.000 iterations, 10% of panel observations are randomly removed without replacement, and the entire fsQCA pipeline — including recalibration of all conditions on the subsample's empirical distribution, truth table reconstruction, and Boolean minimization — is re-executed. This is a critical design choice: robustness tests that perturb only the minimization stage leave calibration and truth table construction — precisely the stages where Krogslund et al. (2017) and Arel-Bundock (2022) locate the most consequential researcher degrees of freedom — entirely unchallenged. Each configuration's survival frequency across iterations — the proportion of subsamples for which it appears in the minimized solution — is used to classify findings as robust (frequency ≥ 0.80), conditionally robust (0.50–0.80), or non-robust (< 0.50). An identical resampling procedure is applied to necessity analysis, recording the proportion of subsamples for which each condition satisfies the necessity inclusion threshold of 0.90. Only conditions that meet this stability criterion in at least 80% of iterations are reported.

Every sufficient configuration and necessary condition reported in this study simultaneously satisfies four independent criteria: pooled consistency ≥ 0.70, PRI ≥ 0.50, resampling survival frequency ≥ 0.80 across 1.000 trials, and temporal generalizability (see the analytical strategy for Panel Diagnostics below). This four-criterion standard is, to the best of our knowledge, the most demanding applied in any large-N panel fsQCA study of entrepreneurial activity on a regional scale within a set theoretical perspective.

3.2 Panel Diagnostics

A further limitation, rarely acknowledged, is that cross-sectional and even pooled fsQCA cannot assess whether identified configurations are stable structural relationships or temporal artifacts of the observation window. This is a critical issue when considering that the configurational nature of EE across regions is increasingly perceived as a manifestation of Complex Adaptive Systems' properties and dynamics (Fischer et al., 2024). In this respect, the combination of elements at any given point in time is not – at least necessarily – constant over time. In fact, a key criticism of conceptual EE models resides in its static nature (Alvedalen & Boschma, 2017; Audretsch et al., 2022; Cao & Shi, 2021). We tackle this gap in literature through the panel set-theoretic framework of Garcia-Castro and Ariño (2016), operationalized by Bhattacharya (2023), which decomposes solution performance along three independent axes. Pooled consistency (POCONS) and pooled coverage (POCOV) aggregate performance across all CBSA–year observations in a period, providing the headline estimate. Two additional diagnostics, absent from the vast majority of published large-N fsQCA work (Wagemann et al., 2016), disaggregate this picture. BECONS measures temporal stability as the share of calendar years within the panel for which year-specific consistency meets the standard threshold:

$$BECONS = \frac{\left| t \in T_p : CONS_t(C \subseteq Y) \geq 0.70 \right|}{\left| T_p \right|} \quad (1)$$

A configuration with BECONS = 1.00 meets the consistency threshold in every year of the panel — strong evidence that the relationship is structurally stable rather than driven by a few temporally proximate observations. WICONS performs the analogous decomposition at the case level, measuring the share of CBSAs for which case-specific consistency holds across their longitudinal trajectories:

$$WICONS = \frac{|i \in scriptC: CONS_i(C \subseteq Y) \geq 0.70|}{|scriptC|} (2)$$

Cases with low WICONS are those that switch configurations across the observation window — a substantively important finding identifying regions undergoing ecosystem transformation. Together, BECONS and WICONS provide a characterization of configurational robustness that is structurally unavailable in cross-sectional designs.

3.3 Ecosystem Readiness Score

To translate set-membership into a continuous measure of regional configurational alignment, this study proposes the Ecosystem Readiness Score (ERS) — a metric that captures how closely a regional entrepreneurial ecosystem approximates the empirically sufficient conditions for the outcome of interest. This is based on a novel way of synthesizing fsQCA information drawn from the sets of combinations across regions, sectors, and time. Its value resides in generating a simple metric that captures the consistency of EE structural properties in driving specific output specifications. However, this should not be taken as a ranking tool. Rather, it performs the role of a diagnostic tool oriented towards capturing the capacity of EE features to reach their goal of fostering a nurturing environment for new firms to emerge.

Unlike conventional composite indicators, the ERS is grounded in the set-theoretic principle of conjunctural causation: what matters is not whether individual conditions are present in isolation, but whether they co-occur in the specific combinations that fsQCA identifies as sufficient. A CBSA that closely matches a validated sufficient configuration score high on the ERS regardless of its average condition level, making the index sensitive to structural alignment rather than mere attribute accumulation.

Formally, for each CBSA *i* × year *t* observation, membership in configuration *k* is the minimum across its constituent condition memberships — following the standard set-theoretic intersection operator — averaged across the KbK_b Kb configurations recovered in iteration *b*, then averaged across all NiN_i Ni panel observations for that CBSA. Critically, the configurations {Ck(b)}\{C_k^{(b)}\} {Ck(b)} are recovered by re-executing the full fsQCA pipeline on a randomly drawn subsample in each iteration *b*, but applied to score all CBSAs on the complete calibrated dataset. The final robust ERI is the mean of these iteration-specific estimates across all B=1,000B = 1{,}000 B=1,000 iterations:

$$ERI_i = \frac{1}{B}\sum\frac{1}{N_i}\sum\frac{1}{K_b}\sum mu_k^{(b)}(i,t) (3)$$

where $mu_k^{(b)}(i,t)$ denotes the fuzzy membership of CBSA *i* in year *t* in configuration *k* as recovered in iteration *b*. A companion baseline ERI is computed from the full-sample solution. The coefficient of variation (CV) of the ERI across iterations serves as a stability diagnostic: high mean ERI with low CV signals consistent configurational alignment; high mean paired with high CV signals sensitivity to the subsample used in minimization. Computed for every CBSA × sector × period cell, the ERI enables cross-sector readiness profiles, within-sector CBSA rankings, and cross-period alignment trajectories.

In aggregate, the full estimation procedure — 872 CBSAs × 19 sectors × 3 periods × 1,000 resampling iterations, each re-executing calibration, truth table construction, Boolean minimization, and ERS values — required approximately 49.8 million individual pipeline executions, making this, to the best

of the authors' knowledge, the most computationally intensive application of set-theoretic methods in the entrepreneurship literature.

4. PRELIMINARY RESULTS

Necessity analysis yields a consistent null across all period–outcome combinations: no condition achieves the necessity stability threshold in any sector or period, confirming the equifinal nature of regional entrepreneurial activity — no single structural attribute is an indispensable prerequisite for firm formation. For sufficiency, New Business Starts exhibit an expanding configurational landscape — 3 robust paths in 2009–2013, growing to 5 in 2014–2018 and 7 in 2019–2023 — alongside declining temporal stability (BECONS: 1.00 → 0.80 → 0.60). More viable pathways to entrepreneurial activity are available across US urban economies over time, but each is less stable year-to-year, consistent with rising structural heterogeneity and configuration churning in the post-2014 period.

Table 1 presents mean ERS by sector, averaged across all 872 CBSAs and three periods. Mean ER rises from 0.176 (P1) to 0.201 (P3), with a right-skewed distribution in all periods. Three substantive patterns emerge. First, sectoral heterogeneity is substantial: Other Services (0.303) and Construction (0.285) exhibit the most geographically distributed sufficient configurations, while Information (0.119) and Logging (0.076) remain the most structurally restrictive — sufficient configurations in these sectors require a density of complementary assets concentrated in large metros. Second, no metro holds a stable top position across all sectors and periods, confirming that ecosystem–sector alignment is dynamic. Third, the MSA–μSA gap is structurally heterogeneous: in Manufacturing, university-adjacent μSAs such as Elkhart-Goshen IN nearly match leading MSAs; in Education, Ames IA reaches ER = 0.44 — above the MSA mean — reflecting anchor-institution effects. By contrast, in Finance & Insurance and Information the gap is wide and persistent.

Table 1. Ecosystem Readiness Score by sector: average ERS, cross-period change, and leading areas.

Sector (NAICS)	Avg ERS	Δ ERS P1→P3	Leading MSA (ERS)	Leading μSA (ERS)
81 — Other Services	0.303	+0.031	Boston MA (0.82)	Ames IA (0.41)
23 — Construction	0.285	+0.027	Minneapolis MN (0.79)	Bozeman MT (0.38)
62 — Health Care	0.256	+0.022	Boston MA (0.76)	Blacksburg VA (0.35)
56 — Admin & Support	0.213	+0.018	Washington DC (0.74)	Ames IA (0.31)
54 — Prof. & Sci. Serv.	0.212	+0.024	San Jose CA (0.77)	Bozeman MT (0.36)
53 — Real Estate	0.210	+0.015	New York NY (0.71)	Hilton Head SC (0.29)
72 — Hotels & Food	0.193	+0.019	Austin TX (0.72)	Steamboat Springs CO (0.33)
31-33 — Manufacturing	0.181	+0.008	Pittsburgh PA (0.69)	Elkhart-Goshen IN (0.37)
52 — Finance & Insurance	0.165	+0.011	New York NY (0.73)	Ames IA (0.26)
44-45 — Retail Trade	0.145	+0.014	Los Angeles CA (0.62)	Bozeman MT (0.24)
71 — Arts & Entertainment	0.144	+0.013	New York NY (0.68)	Steamboat Springs CO (0.38)
48-49 — Transportation	0.132	+0.009	Memphis TN (0.61)	Elkhart-Goshen IN (0.28)
42 — Wholesale Trade	0.130	+0.007	Los Angeles CA (0.59)	Holland-Zeeland MI (0.25)
61 — Education	0.128	+0.016	Boston MA (0.67)	Ames IA (0.44)
51 — Information	0.119	+0.018	San Francisco CA (0.71)	Bozeman MT (0.27)
11 — Logging	0.076	+0.003	Portland OR (0.38)	Wenatchee WA (0.29)

Note: Avg ERS = mean robust Ecosystem Readiness Score across all 872 CBSAs and three periods. Δ ERS = change P1 (2009–13) → P3 (2019–23). ERS averaged over 999 resampling iterations (Eq. 3). MSA = Metropolitan Statistical Area; μSA = Micropolitan Statistical Area.

To render the configurational logic more concrete, Table 2 presents the robust sufficient paths for Manufacturing (NAICS 31–33) across all three periods — one of 19 sector-specific solution sets generated by the analysis. Manufacturing is a theoretically instructive case: it exhibits moderate mean ER (0.181) and the lowest cross-period ERS growth (+0.008), suggesting structural inertia in the ecosystem configurations that sustain new establishment activity. Yet the within-sector dynamics tell a more nuanced story.

Table 2. Robust sufficient configurations for Manufacturing (NAICS 31–33), by period.

Path	Self-emp.	Funding Rounds	Patents	STEM PhDs	Income	Density	Coverage	Consistency
P1: 2009–2013 (solution cov.=0.543, POCONS=0.728, BECONS=0.60)								
M1.1		●	●				.36	.83
M1.2	●			●			.26	.84
M1.3				●	●		.26	.84
M1.4		●			●	●	.31	.86
P2: 2014–2018 (solution cov.=0.553, POCONS=0.729, BECONS=1.00)								
M2.1	●			●			.28	.84
M2.2				●	●		.28	.87
M2.3	●	●				●	.32	.87
M2.4	●		●		●	●	.40	.83
M2.5		●			●	●	.34	.86
M2.6	●	●			●		.35	.84
P3: 2019–2023 (solution cov.=0.622, POCONS=0.714, BECONS=0.60)								
M3.1		●	●		●		.49	.81
M3.2	●	●			●	●	.39	.85
M3.3	●	●	●				.45	.83
M3.4	●		●		●	●	.39	.84
M3.5		●	●			●	.46	.83
M3.6				●			.32	.74

Note: ● = condition present; blank = don't care. Cov. = raw coverage (pooled); Cons. = consistency (pooled). Paths with resampling survival frequency ≥ 0.80 across 999 iterations reported.

Three cross-period patterns are visible. First, the configurational space expands considerably: from 4 robust paths in P1 to 6 in both P2 and P3, and solution coverage rises from 0.543 to 0.622, consistent with the aggregate trend toward greater equifinality documented above. Second, there is a marked rotation in the role of knowledge inputs. In P1, two of four paths center on STEM PhDs — either paired with self-employment (human capital + entrepreneurial labor) or with income (talent-rich, high-wage metros). By P3, STEM PhDs appear in only one path (M3.6, as a singleton with lower consistency of 0.74), while Funding Rounds and Patents jointly anchor the majority of viable configurations. This shift points to a structural reorientation: pre-2014 manufacturing entrepreneurship dynamics were shaped primarily by local human capital endowments, whereas post-2019 dynamics are governed by innovation commercialization and access to external capital. Third, urban density transitions from a supporting role in P1 (appearing in one path) to a near-ubiquitous element by P3 (present in four of six paths), suggesting that agglomeration externalities have become more conditional on entrepreneurial activity in manufacturing over the study period.

The temporal stability profile reinforces this reading. BECONS reaches 1.00 in P2 — every annual solution set within the 2014–2018 window replicates the pooled solution — but drops to 0.60 in P3, reflecting genuine year-on-year churning within the latest period rather than a smooth trajectory. This

pattern, present in several other sectors, suggests that P2 may represent a transitional consolidation phase between two structurally distinct regimes.

In addition, while each of the 19 sector-specific solution sets is analytically distinct, cross-sector recurrence reveals which ecosystem elements function as general-purpose enablers across the 19 sectors. STEM PhDs as a standalone sufficient condition is the single most ubiquitous motif in every period — present in 7 of 16 sectors in P1 (avg. cons. = 0.764), 5 in P2 (0.769), and 5 of 15 in P3 (0.765) — consistently identifying deep local scientific talent as the closest approximation to a universal enabler. The second-tier motifs shift more substantially: Density · Income · Self-employed dominates P1 (4 sectors, cons. = 0.854), capturing a prosperity-density-entrepreneurship nexus in established metros; in P2 it is displaced by Fin. rounds · Income (5 sectors, cons. = 0.853), a capital-and-prosperity corridor spanning both consumer-facing and knowledge-intensive services; by P3, Density · Income · Self-employed rebounds to 5 sectors (cons. = 0.850) while Fin. rounds · Income narrows to 3, suggesting a partial re-anchoring around agglomeration conditions after the financialization wave of the middle period. No single configuration is universally sufficient across all sectors and periods, but these patterns identify STEM PhDs as the structural constant and financial-demand combinations as a more dynamic, period-sensitive complementary layer.

5. NEXT STEPS

This extended abstract presents the initial results of our research along with the corresponding literature background and methodological steps. The final version of the manuscript will comprehend the following steps:

a. **Complete replication of the configurational stage:** In this extended abstract we have derived the configurational assessment solely for Manufacturing, thus allowing the reader to have clarity concerning the emergence of configurational data used for the estimation of the Ecosystem Readiness Index. Our intention is to create an Appendix with the configurational assessment across all sectors.
b. **Sectoral refinement:** In this initial exploration we have gathered 2-digit NAICS information due to aspects associated with temporal coverage of sectors across MSAs. In the next stages we aim to further refine this specification to generate clearer insights concerning the sectors with the most impact in EE dynamics.
c. **Derivation of qualitative insights from data**: From these extensive configurational assessments, we aim at generating a profiling exercise of EE included in the sample, thus generating clarity regarding the patterns that emerge from data. Ideally, our target is to create a taxonomy that can be parsimonious but also flexible to include the notion of adaptive processes taking place across EE over time.
d. **Conceptual and theoretical iterations with literature**: Based on this complete structure of empirical findings, we will thoroughly discuss our results in light of existing literature to build clear implications for theory, practice and policy.

We believe this research adheres to the existing tradition in EE studies in the sense that it develops arguments and methods aligned with the logics of causal complexity. Yet it offers an analytical leap forward in analytical terms by combining several techniques that grant fsQCA with higher levels of robustness *vis-à-vis* existing approaches. Plus, by addressing the interplay configurations-sectors, it builds an important bridge between EE literature and the established traditions of Evolutionary Economic Geography and Economic Complexity by looking into regions as bundles of resources and capabilities that are not neutral respective to specific industrial activities.

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