Who Benefits from Scientific Entrepreneurship Training?

New Heterogeneity Angles — v8

Helena Montoya Calero · May 2026 · Preliminary / Exploratory

Context. Individual-level HTE is null across 480+ cells (v7). This note reports five new angles that ask different questions: not "who benefits more from training" but "what does the training change, in whom, and with what consequences."

1. Does training equalise or polarise the distribution of ΔSI?

Method. Bartlett variance-equality test (T vs C) by period. Density comparison.

Result. Training does **not** change the variance of ΔSI. SD is virtually identical across arms at all periods (P1: SD_T=1.116, SD_C=1.038; Bartlett $p = 0.29$; P2: $p = 0.34$). The uniform mean ATE is also a uniform distribution — the whole density shifts up, it does not compress or spread.

Implication. The null individual HTE is not hiding heterogeneity in variance. SDM training shifts a rigid distribution: it does not create winners and losers, nor does it narrow the gap between high and low performers.

2. Who sustains ΔSI gains from P1 to P2?

Method. Construct maintenance = $\Delta SI_{P2} - \Delta SI_{P1}$ for the 357 founders observed at both periods ($N_T = 259$, $N_C = 98$). OLS: maintenance ∼ moderator within treated arm.

Result. ATE on maintenance = 0.016 ($p = 0.87$) — gains fade at the same rate for both arms. Within treated founders, no moderator predicts maintenance (all $p > 0.13$). Both arms lose roughly the same amount between P1 and P2.

Implication. The fade-out of ΔSI is also homogeneous. There is no "persistent learner" subtype that can be identified from baseline characteristics.

3. Which SI sub-dimensions does training move most?

Method. OLS ATE on each of the five SI sub-indices at P1 and P2. Standardised effect size: ATE / $SD_{control}$ (Cohen's d).

Sub-index	ATE P1	ATE P2	Cohen's d	p P1
Evidence collection	+0.870	+0.760	0.53	< 0.001
Evaluation	+0.767	+0.791	0.48	< 0.001
Decision-making	+0.717	+0.720	0.42	< 0.001
Hypothesis-testing	+0.398	+0.394	0.42	< 0.001
Theory / hyp. gen.	+0.332	+0.373	0.33	< 0.001
SI Overall (ref.)	+0.603	+0.592	0.58	< 0.001

Result. All sub-indices move significantly (all $p < 0.001$). The **empirical side** of SDM — evidence collection and evaluation — moves most (Cohen's $d \approx 0.5$). The **theoretical side** — hypothesis generation and theory formation — moves least ($d \approx 0.33$). Effect sizes are stable P1 to P2.

Implication. SDM training is more effective at teaching the *empirical* component (how to collect and evaluate evidence) than the *theoretical* component (how to build and articulate causal theories). This is a statement about the design of the IBL programme, not about who benefits. The empirical/theory asymmetry may explain why the ΔSI–pivot mediation is partial: founders learn to evaluate evidence well but the theory-building side (which would produce more purposeful pivots) is harder to instil.

4. Pivot count and quality: do treated founders pivot better, not just more?

Method. Outcome: `n_pivoting_any` (count), $P(\geq 2 \text{ pivots})$, `category_pivot_r` (0–3, higher = more radical/substantive).

Outcome	T&E	Control	ATE	p
Mean pivots (count)	1.993	0.949	+1.044	< 0.001
P(≥ 2 pivots)	57.7%	24.1%	+33.6pp	< 0.001
Any pivot (binary)			+17pp	0.004

Category distribution (`category_pivot_r`, P1, $N = 489$): treated arm concentrates in categories 2–3 (substantive/radical pivots); control concentrates in 0 (no pivot) and 1 (minor adjustment).

Result. Treated founders make roughly **twice as many pivots** in total and are **34 pp more likely to pivot at least twice**. The category distribution shifts toward more substantive pivots in the treated arm.

Replication note. This replicates Camuffo et al. (*SMJ* 2024) at the individual level. Their aggregate finding — trained firms pivot focusedly (1–2 times, neither zero nor excessively) — is visible here as a shift in the full distribution, not just the binary. The count outcome (+1.04) is a stronger effect than the binary (+17pp) used in prior analyses.

Implication. There is unexploited information in the *number* and *type* of pivots that the binary outcome discards. Future analysis: does SI predict pivot count (mediation on count)? Does the empirical/theory asymmetry in SI sub-indices predict pivot quality?

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5. Does learning more make you stay or leave?

Method. P1 sample ($N = 488$). Outcomes: dropout by P2, dropout by P3. OLS: dropout $\sim \Delta$SI within each arm; interaction dropout $\sim T \times \Delta$SI.

Result.

- Within **treated** arm: ΔSI does not predict retention (dropout-by-P2 $p = 0.82$; dropout-by-P3 $p = 0.18$).
- Within **control** arm: same, no predictive power.
- Interaction $T \times \Delta$SI on dropout-by-P3: $\hat{\beta} = +0.077$, $p = 0.085$. Higher ΔSI in the treated arm is marginally associated with *higher* probability of exiting by P3.
- Retention by ΔSI quartile (treated arm): flat — Q1=76.8%, Q2=78.0%, Q3=81.5%, Q4=81.5%.

Implication. Learning more does not retain founders; if anything, it marginally liberates them to exit. A possible mechanism: founders who learn a lot pivot radically, reach a conclusion faster, and exit with conviction (or pivot into a new venture outside the programme). This is consistent with the SDM logic — good scientific thinking may lead to confident termination, not prolonged persistence.

Synthesis: updated evidence map.

Question	Finding	Contribution potential
Who benefits more?	Null — all 12 moderators, 3 estimators	Confirmed null: SDM is an equaliser
Variance / distribution	Null — uniform shift, no compression	Strengthens null claim
Who sustains gains?	Null — fade-out is homogeneous	No “persistent learner” type
Which SI dimension?	Evidence > theory (d=0.53 vs 0.33)	Design insight: empirical > theoretical teachability
Pivot count/quality	+1.04 pivots, +34pp multi-pivot	Stronger effect than binary; replicates SMJ 2024
Learning × retention	Higher ΔSI slightly → exit	Learning liberates, not retains
Mediation (v7)	T→ΔSI→pivot (21–26%)	Mechanism unpublished
Control deterioration (v7)	60% control negative ΔSI	Prevention story, novel
Pending: cognitive battery (Diego) — risk/unc. aversion, learning orient., competitiveness		

Strongest paper angles without Diego’s data: (1) Mechanism paper: T→ΔSI→pivot partial mediation + empirical/theory asymmetry in sub-indices as explanation of why mediation is only partial. (2) Null-as-contribution: SDM training moves all founder types uniformly — variance, fade-out, and individual moderators all confirm this. (3) Pivot count as better outcome: +1.04 pivots vs +0.17 binary; the count better captures what the programme does.

Script: `17_new_heterogeneity_angles.R` **Prior:** v7 (mediation, pivot literature, routes 1–5) **Data:** `ERC_RED_HMC_clean.dta` (N = 6,732, 8 sites) All results labeled EXPLORATORY.