Who Benefits from Scientific Entrepreneurship Training?

Integrated findings — v10 · Analyses 01 + 02

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The Central Argument

Theory-based (SDM) training deposits knowledge uniformly — everyone absorbs it similarly. But performance conversion is massively heterogeneous. The bottleneck is not learning capacity; it is the human capital and strategic posture that determine whether a founder can *act* on what they learned.

From Analysis 01: What the Training Does

Finding 1 — Two families of scientific learning (SI).

	Empirical family evidence, evaluation, decision-making	**Theoretical family** causal theory, hypothesis generation
ATE at P1	+0.72 to +0.87*	+0.33 to +0.40*
Trajectory	Collapses at P3 (fades out)	Persists through P5
Mediates pivoting?	**Yes (16–27%, Sobel $p < 0.01$)**	No (2–4%, ns)

The programme teaches two distinct things. Empirical capacity (how to collect evidence, evaluate it, decide) drives pivoting behaviour and fades quickly. Theoretical capacity (how to form and test hypotheses) persists but does not drive pivots.

Finding 2 — Learning HTE: mostly null, one exception.

Across 12 baseline moderators and 3 estimators (RF, GenericML, DML), no single moderator robustly predicts who gains more in SI. Training is pedagogically universal. The control group deteriorates: 60% of control founders show negative ΔSI at P1–P2. Training partly prevents a natural decay in scientific thinking.

Finding 3 — Mechanism.

$T \rightarrow \Delta$SI (empirics) $\rightarrow$ pivot: partial mediation 21–26% (Sobel $p < 0.01$). The direct $T \rightarrow$ pivot path survives ($c' \approx 0.12$), suggesting theoretical capacity acts through a channel not captured by ΔSI. Pivot count: +1.04 pivots (ATE, $p < 0.001$); +34pp P($\geq$2 pivots).

From Analysis 02: Who Benefits

Spec. GenericML (lasso + rf, 250 splits), 26 baseline moderators Z_i, 14 outcomes across 3 families (scientific learning, business performance, strategic behavior), panel P1–P5 period-FE residualized. Two comparisons: TE vs EB and TE vs Control. Data: 6 RCTs, $N = 1{,}187$ startups, ITT (= randomized assignment).

Finding 4 — Performance HTE is massive; learning HTE is not.

	TE vs EB		**TE vs C**		
Outcome	β_1	β_2	β_1	β_2	**Read**
SI empirics	ns	ns	0.53***	ns	Uniform: everyone gains vs C
SI theory	ns	0.54**	0.15**	ns	Mild HTE TE vs EB
Log sales	0.52***	**0.51*** **	ns	**0.79*** **	Massive HTE
Log(sales/emp)	0.61***	**0.67*** **	ns	**0.94*** **	Massive HTE
TFP	0.63***	**0.62*** **	ns	**0.94*** **	Massive HTE
Pivot combined	—	—	0.24***	0.73**	

β_1 = ATE signal; $\beta_2 > 0$ = HTE signal. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Finding 5 — TE vs Control reveals that G1 is hurt.

	TE vs EB			**TE vs Control**		
Outcome	G1	G2	G2−G1	G1	G2	G2−G1
Log sales	+0.11	+0.94***	+0.83**	−0.84**	+0.86**	+1.73***
Log(s/emp)	−0.05	+1.25***	+1.30***	−0.90**	+1.23***	+2.08***
TFP	−0.08	+1.33***	+1.38***	−1.09**	+1.44***	+2.45***

G2 = top 50% predicted benefit (GATES median split). CGJ replication (log sales TE vs EB): G1=−0.46 ns, G2=+1.65***, gap $p = 0.000$.

The G1 effect vs Control is significantly *negative*: the training does not just fail to help some founders, it can hurt them. For G1 founders, the causal framework misallocates attention.

Finding 6 — The paradox: who learns vs who performs (CLAN).

Moderator	G2 learns more SI theory	G2 performs better	Same direction?
exit_probability	Higher (+11.8***)	Lower	**Opposite**
major_pivot_prob	Higher (+4.1**)	Lower (−11.0***)	**Opposite**
work_experience	ns	Higher (+4 yrs)	—
hours_worked	Lower (−11***)	Lower (−lower)	Same
aspiration (scale)	Lower	Lower	Same
age	ns	Higher (+3 yrs)	—

The founder who absorbs most causal theory (open, flexible, high exit/pivot probability, earlier stage) is *not* the same founder who converts training into performance gains (experienced, committed, focused, low pivot probability). These are opposite profiles on the key moderators.

OLS robustness (triangulation). Single-moderator parametric check: TFP × major_pivot_prob: $\hat{\beta}_{\text{INT}} = -0.374$ ($p = 0.034^{**}$, direction matches CLAN); log(s/emp) + TFP × idea_aspiration_2 (TE vs C): $p \approx 0.07$–0.08^{*}.

The Integrated Story

1. **Training works on learning** — SI ATE positive vs C. Empirical skills (evidence, evaluation) large but temporary. Theoretical skills smaller but persistent.
2. **Learning is (mostly) uniform** — Null HTE across 12 moderators on SI. Empirical capacity: truly uniform. Theoretical capacity: mild HTE — open/flexible founders absorb more.
3. **Performance is not uniform** — $\beta_2 = 0.51$–0.94^{***} for sales, productivity, TFP. Average ATE ≈ 0 vs C, driven entirely by HTE.
4. **Two opposite profiles** — Who learns theory: open, high pivot/exit prob. Who performs: experienced, committed, focused. Not the same founder.
5. **The bottleneck is conversion** — Learning capacity is not the constraint. Human capital accumulated before training determines who can act on what they learned.
6. **G1 is hurt** — vs Control, G1 performance is significantly negative. Misallocation of attention is real, not just zero returns.

Pending

Mechanism test	Does ΔSI at P1 predict G2 membership for performance? Does the G2 founder learn *differently*, or just convert differently from the same learning?
Cognitive battery (Diego)	Risk aversion, uncertainty aversion, learning orientation. Only family of moderators not yet tested.
P1 behavioral robustness	Restrict pivoting to P1 (before attrition diverges).
Targeting	If G1 is hurt, who should be enrolled? Welfare analysis by founder profile.

Analysis 01 scripts: 01–18 (randomforest, DML, GenericML D1–D7, mediation, sub-indices, pivot count, control dynamics)
Analysis 02 scripts: `01_snapshot.do`, `02b_ate_cgj_spec.do`, `03c_hte_scanner_outcomes.R`, `04_ate_cgj_comparison.R`, `05_ols_interacti`
Data: `ERC_RED_HMC_clean.dta` ($N = 6{,}732$, 6 RCTs, 3 arms). R: `/usr/local/lib/R/bin/Rscript` (x86_64 R 4.5).