Innovation Capacity, Robot Adoption, and AI Adoption as Parallel Transmission Channels to Productivity

Cross-National Evidence

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Two literatures, one open question

Innovation capacity → prosperity

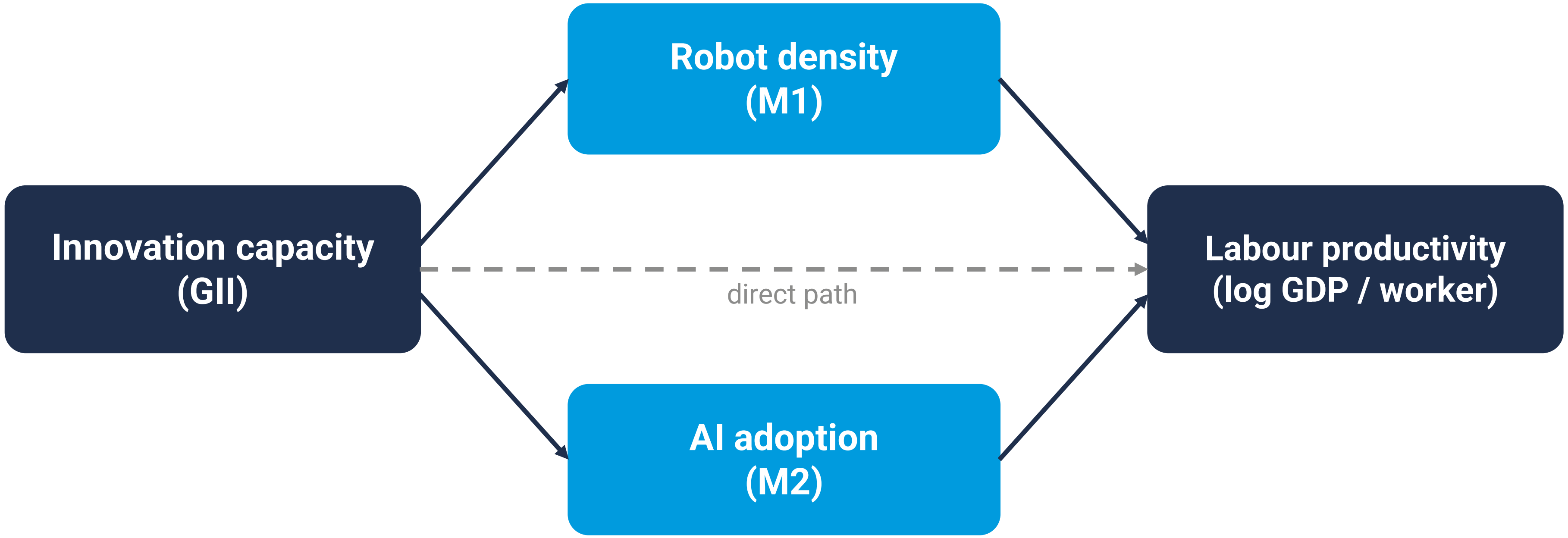
- National innovation systems, GII-type composite indices
- Strong cross-country association with income and productivity levels

Robots → productivity & labour

- Graetz & Michaels (2018); Acemoglu & Restrepo (2020)
- Robot density as the workhorse measure of automation

Gap: Does innovation capacity translate into productivity **through** automation adoption - or alongside it? And do “old” automation (industrial robots) and “new” automation (AI) share the same antecedents?

Research questions and conceptual model



Parallel-mediation model (Preacher & Hayes, 2008)

RQ1

Does national innovation capacity predict the adoption of industrial robots and of AI?

RQ2

Do the two channels respond differently to the input vs. output dimensions of innovation capacity?

RQ3

To what extent is the innovation-productivity association mediated by automation adoption?

Data: a cross-national secondary panel, 2021-2025

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Construct	Source	Measure / coverage
Innovation capacity	WIPO Global Innovation Index, editions 2021-2025	Overall score; input and output sub-indices; z-standardised within edition
Robot adoption (M1)	IFR World Robotics, 2023 & 2024 [1]	Robots per 10,000 manufacturing employees; log; 21-22 economies / year; China 2024 excluded [2]
AI adoption (M2)	Eurostat isoc_eb_ai, 2021 / 2023 / 2024 / 2025 [3]	% of enterprises (≥10 employees) using ≥1 AI technology; total economy & manufacturing; 32 European economies
Labour productivity (Y)	Penn World Table 11.0	Real GDP per worker (log)
Development control	UNDP Human Development Index	Robustness specifications (dynamic model; cross-section)

GII z-scores neutralise methodological revisions across editions · productivity enters as a level, not a growth rate (cross-sectional growth is dominated by conditional convergence).

[1] IFR publishes robot densities free of charge only in its annual press releases, which cover the top ≈20 economies; the full country-year panel is part of the paid World Robotics database.
[2] IFR recalculated China's 2024 density (166 vs. 470 in 2023) on an updated employment base from China's National Bureau of Statistics - a break in the series, not a decline in robots.
[3] The Eurostat enterprise ICT survey rotates topic modules; the AI module was fielded in 2021, 2023, 2024 and 2025, but not in 2022.

Methods

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1	**Parallel mediation**	GII → {log robot density, AI adoption} → log productivity, estimated by OLS
2	**Bootstrap inference**	5,000 resamples, percentile CIs for indirect effects, fixed seed (Preacher & Hayes, 2008)
3	**Dynamic check**	GII 2021 → growth in AI adoption 2021→2025 (temporal precedence)
4	**Level check**	Two-way fixed effects (country, year), cluster-robust SE by country
5	**Diagnostics**	VIF, normality, heteroskedasticity, Cook's distance; theory-guided sensitivity analyses

Result 1 · Innovation capacity precedes AI adoption

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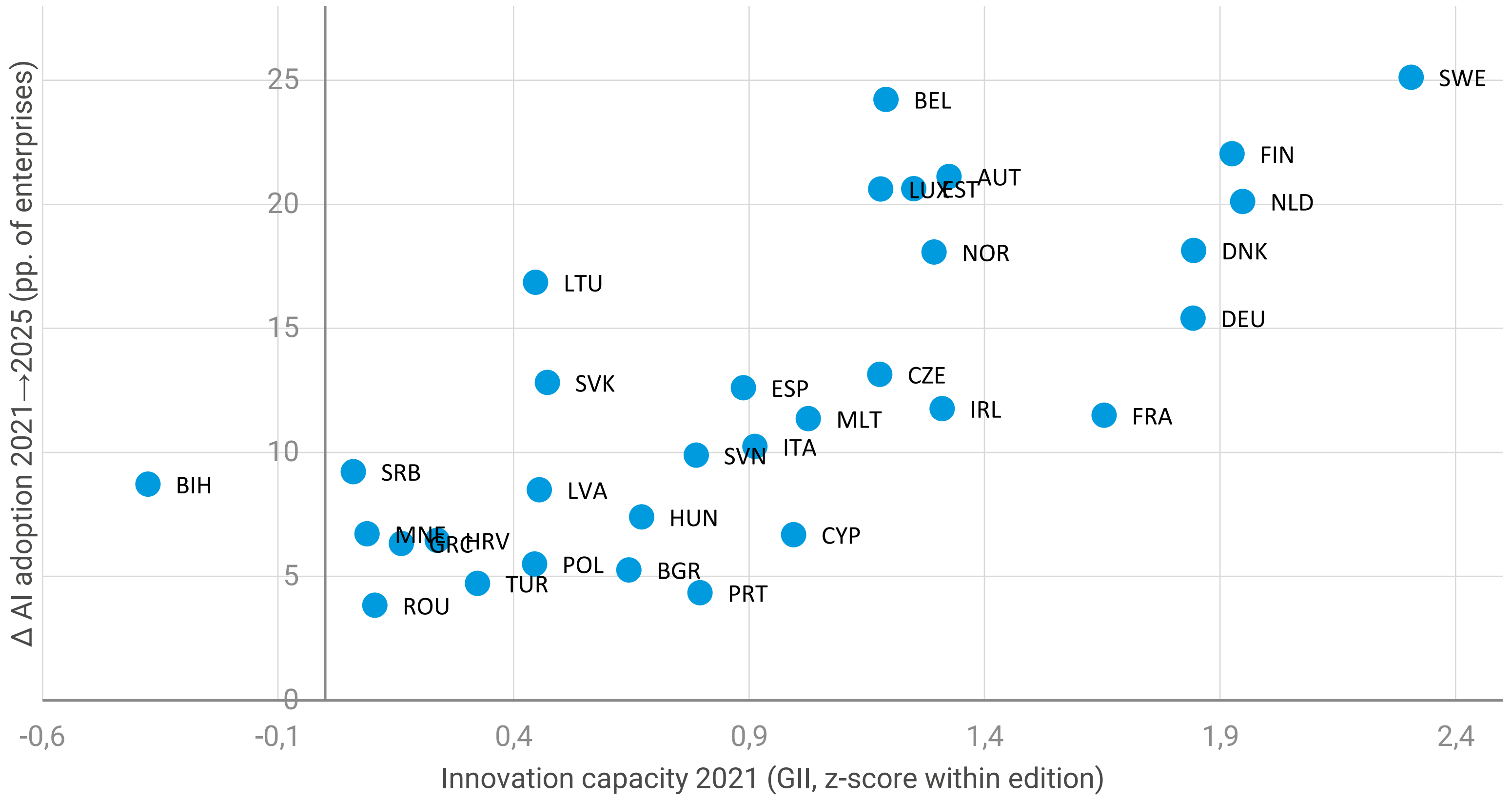
r = .74

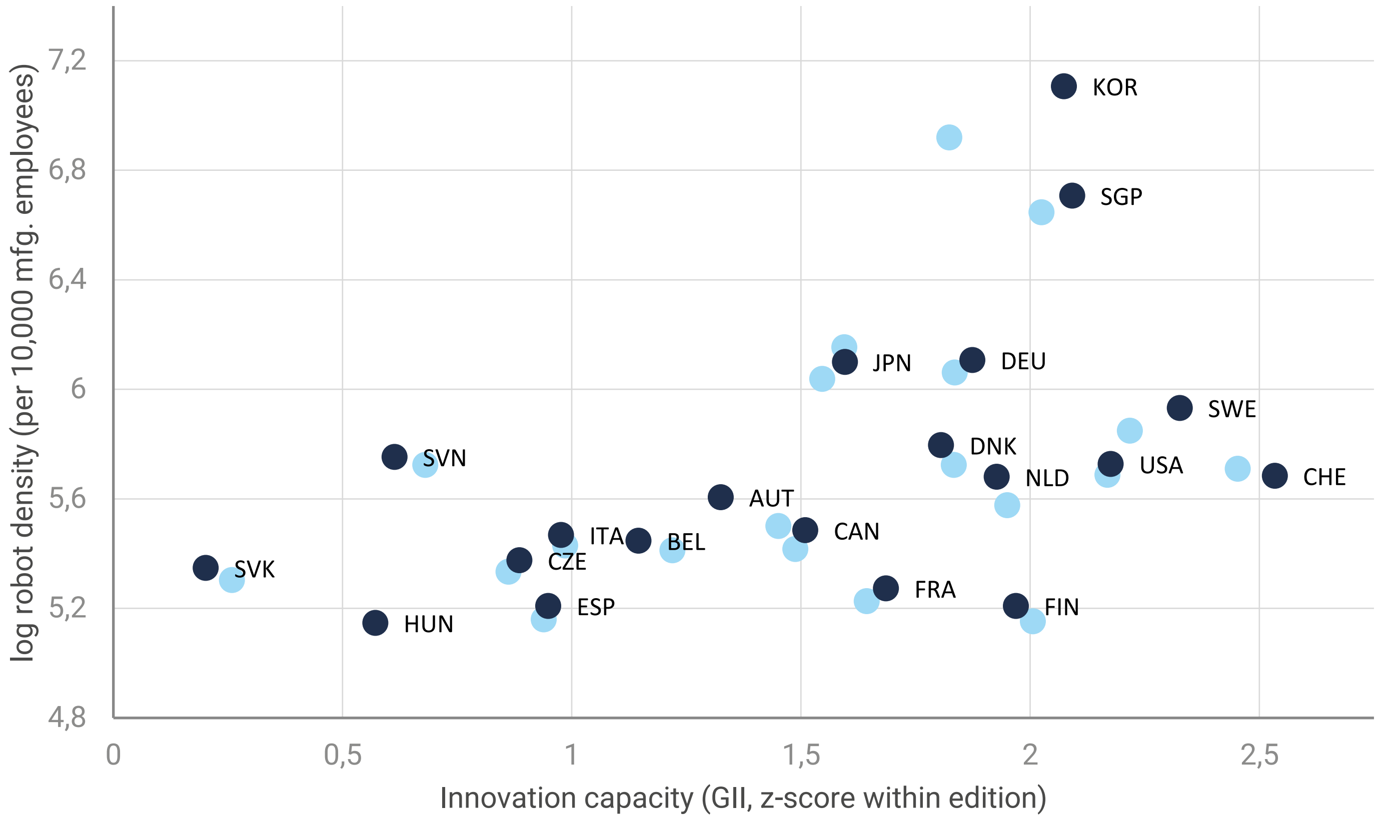
GII 2021 → growth in AI adoption 2021→2025
32 European economies · $R^2 = .54$ · $p < .001$

Each point: one economy. Source: WIPO GII 2021; Eurostat isoc_eb_ai, enterprises ≥ 10 employees, total economy.



Innovation capacity precedes AI adoption growth - the association survives controls for initial adoption level and development (HDI).

Result 1 · Both channels relate to capacity



r = .45

GII × log robot density · IFR 2023 (light) & 2024 (dark)
N = 40
p = .003 · China 2024 excluded (revised base)

r = .58

GII × AI adoption, total economy
Eurostat 2021/23/24/25 pooled, N = 128
p < .001

Innovation capacity is associated with both channels. For robots the evidence is weaker: a small, range-restricted IFR sample - and China illustrates the comparability problem in the published density series.

Result 2 · Between countries, not within

Between countries

$r = .58 / .74$

- High-capacity economies adopt more - and adopt faster
- Ordering established: capacity in 2021, adoption growth after

Within countries (two-way FE)

$\beta = -0.11, p = .61$

- Year-to-year GII changes do not track adoption changes
- GII is highly persistent; AI adoption rises steeply almost everywhere

Reading: the contribution is comparative. The dynamic result establishes ordering, not exogeneity - no within-country causal claim.

Result 3 · AI and robots have different antecedents

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AI adoption (M2)

GII input sub-index	$\beta = 10.37$, $p < .001$
GII output sub-index	n.s.

Adoption loads on institutions, human capital, infrastructure, market and business sophistication - the absorptive side of the innovation system.

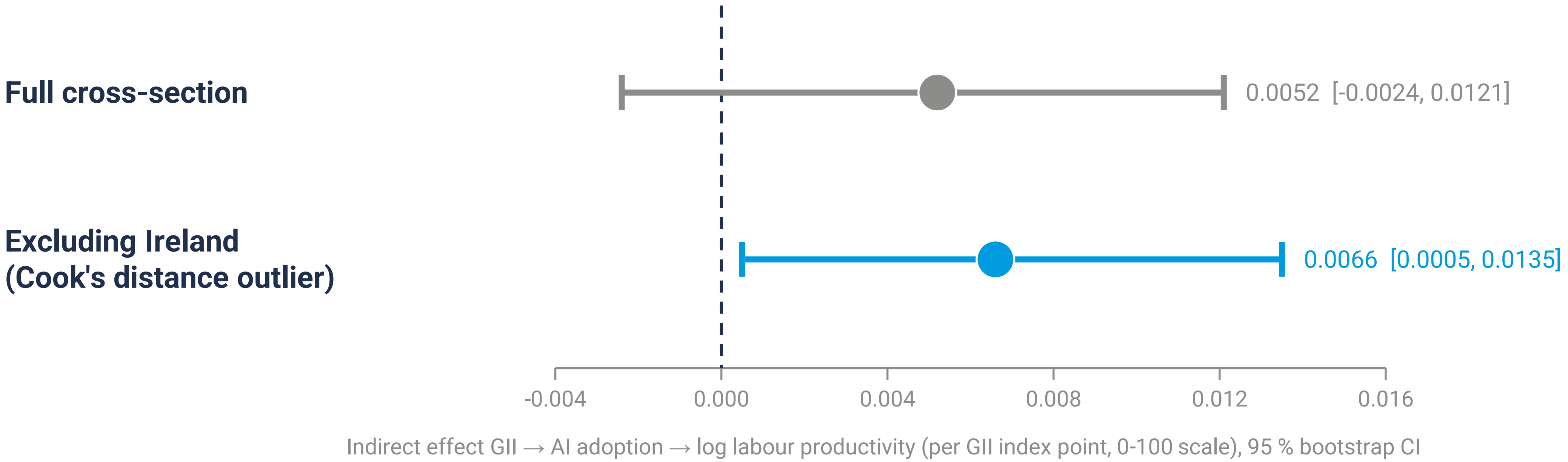
Robot density (M1)

GII input sub-index	no input dominance
GII output sub-index	no comparable pattern

Robot density relates to overall capacity, but does not separate cleanly along the input/output contrast.

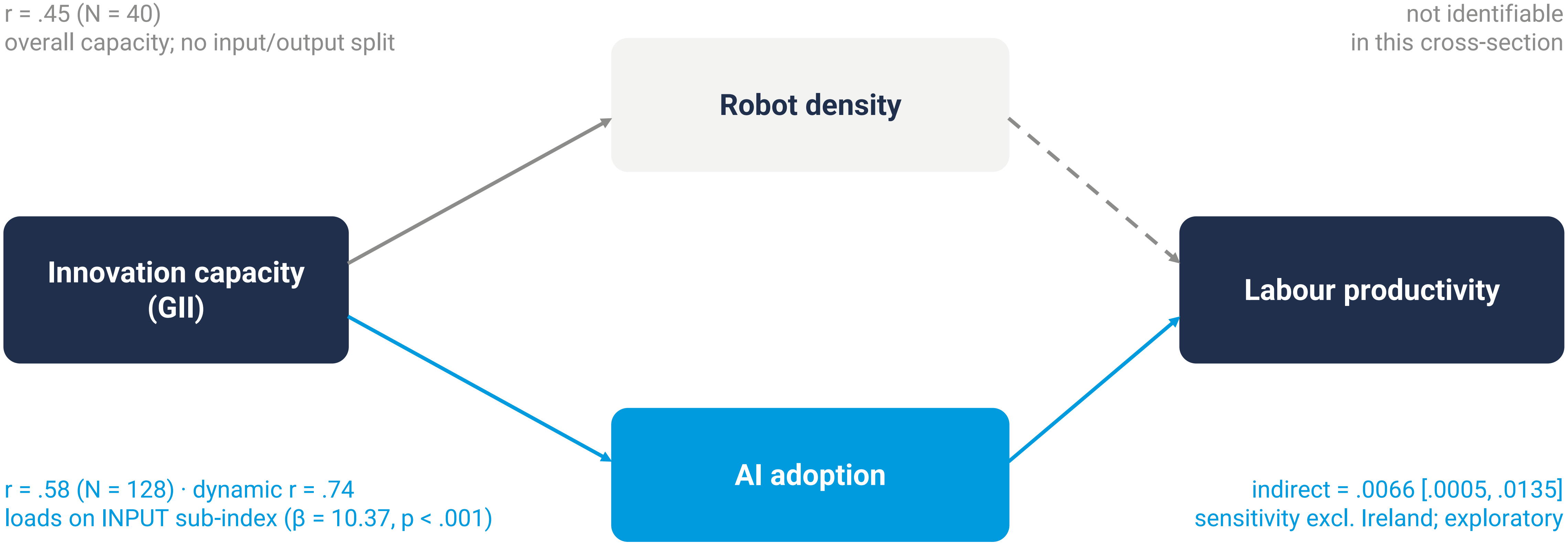
AI adoption loads on innovation inputs; no comparable input/output pattern is detected for robots. Consistent with an absorptive-capacity reading - not a causal decomposition.

Result 4 · Productivity stage (exploratory)



- AI channel: full-sample result inconclusive (CI includes zero). Excluding Ireland (multinational profit-shifting inflates measured productivity) is a sensitivity result, not the main inference - and not causally identified
- Robot → productivity path not separately identifiable in this short, range-restricted cross-section

What the data say - in one picture



All relationships are between-country; within-country FE coefficient n.s.

Discussion · Fast-moving software vs. slow-moving capital goods

	AI adoption (Eurostat)	Industrial robots (IFR)
Where it is adopted	Total economy - office and service tasks included	Manufacturing only, physically integrated
Capital intensity	Low; builds on existing IT infrastructure	High; long-lived equipment, amortised over years
Cost of error	Embarrassing, correctable (hallucination, misread)	Scrap, downtime, damage, safety - unacceptable
Adoption cycle	Test, replace, update within months	Safety validation, process redesign, years
Visible in 2021-2025?	**Yes - diffusion phase captured**	**Only partly - proof-of-concept to standard takes longer**

Sector-aligned check (backup): manufacturing-only AI gives the same pattern. What remains different is the unit (share of firms vs. robots per worker) and, plausibly, the diffusion clock.

Discussion · Why the input side matters for AI

Human capital & research	The skills to specify, verify and integrate AI output - absorptive capacity, not invention
Infrastructure & ICT	AI adoption rides on the installed digital base; no physical retooling required
Market & business sophistication	Firms with process maturity and access to finance experiment earlier and scale faster
Outputs (patents, high-tech exports)	Not needed to adopt: AI is bought or accessed, not produced domestically

Innovation inputs are strongly associated with uptake - consistent with an absorptive-capacity interpretation; innovation and diffusion policy look like complements.

Limitations - what these data cannot identify

Level

Between-country only; no within-country identification, no exogeneity claim

Window

2021-2025 captures AI diffusion, not the full robot investment cycle

Measures

AI share of firms (total economy) vs. robots per worker (manufacturing): scope, unit and cost differ

Sample

32 European economies for AI; 21-22 for robots; range restriction in robot density

Influential cases

Ireland (profit-shifting) flips the mediation CI; China 2024 excluded (revised denominator)

Composite index

GII is a policy index; z-scores neutralise revisions but not construct drift

Contribution and next steps

Contribution

- Innovation capacity as a temporally prior correlate of AI diffusion across countries; positive association with robot density in the available IFR sample
- An input/output contrast that empirically separates AI-based from robot-based automation
- Cross-national mediation evidence on the AI channel - with its identification limits stated

Full paper

- Extend the productivity stage with the long within-country IFR robot-density panel
- Manufacturing-only AI measure carried through all stages (first check: backup slide)
- Longer horizon and lagged specifications matched to the robot investment cycle
- Sensitivity to GII pillar composition and alternative capacity measures
- Working title: "Innovation Capacity and the Diffusion of AI and Robots: Cross-National Evidence on Two Automation Channels"

Take-aways

1 **Innovation capacity precedes AI diffusion**

GII 2021 is strongly associated with subsequent AI adoption growth (r = .74), net of initial adoption and development level.

2 **AI and robots show different empirical patterns**

AI loads on GII inputs; no comparable input/output pattern appears for robots.

3 **The AI-productivity mediation is suggestive, not identified**

Positive point estimate; full-sample CI includes zero; sensitive to Ireland and to development controls.

4 **The asymmetry may reflect different diffusion clocks**

Software adoption is visible within the window; capital-intensive robot diffusion is not - a plausible explanation, to be tested with the long IFR panel.

Thank you - I look forward to the discussion.

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Raw data and methods documentation available on request.

References

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Backup · Specification details and diagnostics

Specification

- Outcome: log real GDP per worker (PWT 11.0), level
- Mediators: log IFR robot density (manufacturing); Eurostat AI share (total economy)
- Exposure: GII overall score, z-standardised within edition; input and output sub-indices separately
- Control: HDI
- Bootstrap: 5,000 resamples, percentile CIs, fixed seed
- FE check: country + year fixed effects, SE clustered by country → within-GII $\beta = -0.11$, $p = .61$

Diagnostics & sensitivity

- Variance inflation factors, residual normality, heteroskedasticity tests reported for every model
- Influential cases via Cook's distance - Ireland is the single influential case in the mediation stage
- Indirect effect (AI channel): full sample .0052 [−.0024, .0121]; excl. Ireland .0066 [.0005, .0135]
- Robot → productivity path not separately identifiable (2 years, 21-22 economies, restricted range)
- China 2024 excluded from longitudinal robot comparisons (revised employment denominator)

Backup · AI adoption in manufacturing only

	AI adoption, total economy (as presented)	AI adoption, manufacturing only (isoc_eb_ain2)
Pooled correlation with GII (z)	r = .58, N = 128	r = .55, N = 126
Input vs. output sub-index (β, cluster-robust)	input 10.37 ($p < .001$) · output −2.33 (n.s.)	input 11.00 ($p < .001$) · output −3.41 (n.s.)
Dynamic: GII 2021 → Δ adoption 2021→25	r = .74, N = 32	r = .63, N = 31
Indirect effect on log productivity, 2023	0.0052 [−0.0024, 0.0121], N = 32	0.0052 [−0.0012, 0.0109], N = 32
… excluding Ireland	0.0066 [0.0005, 0.0135], N = 31	0.0063 [0.0011, 0.0123], N = 31
Correlation with log robot density (EU robot sample)	r = .44, N = 27	r = .40, N = 27

Aligning the AI measure to manufacturing changes almost nothing (the two series correlate at r = .97). The AI-robot asymmetry is therefore not an artefact of sectoral scope; it reflects the adoption clock and the unit of measurement.

Manufacturing column: identical procedure (OLS, 5,000 percentile-bootstrap resamples, seed fixed); missing FIN 2025 and MNE 2024. Replicating the total-economy column with this code reproduces the presented values to ±0.0003.

Backup · Robustness of the dynamic result

	Specification	GII coefficient	Added control
Dynamic: Δ AI 2021→25 ~ GII 2021 (N = 32)	baseline	7.23 ($p < .001$), $R^2 = .54$	-
… + initial AI adoption 2021	ceiling / base-effect check	5.97 ($p < .001$)	AI 2021: 0.23 ($p = .31$)
… + HDI 2021	development-level check	5.13 ($p = .013$)	HDI: n.s. ($p = .28$)
… + log productivity 2021	income-level check	6.63 ($p < .001$)	lprod: n.s. ($p = .58$)
… input vs. output 2021 + HDI	RQ2 in the dynamic model	input 11.6 ($p = .001$) · output n.s.	HDI: n.s.
Cross-section 2023: AI ~ GII (a-path)	baseline	0.29 ($p < .001$)	-
… + HDI 2023	development-level check	0.12 ($p = .25$)	HDI: 47.2 ($p = .05$); r(GII, HDI) = .85

The dynamic result is robust to initial adoption level, development level and income level. The 2023 cross-section is not: with HDI in the model, innovation capacity and development level cannot be separated (N = 32) - one more reason to treat the mediation stage as exploratory.

OLS with heteroskedasticity-robust SE (dynamic) / classical SE (cross-section). Relative growth (log ratio 2025/2021) is negatively related to GII 2021 ($p = .09$): low-adoption economies catch up in relative terms; the result concerns percentage-point growth. Robot correlation without KOR and SGP: $r = .43$ (N = 36).