SESSION 4 · ECONOMIC IMPLICATIONS OF AI

How much can AI add to productivity and GDP?

Evidence for Latin America

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How much will AI add to productivity and GDP?

The forecasts are large, and far apart

- Goldman Sachs (2023): +1.5 points of US productivity growth a year for a decade
- McKinsey (2023): +1.5 to 3.4 points of annual GDP growth in advanced economies
- Penn Wharton Budget Model (2025): +1.5% of GDP by 2035, peaking at +0.2 points of growth a year

Today: two steps for 11 Latin American countries, with public data

(a) Hulten's accounting (Acemoglu, 2025)

- Gain = GDP weight of the tasks AI makes cheaper × how much cheaper
- A task worth 1% of GDP that becomes 10% cheaper raises GDP by 0.1%

(b) Baumol's cost disease through structural transformation

- Sectoral weights are not fixed: employment and GDP shares respond to sectoral productivity
- Baumol (1967): the sectors that progress fastest shrink in weight; the stagnant ones grow
- Paradox: productivity growth converges to the growth of the sector without the technological improvement
- Structural transformation can matter due to non-linearities

> **A historical lens.** US agriculture: 41% of workers in 1900, under 2% today, while its productivity grew faster than any other sector's

Acemoglu's bound is a product of four factors

TFP =

e
Exposure
Share of the wage bill in tasks AI could perform

EACH COUNTRY
Employment by occupation and relative wages, ILOSTAT; task exposure by occupation, Eloundou et al. (2024)

×

q
Profitability
Share of those tasks worth automating within ten years

EACH COUNTRY
Earnings in dollars vs the US and employer contributions, ILOSTAT; cost curve of Svanberg et al. (2024)

×

a
Cost savings
Labor-cost reduction per task

AS IN THE PAPER
27%, from US experiments with generative AI

×

s_L
Labor share
Turns the wage-bill share into a GDP share

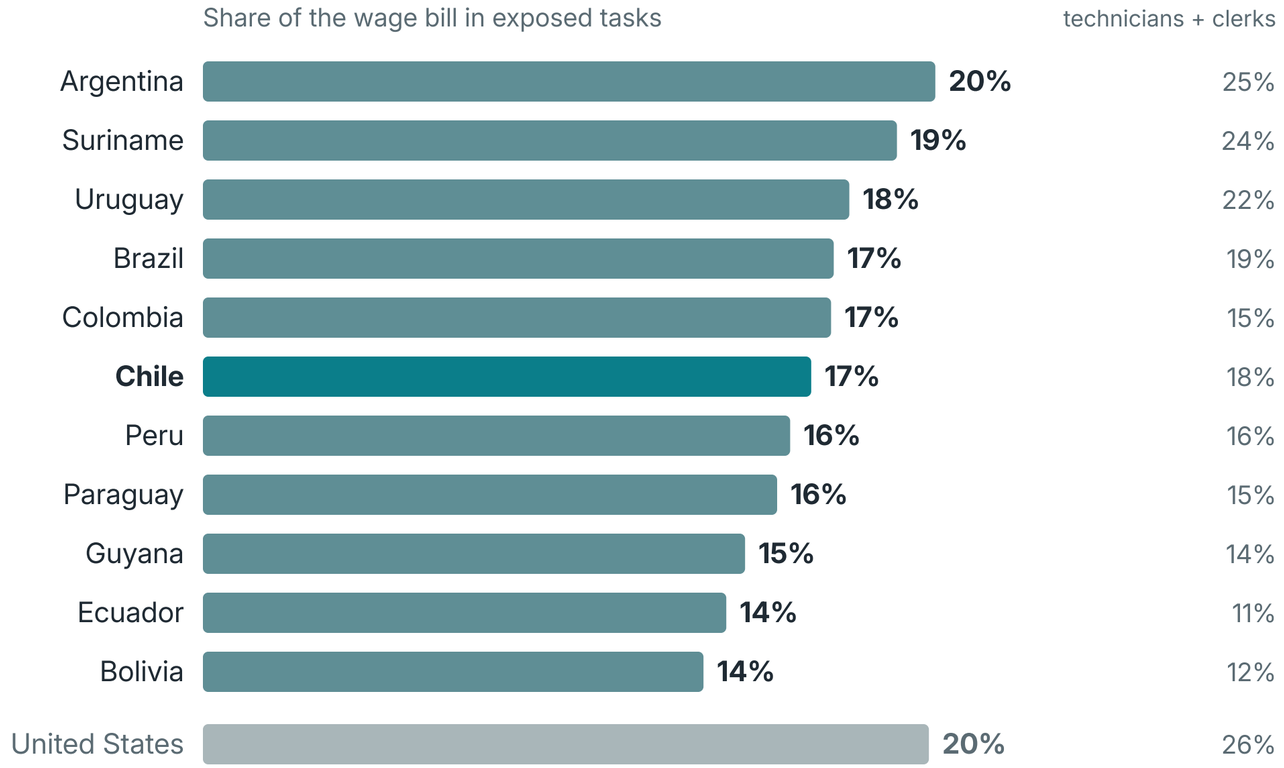
EACH COUNTRY
Labor income share, ILOSTAT; value added by activity, CEPALSTAT

GDP = TFP / s_L

Capital adjusts to keep the capital-output ratio constant, so the multiplier is $1/s_L$: 1.75 in the US, 1.73 to 2.32 in the region

Equations (14), (15) and section 3.4 of Acemoglu (2025), *Economic Policy*. Chile in detail with household-survey data in the appendix (A1 to A4). The weights of the sum are the sectoral shares: part (b) lets them move

14% to 20% of the wage bill is in exposed tasks; US: 20.0%

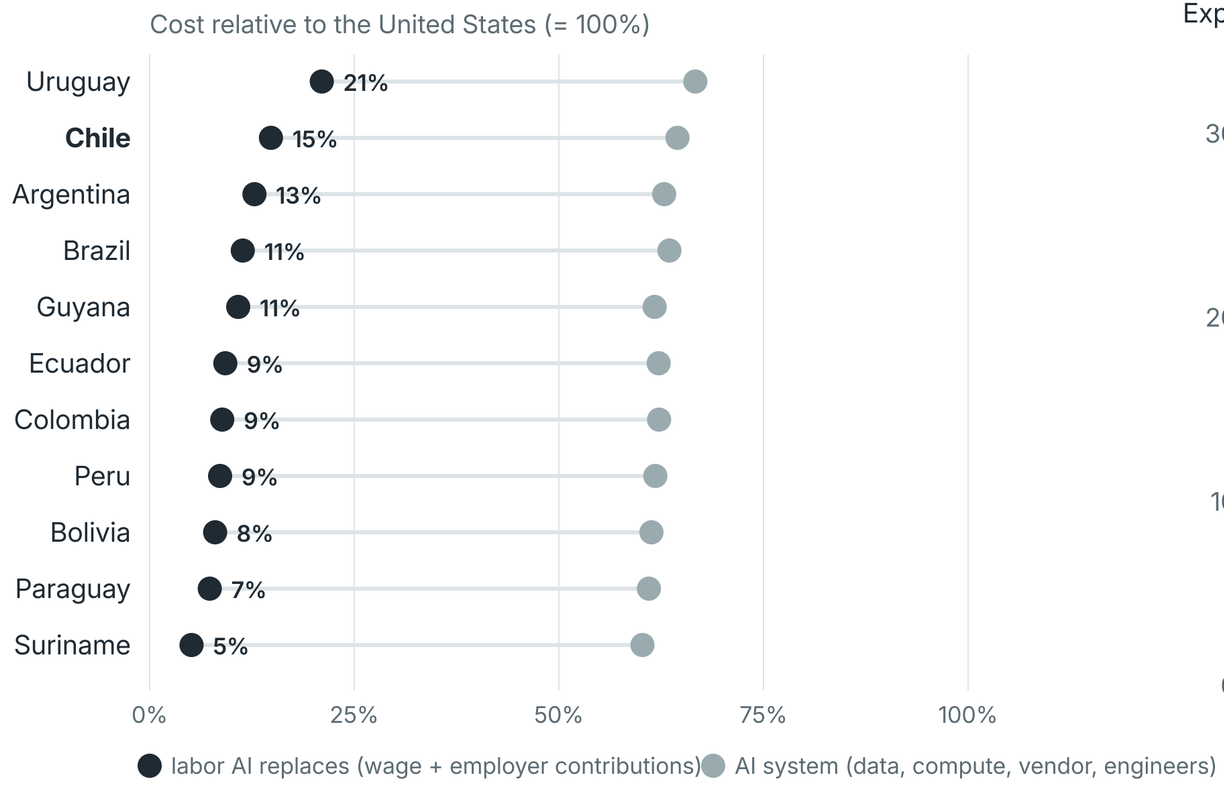


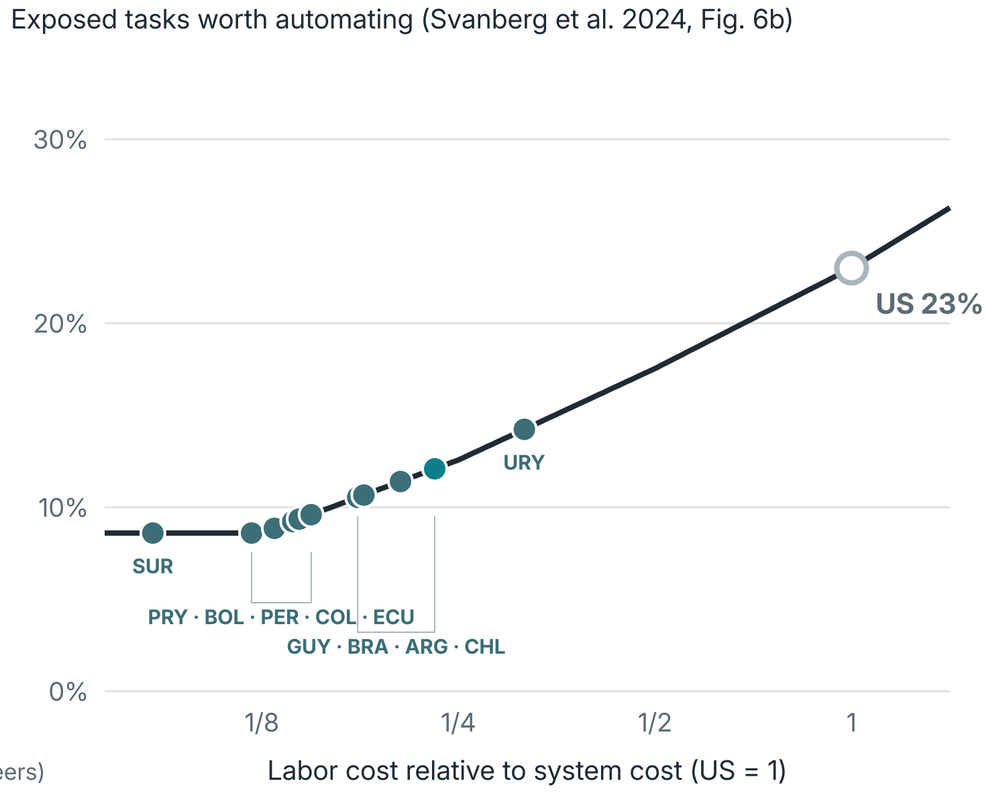
Same task exposure for each occupation (19,265 O*NET tasks scored by Eloundou et al.); only the **weights** change: each country's wage bill by occupation

A narrow band. The most exposed groups, technicians and clerks, weigh 11% to 25% of the wage bill in the region, 26% in the US.

Checks. Chile with household-survey data gives 17.4% against 16.7% here. The ILO index (Gmyrek et al. 2025) puts Chile between 15.2% and 18.6%. Appendix A1

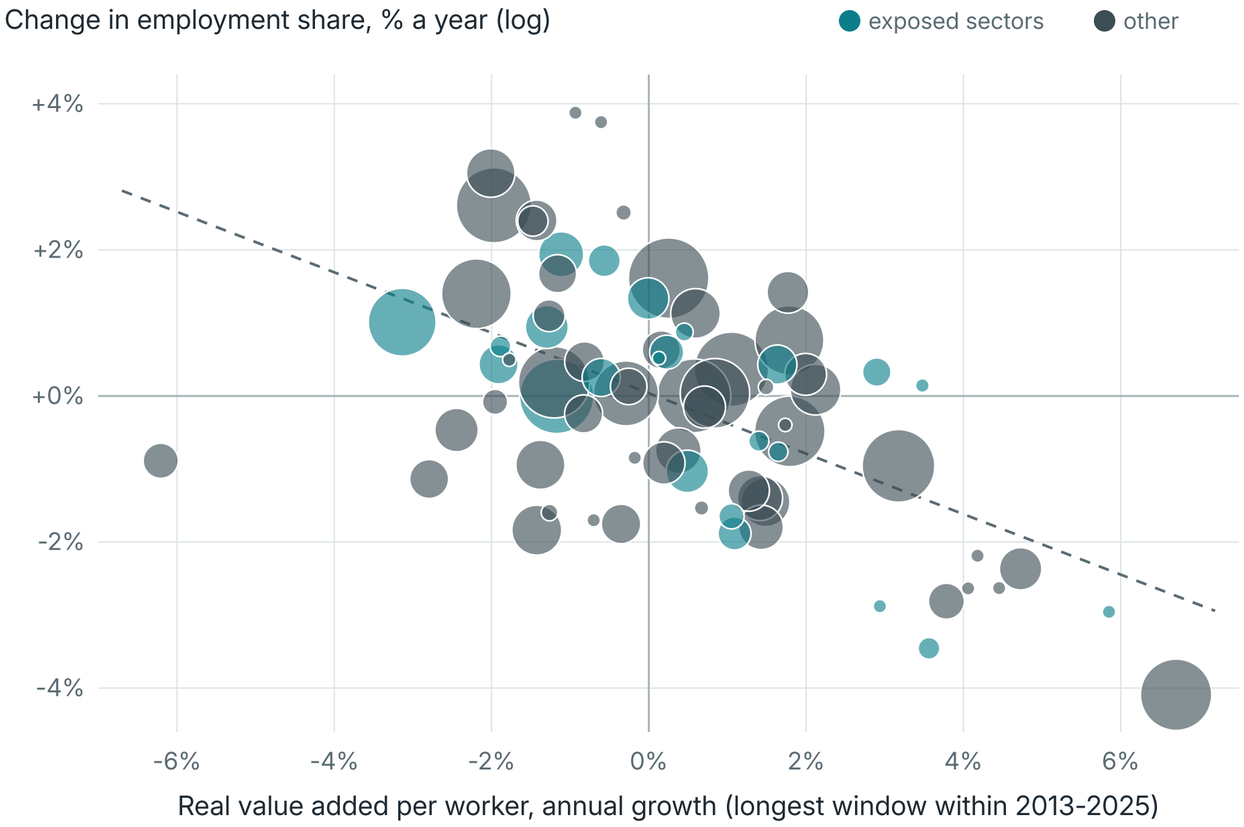
Only 9% to 14% of exposed tasks pay off in the region, versus 23% in the US





Labor costs 5% to 21% of the US level; the AI system 60% to 67%, because data, compute and vendors are paid in dollars. The ratio, **0.09 to 0.32**, read on the Svanberg et al. curve gives **9% to 14%**. Cheap labor makes automation less profitable

Sectoral shares respond to productivity: Baumol cost disease



Observed data (CEPALSTAT, ILOSTAT), 7 countries × 11 sectors (ISIC sections); area: employment 2022
Correlation −0.55 pooled, −0.48 to −0.76 by country

PREFERENCES (HUNEEUS-ROGERSON 2024; COMIN, LASHKARI, MESTIERI 2021)

$$U = \alpha_a \log(c_a - \bar{c}_a) + (1 - \alpha_a) \log C$$

$$s_i = \Omega_i \left(\frac{p_i}{E_n} \right)^{1-\sigma} C^{\varepsilon_i}, \quad \sum_i s_i = 1$$

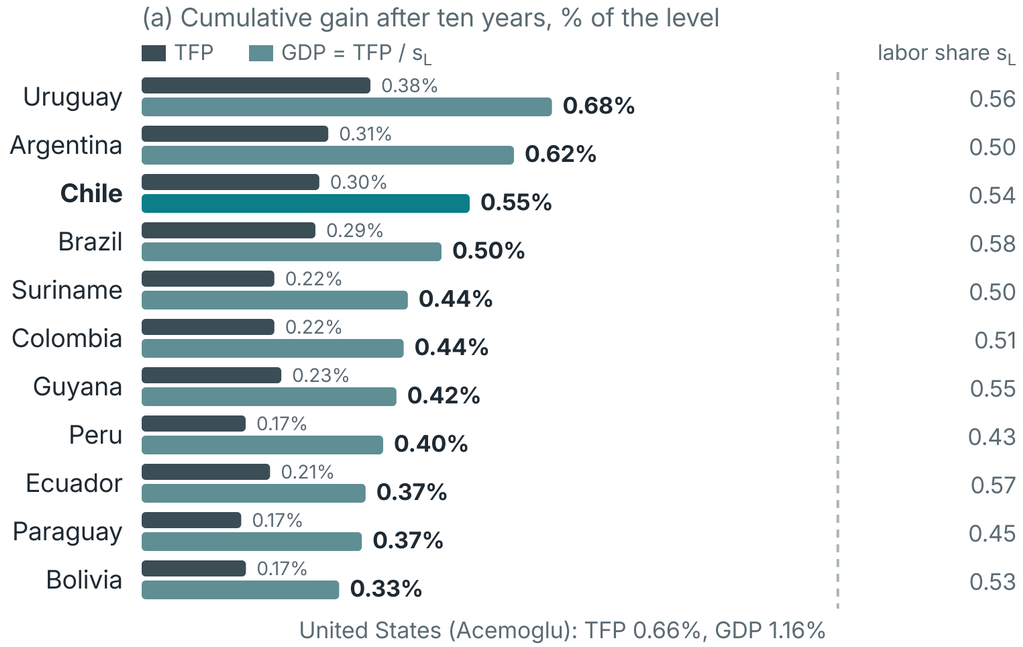
- $\bar{c}_a$: subsistence in agriculture (Engel, income effect); C: the non-agricultural aggregate
- s_i: share of sector i in non-agricultural spending $E_n = \Sigma\, p_i c_i$; $\Sigma\, s_i = 1$ pins down C
- $\sigma = 0.35$: complements across sectors (Baumol, substitution effect)
- ε_i: income elasticities; finance and business 1.73, trade 1.38, mining 0.08 (manufacturing = 1)

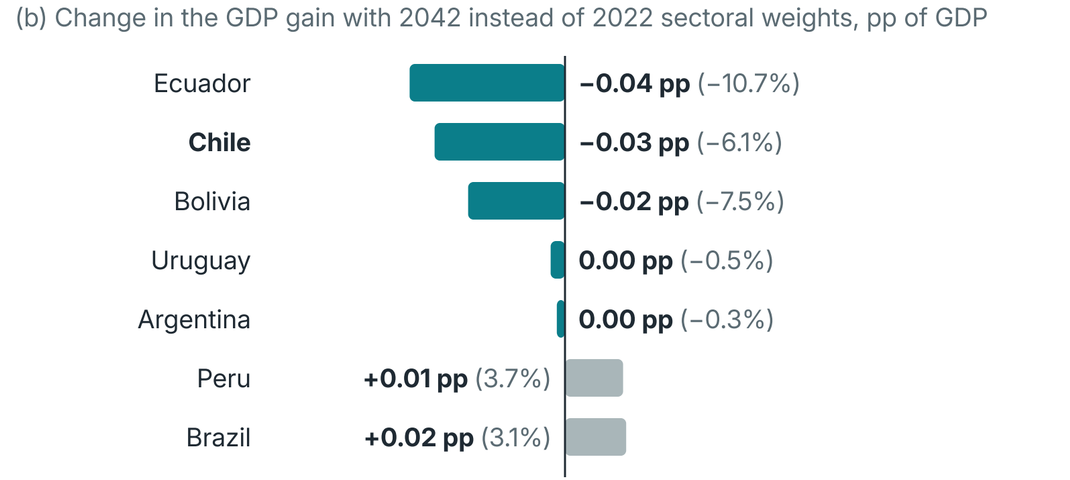
- Production: Cobb-Douglas in labor and capital by sector; labor mobile; capital rented at a fixed price, so the capital-output ratio is constant (Acemoglu's multiplier). CES capital-labor as robustness (slide 10, A8)
- Each sector's productivity follows its observed 2013-2025 trend; the AI gain of part (a) enters sector by sector, on top of it
- With σ < 1 the fastest-growing sectors get cheaper, lose **nominal GDP weight** and release workers: the Hulten weights drift

Validation, in sample. Run over each country's own window (2013-2025 where available) with the observed productivity growth: predicted and actual changes in employment shares correlate 0.37 to 0.78 by country. No parameter is fitted to these paths; σ and ε_i come from the literature

This has happened before: agriculture, then industry, now services

28% to 59% of the US effect, and a slow drift over twenty years





Not computed: Colombia, Guyana, Paraguay, Suriname (data window or model range)
Chile: 0.55% with 2022 weights, 0.51% with 2042 weights: −0.03 pp (−6.1% of the gain)
Twenty years of the observed sectoral trends; the AI gain itself stays the ten-year bound of part (a)



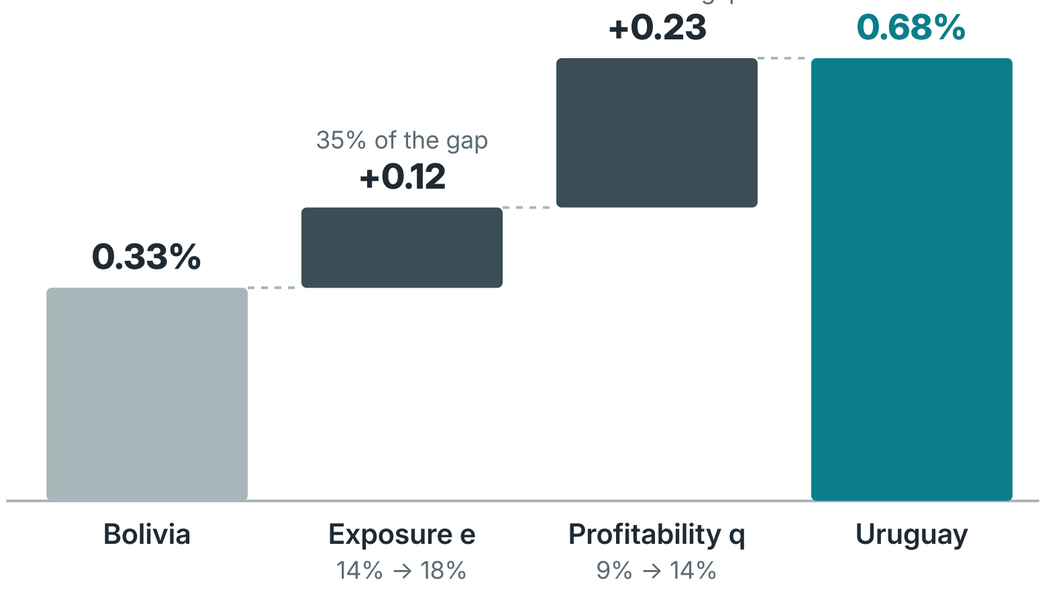
(a) A level gain cumulated over ten years, not a growth rate: GDP 0.33% (Bolivia) to 0.68% (Uruguay), 0.03 to 0.07 points of annual growth; TFP 0.2% to 0.4%. The labor share scales TFP and cancels in GDP = e × q × a

(b) The same GDP gain with the sectoral weights the trends produce by 2042: −0.04 pp (Ecuador) to +0.02 pp (Brazil). It shrinks where the sectors with the largest AI gains are fast-productivity ones that lose weight; it grows where they are laggards that gain weight (Brazil and Peru)

Uruguay vs Bolivia: 65% of the gap is profitability, 35% exposure

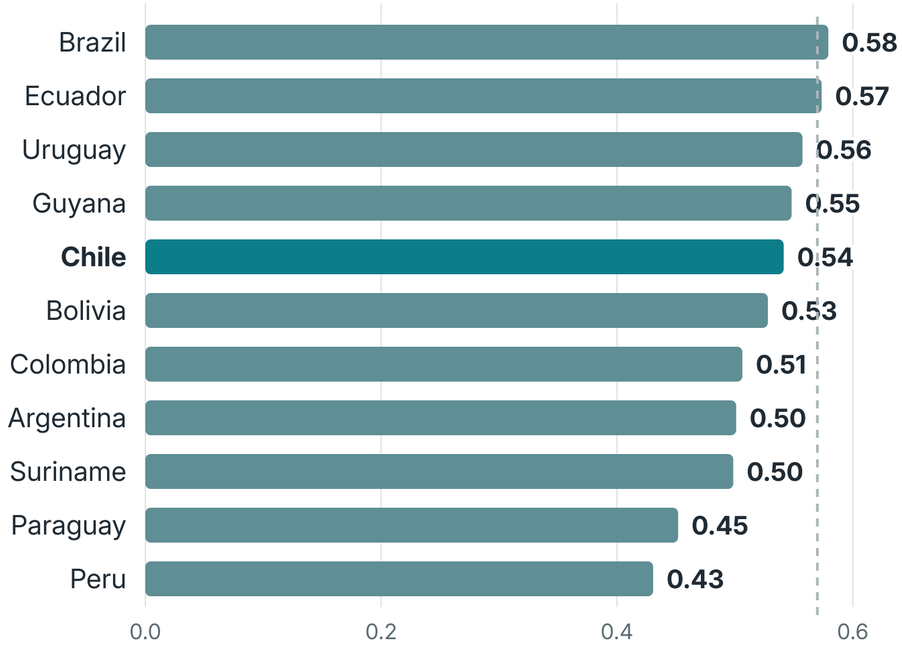
(a) GDP bound in ten years, % of GDP: from the lowest country to the highest

GDP = e × q × a; a = 27% everywhere and the labor share cancels, so the gap splits exactly between e and q



Behind q: exposed-occupation labor costs 21% of the US level in Uruguay, 8% in Bolivia; the AI system costs 67% and 61%, so m = 0.32 against 0.13 on the Svanberg curve

(b) Labor income share s_L (ILOSTAT): multiplies TFP, cancels in GDP



United States as in Acemoglu: 1 − 0.43 = 0.57

(a) The gap, 0.35 points of GDP, split in logs between the two factors that differ: exposure 14% → 18% and profitability 9% → 14%. Profitability dominates because Uruguay's exposed-occupation labor costs 21% of the US level and Bolivia's 8%, while the AI system costs about the same in both

(b) The labor share, 0.43 (Peru) to 0.58 (Brazil), multiplies TFP and cancels in GDP: 7% of the Uruguay-Bolivia TFP gap, none of the GDP gap

Where the workers go: the trends, not AI, move employment across sectors (appendix A13) →

Exposure variants barely move the bound; the cost of adoption doubles it

COUNTRY · GDP GAIN AFTER TEN YEARS, %	(1) BENCHMARK BOUND	(2) HARD TASKS SEPARATED (7%)	(3) US PROFITABILITY (Q = 23%)	(4) AGHION-BUNEL READING (Q 50%, A 40%)	(5) MODEL GDP, CES CAPITAL-LABOR (Σ_{KL} = 0.7)	(6) DIRECT EFFECT ONLY, NO INPUT-OUTPUT LINKS (TIVA)
Uruguay	**0.68%**	0.54%	1.10%	3.6%	0.60%	·
Argentina	**0.62%**	0.49%	1.25%	4.0%	0.52%	0.39%
Chile	**0.55%**	**0.43%**	**1.04%**	**3.3%**	**0.45%**	**0.31%**
Brazil	**0.50%**	0.40%	1.08%	3.5%	0.44%	0.29%
Suriname	**0.44%**	0.35%	1.19%	3.8%	·	·
Colombia	**0.44%**	0.34%	1.07%	3.5%	·	·
Guyana	**0.42%**	0.33%	0.93%	3.0%	·	·
Peru	**0.40%**	0.32%	1.00%	3.2%	0.30%	0.26%
Ecuador	**0.37%**	0.29%	0.89%	2.9%	0.31%	·
Paraguay	**0.37%**	0.29%	0.98%	3.2%	·	·
Bolivia	**0.33%**	0.26%	0.86%	2.8%	0.27%	·
United States (Acemoglu)	**1.16%**	0.93%	1.16%	12.0%*	·	·

Hard-to-learn tasks at 7% saving (Acemoglu's eq. 15): the bound falls by about 21%, to 0.26% to 0.54%

Adoption cost is the lever. US profitability (q = 23%) doubles the bound, to 0.9% to 1.3%; Aghion and Bunel's reading (profitable share q = 50%, cost saving a = 40%) multiplies it by 5 to 9, to 2.8% to 4.0%

CES capital-labor as robustness (σ_{KL} = 0.7): with complements capital responds less to TFP; model GDP 12% to 24% below the bound (1% to 11% with Cobb-Douglas). TFP gain and Baumol drift unchanged

* Aghion and Bunel's own US number: exposure 60% × q 50% × a 40% = 12% of GDP in ten years (6.8% of TFP, 0.68 pp a year); the country column keeps each country's exposure. (6) Filippucci, Gal and Schief (2024) with OECD TiVA: the direct effect is 56% to 66% of the bound, the rest arrives through cheaper inputs; both add up to the bound (appendix A15 →). Aghion in detail: appendix A14 →

What this means for Latin America

1. Productivity: the lever is the cost of adoption

With wages at a fraction of US levels, fewer exposed tasks pay off: GDP up to 0.33% to 0.68% in ten years, 28% to 59% of the US effect. Local providers, cheaper models and shared infrastructure raise profitability directly

2. Baumol caps the dividend, but the effect is small today

Where the sectors with the largest AI gains lose GDP weight, the same AI wave buys a bit less: −0.04 to +0.02 pp of GDP over twenty years, a few percent of the gain. It becomes first order only if AI reaches the stagnant sectors

3. Robust to most readings, and modest next to the IT revolution

Exposure variants barely move the bound. US profitability doubles it, to about a third of what IT investment added to the region's growth. Only Aghion and Bunel's more optimistic reading (half of the exposed tasks profitable to automate instead of 23%, and a 40% cost saving instead of 27%) reaches that IT pace, 0.28 to 0.40 pp a year against 0.3, still a fifth to a quarter of the US IT boom

4. A replicable, public-data exercise

ILOSTAT and CEPALSTAT are enough. Central banks and finance ministries can produce comparable bounds and update them as adoption costs change

Thank you

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Interactive calculator with all the numbers, by country and scenario

fedehuneeus.com/s/research/ai_latinamerica_dashboard.html

17.4% of Chile's wage bill is in exposed tasks; US: 20.0%



Same task-level exposure for each occupation; the weights are Chile's wage bill by occupation (CASEN 2022 household survey, 4-digit ISCO-08)

The gap is the occupational mix. Technicians are 12.5% of the wage bill in Chile and 18.6% in the US; clerks 5.2% versus 7.8%

Robust to the source. The ILO index (Gmyrek et al. 2025) puts Chile between 15.2% and 18.6%. A Chilean task study (CENIA-SOFOFA 2024) and PIAAC 2023 confirm the translation holds

A different technology than the Central Bank's. The September 2026 IPoM automation-risk measure ranks occupation groups the opposite way (rank correlation −0.62): traditional automation hits manual work, generative AI hits office work. A11

In Chile only 12.9% of exposed tasks pay off, versus 23% in the US

Cost of the AI system

Only in-house engineers get cheaper; data, compute and the external vendor are paid in dollars

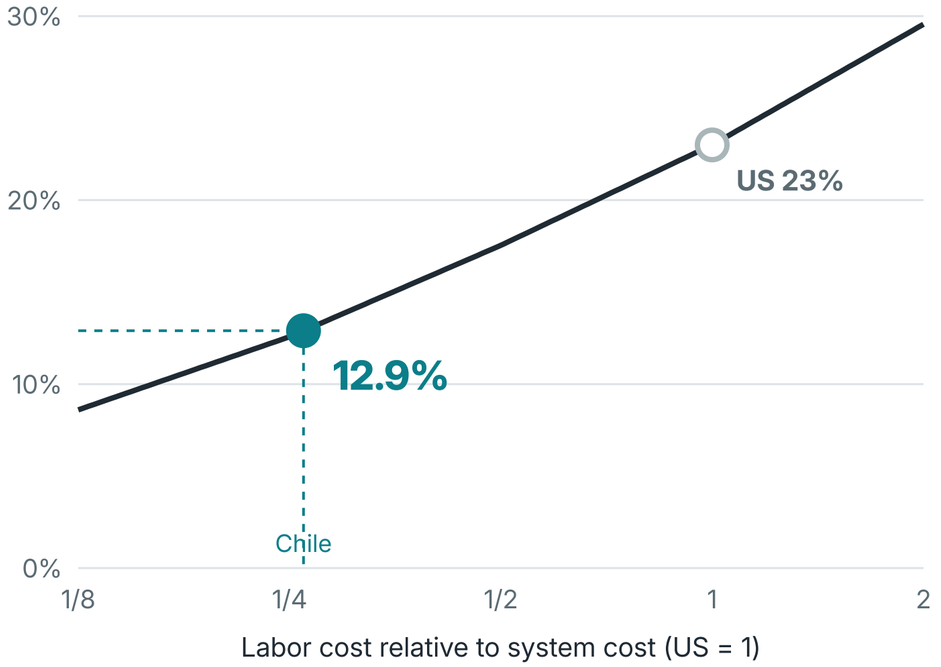


Cost of the labor it replaces

Chilean wage plus employer contributions (INE labor-cost index), relative to the US



Exposed tasks worth automating (Svanberg et al. 2024, Fig. 6b)



> Labor falls to 17% of the US cost, the system only to 66%. The ratio, **0.26**, read on the Svanberg et al. curve gives **12.9%**

Half the US effect, and eroding slowly as sectoral weights move

(A) WITH TODAY'S WEIGHTS (2022)

0.32% TFP

0.60% GDP

in ten years; 0.25% and 0.48% with hard tasks. United States: 0.66% and 1.16%

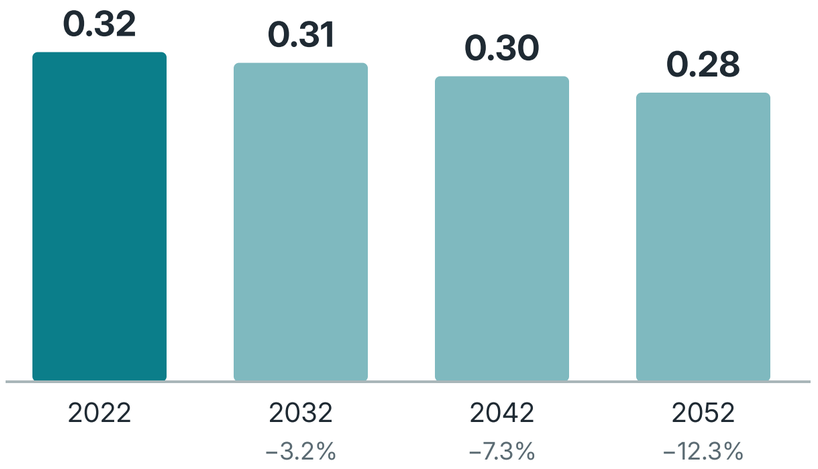
(B) WITH THE WEIGHTS OF 2032

0.31% TFP

0.57% GDP

−3.2% relative to 2022 weights: the activities AI touches lose GDP weight (39.5% → 39.4%) even as they gain workers (46.5% → 47.5%)

TFP gain of the same AI wave, by the year of the GDP weights, %



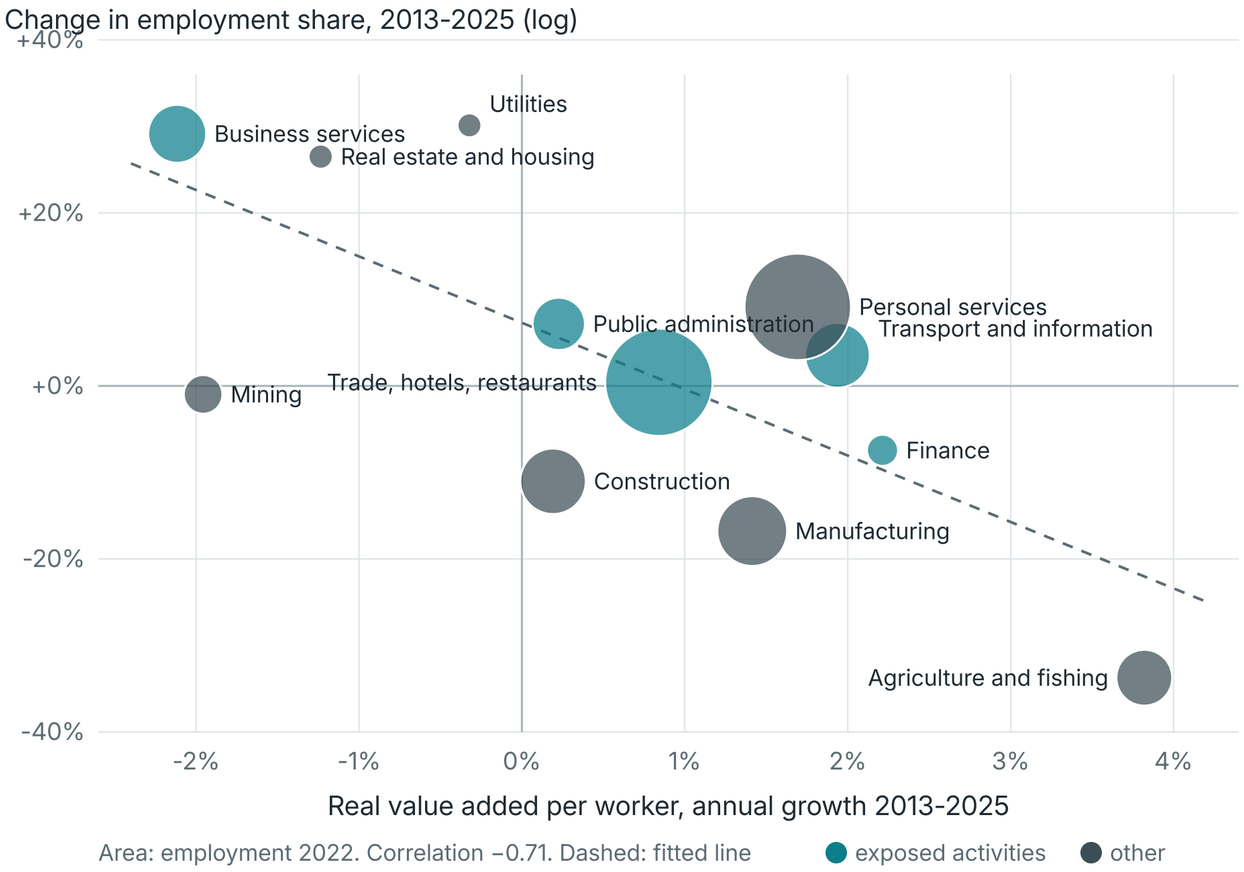
The same AI wave buys a bit less each decade: 0.30% with 2042 weights, 0.28% with 2052 weights (−12.3%). The exact GDP effect in the model is 0.55% against 0.59% from the formula (the income effect); 0.50% with CES capital-labor (multiplier 1.60 instead of 1.85, robustness)

Profitability explains almost all of the gap with the US



Each bar replaces one US factor with its Chilean value, in this order. In any of the 24 orders, profitability is by far the largest bar (between −0.44 and −0.55 points). Without separating hard tasks

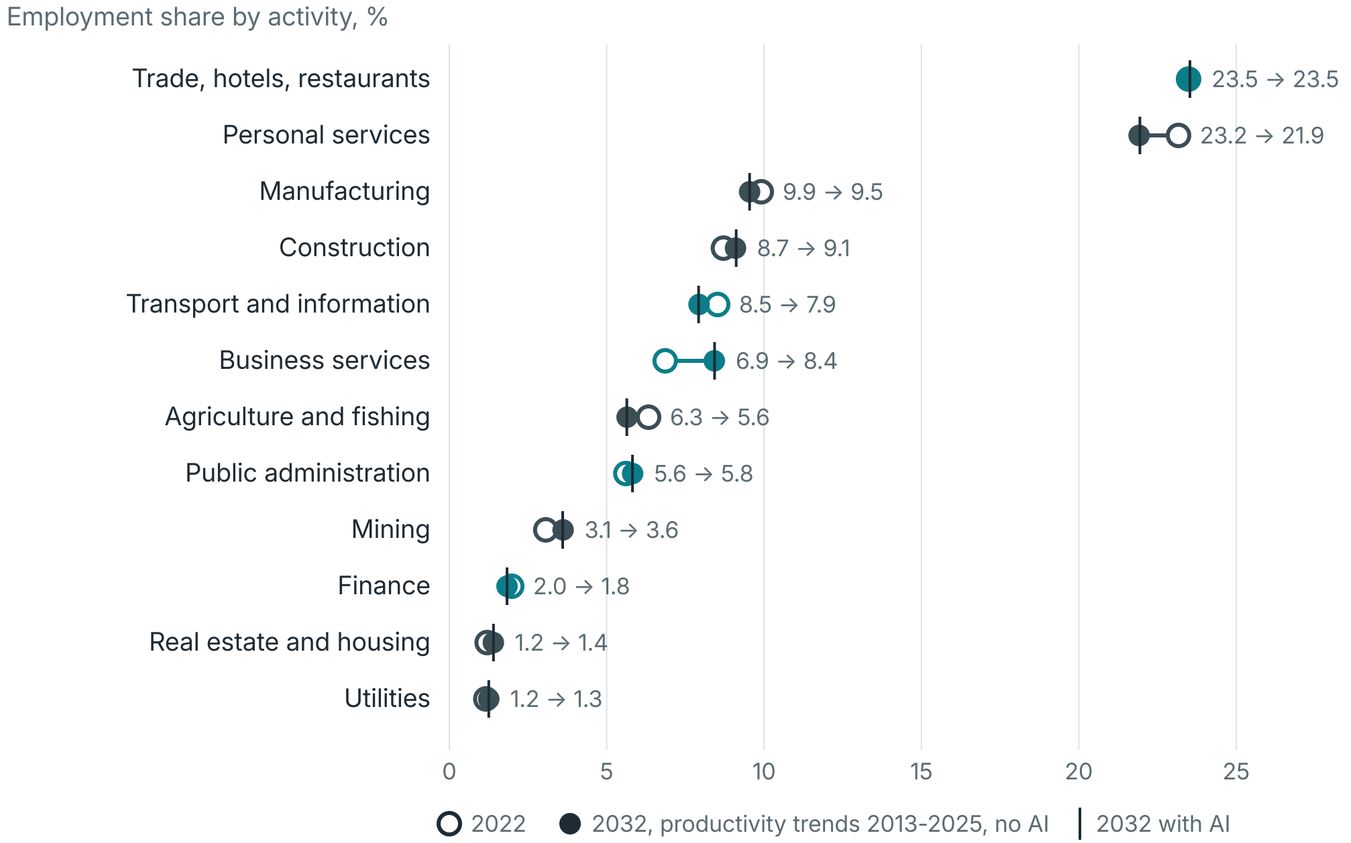
Chile 2013-2025: faster productivity, falling employment share



- Twelve activities of the Central Bank's national accounts; employment from the INE survey via ILOSTAT.
- Correlation −0.71: employment moves to the activities where productivity lags
- Colored: the exposed activities (trade, transport and information, finance, business services, public administration)

Validation, 2013-2025. Fed with observed productivity growth by activity, the model predicts employment-share changes with correlation 0.70 and slope 1.05; without the agricultural income effect, 0.47

Productivity trends move employment across sectors; AI does not



Colored: exposed activities (exposure of their workers ≥ 0.20). Trend reallocation 3.1 pp; AI 0.06 pp

Between 2022 and 2032 the productivity trends move **3.1 points** of employment across activities, toward the lagging ones (construction, business services, mining). AI moves **0.06 points**

> A tenfold larger AI shock would move only **0.6 points** across sectors: AI's employment effects are within sectors (tasks), not between them

What would change Chile's number

VARIANT	TASKS WORTH AUTOMATING	TFP, 10 YEARS	GDP, 10 YEARS
Main estimate (Chilean wages and system cost)	**12.9%**	**0.32%**	**0.60%**
Separating hard-to-learn tasks (7% saving)	12.9%	0.25%	**0.48%**
Exposure from the ILO index (anchored, two variants)	12.9%	0.28% to 0.34%	**0.53% to 0.64%**
All engineering at Chilean wages	18.3%	0.45%	**0.86%**
Labor cost +100% (severance, rigidities; outside the method)	17.9%	0.44%	**0.84%**
The paper's 23% (US adoption economics)	23.0%	0.57%	**1.07%**
Acemoglu's US bound	23.0%	0.66%	**1.16%**

Exposure is robust across sources; what moves the result is the cost of adopting AI. The Baumol erosion is proportional, so it applies to every row

The structural-transformation block under other parameters

CASE	σ	TREND WINDOW	TFP, 2022 WEIGHTS	TFP, 2032 WEIGHTS	CHANGE	EMPLOYMENT MOVED BY AI, PP	BY TRENDS, PP
Benchmark: H-R nest, CLM elasticities, Cobb-Douglas production	**0.35**	**2013-2025**	**0.318%**	**0.308%**	**−3.2%**	**0.056**	**3.05**
Other trend window	0.35	2013-2019	0.318%	0.315%	**−1.1%**	0.055	3.24
Other trend window	0.35	2019-2025	0.318%	0.298%	**−6.3%**	0.059	4.56
Other elasticity	0.50	2013-2025	0.318%	0.311%	**−2.4%**	0.044	2.44
Other elasticity	0.80	2013-2025	0.318%	0.316%	**−0.8%**	0.020	1.25
Other elasticity	1.00	2013-2025	0.318%	0.320%	**0.3%**	0.009	0.87
Other elasticity	1.50	2013-2025	0.318%	0.329%	**3.2%**	0.044	2.68
Hard tasks, benchmark	0.35	2013-2025	0.253%	0.245%	**−3.2%**	0.044	3.05
Paper's 23%, benchmark	0.35	2013-2025	0.568%	0.549%	**−3.2%**	0.101	3.05
Homothetic non-agricultural aggregate	0.35	2013-2025	0.318%	0.307%	**−3.6%**	0.050	3.01
Single homothetic CES over the 12 sectors	0.35	2013-2025	0.318%	0.307%	**−3.5%**	0.048	3.22
No agricultural subsistence term ($\bar{c}$ = 0)	0.35	2013-2025	0.318%	0.307%	**−3.6%**	0.052	2.97
Comin-Lashkari-Mestieri σ = 0.84	0.84	2013-2025	0.318%	0.317%	**−0.5%**	0.017	1.09
Satiation: exposed activities ε = 0.6 (assumption)	0.35	2013-2025	0.318%	0.306%	**−3.8%**	0.122	2.97
CES capital-labor, σ_KL = 0.7 (Oberfield-Raval 2021): model GDP 0.50% vs 0.55% Cobb-Douglas	0.35	2013-2025	0.318%	0.308%	**−3.2%**	0.053	3.05
CES σ_KL = 0.5 (Gechert et al. 2022): model GDP 0.47%	0.35	2013-2025	0.318%	0.308%	**−3.2%**	0.053	3.04
CES σ_KL = 1.25 (Karabarbounis-Neiman 2014): model GDP 0.59%	0.35	2013-2025	0.318%	0.308%	**−3.2%**	0.062	3.05

The accounting and the Baumol block, country by country

COUNTRY	EXPOSURE E	WAGE / US, EXPOSED	PROFIT. Q	LABOR SHARE	TFP BOUND	GDP BOUND	BAUMOL CORR.	VALIDATION CORR.	EROSION 2032
Uruguay	17.8%	0.25	14.2%	0.56	0.38%	**0.68%**	−0.55	0.56	−0.2%
Argentina	20.2%	0.13	11.4%	0.50	0.31%	**0.62%**	−0.51	0.37	−0.2%
Chile	**16.7%**	**0.19**	**12.1%**	**0.54**	**0.30%**	**0.55%**	**−0.64**	**0.66**	**−2.7%**
Brazil	17.4%	0.12	10.7%	0.58	0.29%	**0.50%**	−0.70	0.69	1.9%
Suriname	19.1%	0.06	8.6%	0.50	0.22%	**0.44%**	·	·	·
Colombia	17.3%	0.10	9.4%	0.51	0.22%	**0.44%**	·	·	·
Guyana	14.9%	0.13	10.5%	0.55	0.23%	**0.42%**	·	·	·
Peru	16.2%	0.10	9.2%	0.43	0.17%	**0.40%**	−0.76	0.78	2.6%
Ecuador	14.4%	0.11	9.6%	0.57	0.21%	**0.37%**	−0.48	0.48	−4.9%
Paraguay	15.8%	0.08	8.6%	0.45	0.17%	**0.37%**	·	·	·
Bolivia	13.8%	0.09	8.9%	0.53	0.17%	**0.33%**	−0.74	0.72	−2.7%

Sources: ILOSTAT (employment by occupation at 2 digits of ISCO-08, mean monthly earnings of employees by occupation in US dollars, labor income share), CEPALSTAT (value added by activity at current and constant prices), exposure of Eloundou et al. (2024) by occupation. Employer surcharge: Chile's measured value scaled by each country's statutory rate. Erosion with the structural-transformation block (σ = 0.35, Huneeus-Rogerson nest, Comin-Lashkari-Mestieri income elasticities); · = not computed. Venezuela: no dollar earnings or recent accounts

The paper's numbers across versions

VERSION	TFP BOUND	TFP, HARD TASKS	GDP	GDP, HARD TASKS
Working paper, MIT, April 2024	0.71%	0.55%	1.1%	0.92% (0.90% updated)
NBER WP 32487, May 2024	0.66%	0.53%	1.16%	0.93%
Economic Policy 40(121), 2025 (published; used here)	0.66%	0.53%	1.16% (1.4–1.56% with the full capital response)	0.93%
SSRN entry, revised October 8, 2026	0.66%	0.53%	same abstract as the published version	
Interview, Fortune, June 21, 2026	about 0.55%		1 to 1.5%; about 5% of tasks automated	
NBER WPs 2026 (34854 pro-worker AI; 34910 knowledge collapse; 35036 AI aggregation)	no new macro estimates			

The calculation uses the published version. No later version with new estimates exists as of November 2026; the June 2026 interview restates the published bound

AI exposure versus the Central Bank's automation risk

OCCUPATION GROUP (ISCO 1 DIGIT)	AUTOMATION RISK, MEAN (IPOM)	HIGH-RISK SHARE (IPOM)	AI EXPOSURE, MEAN (THIS STUDY)	SHARE ABOVE MEDIAN EXPOSURE
Managers	0.40	20%	**0.15**	80%
Professionals	0.36	15%	**0.17**	51%
Technicians	0.41	22%	**0.29**	79%
Clerical support	0.43	51%	**0.44**	100%
Services and sales	0.53	62%	**0.23**	80%
Agricultural workers	0.63	97%	**0.07**	0%
Crafts	0.55	85%	**0.04**	3%
Machine operators	0.58	99%	**0.12**	56%
Elementary occupations	0.61	99%	**0.06**	17%

Private salaried workers with a written contract, as in the IPoM box (Albagli et al. 2026, Tables 8 and 9): their automation risk is the Nedelkoska-Quintini (2018) probability by occupation applied to administrative records; our AI exposure is Eloundou et al. (2024) by occupation on CASEN 2022. Rank correlation across the nine groups −0.62, across twelve sectors −0.33

How the model works, step by step

1 · Sectors and data

Agriculture plus 11 non-agricultural sectors (ISIC sections), with value added at constant and current prices (CEPALSTAT) and employment (ILOSTAT), per country

2 · Preferences

Huneeus-Rogerson nest: log utility over agriculture, with a subsistence level $\bar{c}_a$ (income effect), and the non-agricultural aggregate C. C is the nonhomothetic CES of Comin, Lashkari and Mestieri: one elasticity of substitution $\sigma = 0.35$ (from Huneeus and Rogerson) and their income elasticities ε_i by sector (manufacturing = 1)

3 · Production

Cobb-Douglas in labor and capital in each sector, with the sector's labor share; labor mobile across sectors at one wage; capital rented at a fixed real price, so the capital-output ratio is constant (Acemoglu's assumption for the GDP multiplier). Robustness: CES capital-labor with $\sigma_{KL} = 0.7$ (Oberfield and Raval 2021; 0.5 and 1.25 in A8), where the capital response to TFP is $1 + \sigma_{KL}\, s_K/s_L$ instead of $1/s_L$

4 · Trends, no AI

Each sector's productivity grows at its observed 2013-2025 rate (longest window available); the equilibrium is solved year by year for 10, 20 and 30 years. In-sample validation over the same window: predicted vs actual changes in employment shares correlate 0.37 to 0.78

5 · AI on top

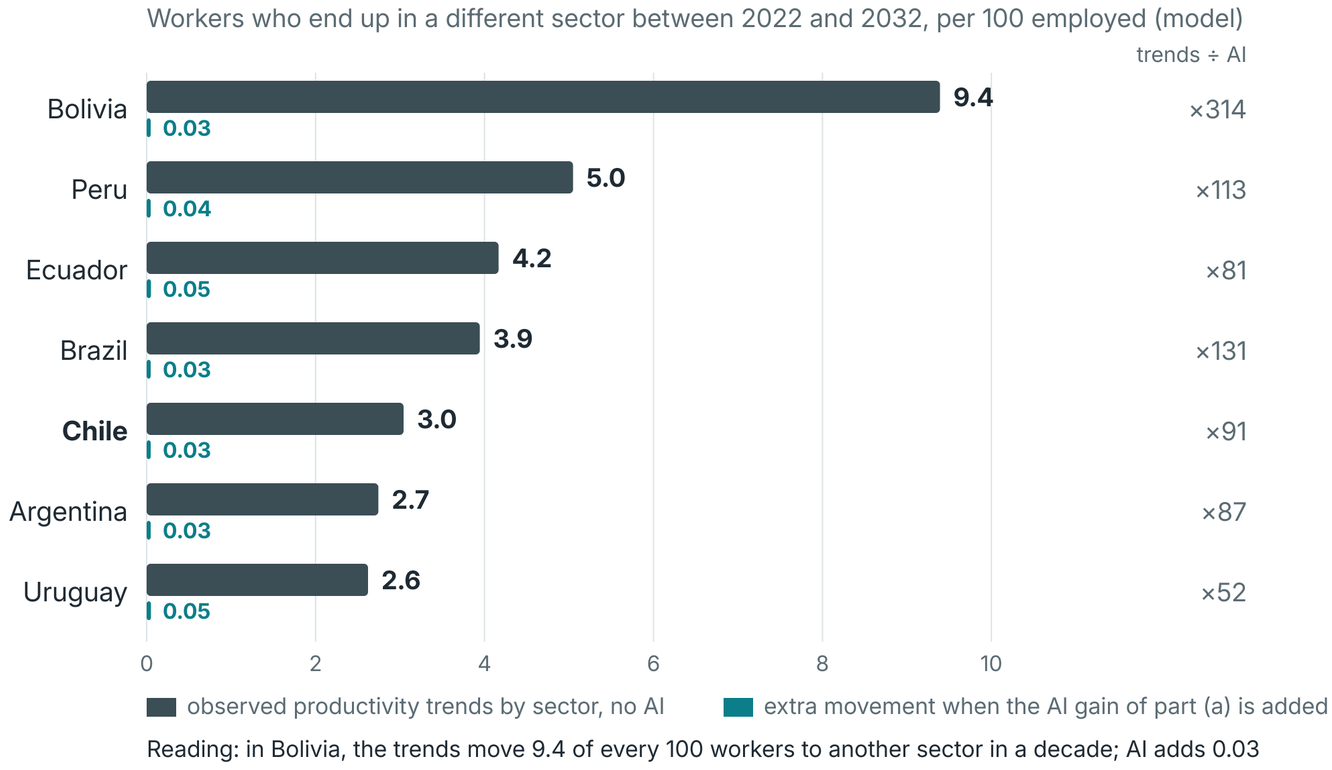
The part (a) gain enters each sector as an extra productivity increase: exposure of its workers × q × a × the sector's labor share, phased over ten years, on top of the trends. Each sector gets a different shock

6 · Outputs

Sectoral GDP and employment shares with and without AI; the Hulten gain $\Sigma\, s_i \times \text{gain}_i$ with the 2022, 2032 and 2042 weights (part (b)); the exact GDP effect in the model (0.51% for Chile vs 0.55% from the formula; 0.45% with CES); workers moved across sectors

← back to the results

Productivity trends move workers across sectors; AI does not



Reading: in Bolivia, the trends move 9.4 of every 100 workers to another sector in a decade; AI adds 0.03

How to read it. For each country, the share of workers who end up in a different sector between 2022 and 2032 in the model: with the observed productivity trends alone (dark), and the extra movement when the AI gain of part (a) is added on top (teal)

A result, not an assumption. The AI gain is 0.2% to 0.4% of TFP over a decade, spread over several sectors. With complements (σ = 0.35) a sector's nominal weight moves by roughly (1 – σ) times its relative productivity gain, so the shift is a few hundredths of a point. The trends are ten times larger every year and cumulate

Why it matters. At Acemoglu's magnitudes AI reshapes tasks within occupations, not the sectoral structure; the Baumol drift of part (b) comes from the trends. A tenfold AI shock would move 0.6 of every 100 workers in Chile (appendix A6)

← back to robustness

Same mechanism as Aghion; here it is measured, and slow

Aghion, Jones and Jones (2019)

- Tasks are gross complements (σ < 1): GDP is limited by its **weak links**, the tasks not yet automated
- Automated goods get cheaper and **lose GDP share**: automation and Baumol's cost disease are the same force
- Result: growth is set by what is essential and hard to improve; even near-complete automation leaves the labor share near two thirds
- An **asymptotic** argument: it binds as the automated fraction approaches one

Aghion and Bunel (2024)

- Acemoglu's formula with a different reading of each term: median **0.68 pp a year** of TFP growth over a decade (range 0.07 to 1.24), against Acemoglu's 0.07
- The gap is in the GDP share of exposed tasks and the profitability term, not in the method
- No Baumol term; the electricity analogy gives 0.8 to 1.3 pp a year
- OECD (Filippucci, Gal and Schief 2024): direct effect + input-output multiplier − a Baumol reallocation drag, 0.25 to 0.6 pp a year for the US

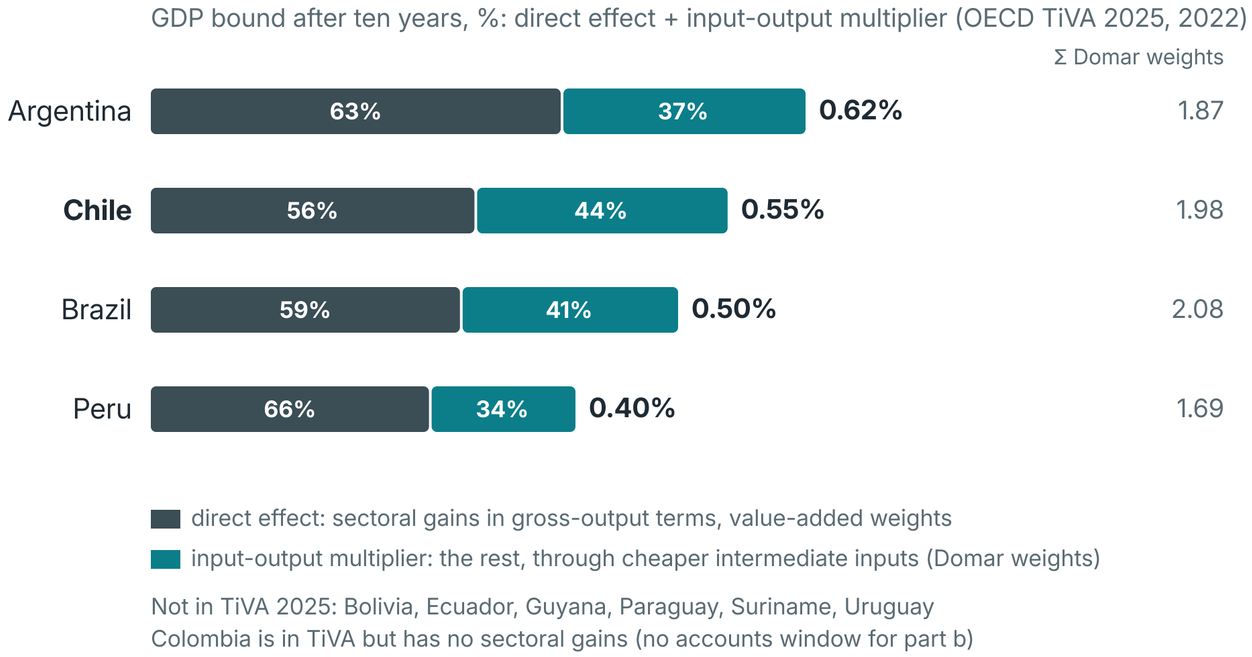
This paper

- The same σ < 1 force, run on **observed sectoral trends** for 7 countries: the weights drift a few points per decade
- The AI gain changes by −0.04 to +0.02 pp of GDP over twenty years (−10.7% to 3.7% of the gain)
- The relative erosion does not depend on the size of the shock; with Aghion and Bunel's tenfold shock it would be ten times larger in points, still a few tenths
- The weak links are the laggard sectors that gain weight (health, education, construction, trade in some countries): they carry small AI gains, which is what caps the aggregate

Agreement on the mechanism, disagreement on the horizon: Aghion's bottleneck binds as automation nears completion; at a 0.2% to 0.4% TFP shock it is a drift of hundredths of a point, and it is the trends, not AI, that move the weights

← back to robustness

Input-output links: already inside the bound, and 34% to 44% of it



The OECD decomposition. A sector's gain in value-added terms, g_i, becomes a gross-output gain $g_i \times VA_i/GO_i$. The **direct effect** weights it by value-added shares; the **input-output multiplier** is the Domar-weighted sum (GO_i/GDP, which add to 1.7 to 2.1) minus the direct effect

Why it adds up to the bound. $(GO_i/GDP) \times (VA_i/GO_i) \times g_i = s_i \times g_i$: with labor-cost savings as the shock, Hulten's value-added accounting already contains the pass-through of cheaper inputs. The exercise shows how much of the bound travels through supply chains, not an extra gain

Data. OECD TiVA 2025 (ICIO) covers Argentina, Brazil, Chile, Colombia, Peru among the eleven countries, so this is robustness, not the benchmark. With TiVA's own sectoral weights the Domar-weighted total is 87% to 99% of the CEPALSTAT-weighted bound (classification differences, mainly finance and real estate). Beyond first order, Filippucci et al. find that general-equilibrium reallocation lowers gains when demand is inelastic, the Baumol channel of part (b)