Generative AI and Occupational Change in Australia

A Task-Based CGE Analysis

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GTAP Conference, June 2026

Motivation

- Generative AI has the hallmarks of a **general-purpose technology**: pervasive, dynamic, complementary innovations (Bresnahan and Trajtenberg, 1995; Eloundou et al., 2024).
- Unlike earlier waves of automation, it reaches **non-routine cognitive work** and unstructured data across many industries.
- Macro estimates of long-run productivity gains cluster around 0.4–1.3% p.a. in leading economies (Aghion and Bunel, 2024; Filippucci et al., 2025), with historical-analogue estimates higher still.
- A central economic distinction: AI can **augment** workers *or* **fully automate** tasks (Brynjolfsson, 2023; Acemoglu, 2025).
- Long-run structural impact is a **general-equilibrium** question — task-level cost changes reallocate factors across occupations, industries, and capital.

Our question

What does a long-run equilibrium look like once AI is fully integrated into production — for output, welfare, occupational employment, and wages?

What we do

A task-based CGE model of Australia with three contributions:

1. **Endogenous mode choice.** Within each occupation, each task is performed in non-AI, AI-*augmented*, or AI-*automated* mode — the cheapest mode is used (cf. Bekkers et al., 2025; Filippucci et al., 2024).
2. **AI on equipment too.** The same structure covers tasks *already* done by machines, which may now be augmented by AI.
3. **Separate calibration of augmentation & automation.** JSA exposure indices uniquely give *distinct* task-based scores for each channel (Jobs and Skills Australia, 2025a,b).

What we find

- Large productivity-driven gains depend heavily on *capital deepening*.
- Mode shifts *within* occupations dominate labour reallocation between them.

Roadmap

1. Task-based production — three modes, Fréchet microfoundation, embedding in the nest
2. Exposure indices — and how they pin down the scale parameters
3. Reference simulation: aggregates, industries, occupations
4. Robustness to global vs. domestic adoption
5. Conclusions and what to take away

Three modes per occupational task

Task production (for each $\tau \in [0,1]$, occupation o, industry i)

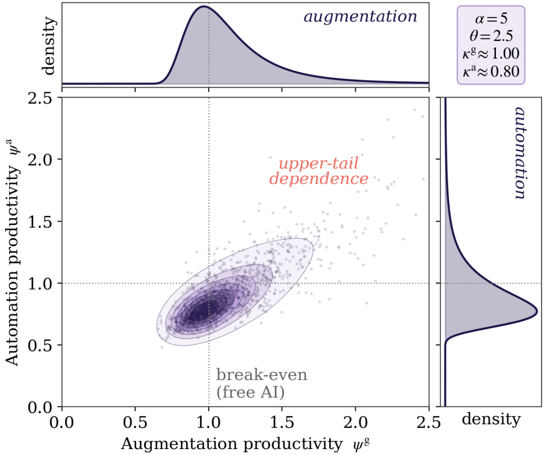
$$x_{o,i}(\tau) = \underbrace{x^{\mathrm{n}}_{o,i}(\tau)}_{\text{non-AI}} + \underbrace{\psi^{\mathrm{g}}_{o,i}(\tau)\, x^{\mathrm{g}}_{o,i}(\tau)}_{\text{augmented}} + \underbrace{\psi^{\mathrm{a}}_{o,i}(\tau)\, x^{\mathrm{a}}_{o,i}(\tau)}_{\text{automated}}$$

Modes are **perfect substitutes**; the cost-minimising mode wins task by task.

Inputs to each mode (Leontief):

- Non-AI: labour
- Augmented: labour + AI services
- Automated: equipment capital + AI services

Microfoundation: correlated Fréchet draws



Each task draws a pair of productivities: **augmentation** ψ^{g}, **automation** ψ^{a}.

- *Fréchet marginals* (shape $\alpha = 5$): right-skewed, with a moderate tail of highly productive tasks.
- *Gumbel copula* (dependence $\theta = 2.5$, so Kendall's $\tau = 0.6$): highly augmentable tasks also tend to be automatable.
- Scales $\kappa^{g}_{o,i}$, $\kappa^{a}_{o,i}$: the **calibration target**, occupation-specific.

From Fréchet to a CES dual

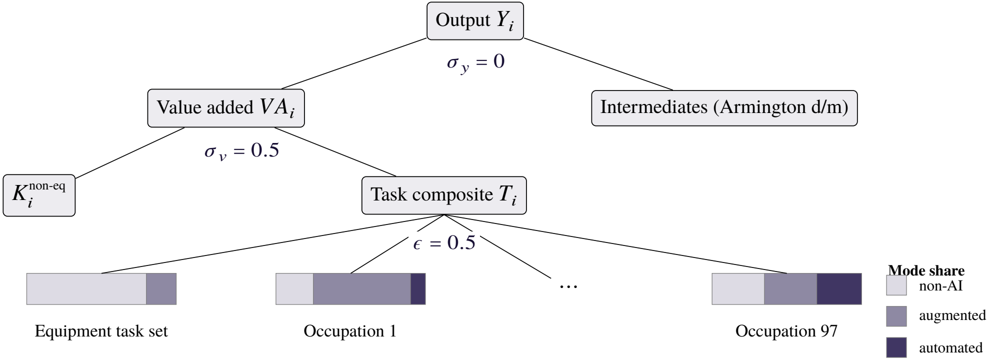
Integrating over the task continuum gives closed-form mode shares $\Gamma^m_{o,i}$, depending on the cost ratios and distributional parameters (κ, α, θ).

Task composite (CES dual)

$$P_{T,i} = \left[\sum_{o,m} \varphi_{o,i}\, \Gamma^m_{o,i}\, (\omega^m_{o,i})^{1-\epsilon} \;+\; \tilde{\varphi}_i \sum_m \tilde{\Gamma}^m_i\, (\tilde{\omega}^m_i)^{1-\epsilon} \right]^{1/(1-\epsilon)}$$

The functional form is that of a CES, but the share weights $\Gamma^m_{o,i}$ are **endogenous** in prices — so the composite is more price-elastic than a standard CES.

Production: nested CES with the task composite



Bars show illustrative equilibrium mode shares of tasks $\tau \in [0, 1]$ in each set; modes within a set are perfect substitutes.

Closing the model

Long-run comparative-static closure:

- **Capital & households**: net rate of return fixed; capital mobile across industries; aggregate saving rate adjusts to support the equilibrium capital stock.
- **Labour**: fixed workforce; nested logit allocation across qualifications ($\sigma_q = 2/3$) and occupations ($\sigma_o = 2$).
- **External**: downward-sloping export demand schedules; trade-balance-to-GDP ratio held fixed; real exchange rate adjusts.

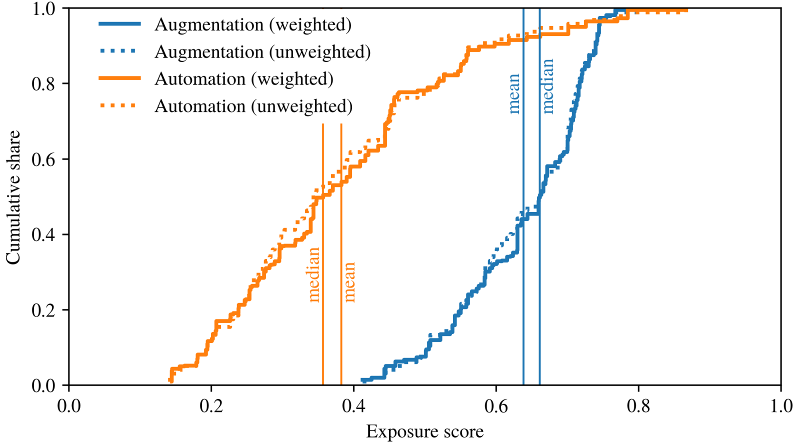
Exposure indices — the JSA data

Most published AI exposure indices give a single score per occupation. Jobs and Skills Australia (2025a) provide **separate task-based scores for augmentation *and* automation** for the 97 three-digit ANZSCO occupations.

Method (building on Gmyrek et al. 2023): decompose occupations into tasks; use LLMs to score each task's potential for (a) augmentation and (b) automation; aggregate to occupation-level indices.

Interpretation: *technological potential* of each mode in isolation — not realised adoption, not relative to AI cost.

Exposure indices — empirical cumulative distributions



Augmentation > Automation almost everywhere in the distribution.

Mapping exposure scores to model parameters

Pin the **Fréchet scales** $\kappa^{\mathrm{g}}_{o,i}, \kappa^{\mathrm{a}}_{o,i}$ so that — with the competing mode shut off and AI services free — the share of tasks above threshold matches the exposure score:

$$\Gamma^{\mathrm{n}}_{o,i}\big|_{\kappa^{\mathrm{a}}=0,\,p_s=0} = 1 - \bar{e}^{\mathrm{g}}_{o} \implies \kappa^{\mathrm{g}}_{o,i}, \qquad \text{and analogously for } \kappa^{\mathrm{a}}_{o,i}.$$

Isolates the scales from copula interaction *and* GE price effects — both of which then bite when the full model is solved.

Shape parameter α_o and dependence parameter θ_o are held common across occupations; specific values and sensitivity ranges on the next slide.

Simulations

Reference simulation. Full long-run integration of AI into production (task modes set by the calibrated exposure scores) *plus* a $+10\%$ outward shift in all export-demand schedules — a stylised proxy for global adoption.

What we vary, and where.

Lever	Reference	Variations	Where
Export-demand shift, $\Delta\bar{E}_g$	$+10\%$	$\{0, 10, 20\}\%$	Conference paper
Fréchet shape, α_o	5	$\{3, 5, 7\}$	Working paper
Gumbel dependence, θ_o	2.5 ($\tau = 0.6$)	$\{5/3, 5/2, 5\}$	Working paper
Task elasticity, ϵ	0.5	$\{0.25, 0.5, 0.75\}$	Working paper
Capital–task elasticity, σ_v	0.5	$\{0.25, 0.5, 0.75\}$	Working paper

Macro context

Income side		Expenditure side	
Component	pp	Component	pp
Technical change	10.1	Consumption	10.8
Capital	19.7	Investment	16.5
Labour (net)	0.0	Net trade	2.5
Non-AI tasks	−31.3		
Augmented	+31.3		
Real GDP	**29.8**	Real GDP	**29.8**

Productivity gains, realised mainly as capital deepening:

- Task-level technical change: ∼1/3 of GDP gain
- Capital deepening: ∼2/3 of GDP gain
- Investment/GDP: 34.5% → 40.7%

Higher capital intensity, hence:

- Capital share of income: 40.0% → 47.6%
- Consumption gain +16.2% cf. GDP 29.8%

Large labour reallocation between modes contributes zero directly.

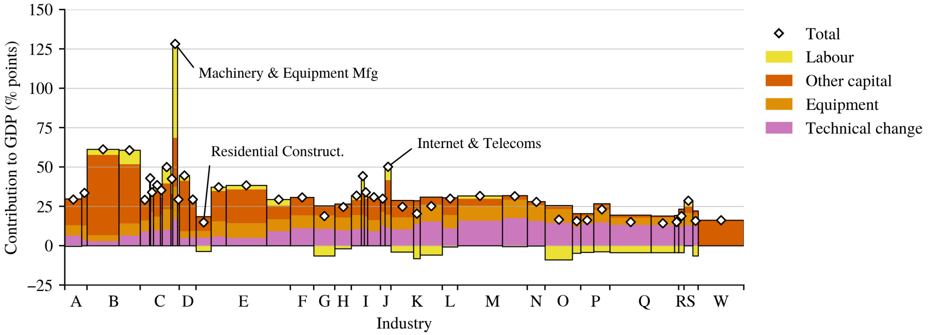
Macro sensitivity — global vs. domestic adoption

Only the export-demand shifter is varied: 0%, $+10\%$ (reference), $+20\%$.

	$+0\%$	$+10\%$ (Ref)	$+20\%$
Real GDP, %	27.4	29.8	32.6
Technical change (pp)	9.9	10.1	10.4
Equipment capital (pp)	6.1	7.3	8.7
Other capital (pp)	11.3	12.3	13.5
Real consumption (pp)	9.9	10.8	11.7
Real investment (pp)	14.7	16.5	18.7
Net trade (pp)	2.8	2.5	2.2

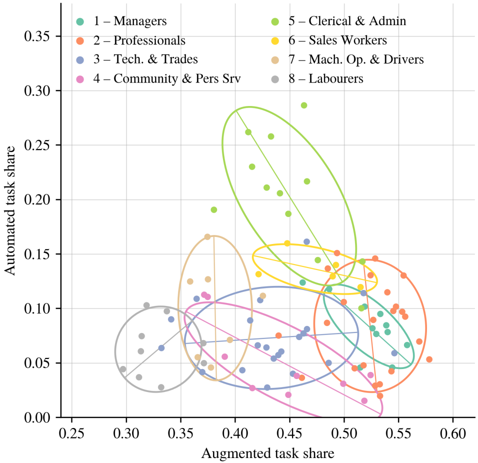
Capital deepening tracks the export-demand response, via imported equipment and AI-services prices.

Industry value added



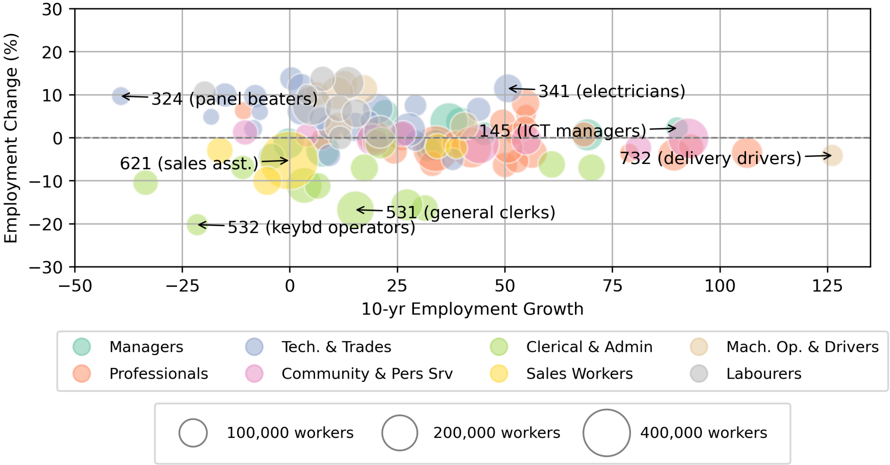
Export-oriented industries (e.g. Mining, Div B) grow more strongly than consumer-oriented industries (e.g. Dwellings). Machinery & Equipment and Internet & Telecoms benefit from equipment and AI services supply.

Mode shares across occupations



Aggregate task allocation: non-AI 44.2%, augmented 46.7%, automated 9.1%.

Between-occupation reallocation is moderate



Within-occupation task reallocation is large

	Non-AI		Augmented		(5) Other	(6) Output	(7) Net
	(1) Ext.	(2) Int.	(3) Ext.	(4) Int.	substitution	growth	('000)
Managers	−2398	−193	1691	−69	20	992	42
Professionals	−4470	−345	3121	−130	31	1713	−78
Tech. & Trades	−1199	−130	847	−34	3	638	124
Community & Pers. Svc.	−603	−65	453	−16	3	224	−4
Clerical & Admin	−1303	−54	740	−22	10	441	−187
Sales	−401	−29	256	−9	5	154	−23
Operators & Drivers	−531	−66	348	−14	4	334	75
Labourers	−269	−47	190	−7	1	185	52
Total	−11178	−933	7650	−305	82	4684	0

Additive decomposition of employment change by ANZSCO Major Group ('000 worker-equivalents; workforce 17.3M). Columns 1–4 show extensive and intensive margin changes at constant output. Columns 5-6 show other substitution and output growth effects. Column 7 shows the net change.

Conclusions

1. **Productivity-driven gains, largely realised as capital deepening.** Welfare gain (+16.2%) is smaller than GDP gain (+29.8%), since the higher capital stock requires a higher saving rate.
2. **Labour-market adjustment is mostly *within* occupations.** Over half of workers' tasks are augmented or automated. Net occupational reallocations are modest.
3. **Augmentation dominates automation** across virtually all industries and occupations, reflecting the exposure scores.
4. **Factor shares are the dominant distributional channel**, not between-occupation wage dispersion: labour share falls from 60.0 to 52.4% of GDP; the occupational wage Gini barely moves.

Caveats and implications

Key caveats

- **Comparative static** — transition path and adjustment costs unmodelled.
- **Exposure scores** represent LLM-assessed *technical potential* by task — intrinsically hard to validate. The existing-task framing also misses entirely new tasks/occupations (e.g. AI governance) (Acemoglu and Restrepo, 2018).
- **AI services** production function is very uncertain.

Implications

- Labour-market focus belongs on **adaptation within occupations** — training, task redesign, complementary skills.
- **Investment is the binding macro constraint**: well-designed regulatory and tax settings will be crucial to reap benefits.
- Addressing **wealth inequality** through **comprehensive tax reform** becomes still more urgent.

Thank you

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Conference paper: *Generative AI and Occupational Change in Australia: A Task-Based CGE Analysis*.
`https://www.gtap.agecon.purdue.edu/resources/res_display.asp?RecordID=7737`

Full working paper: *Occupations, Tasks and Generative AI: A Computable General Equilibrium Analysis*
`https://www.copsmodels.com/elecpapr/g-367.htm`

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Backup — AI services cost composite

Block (share of total)	Industry	% of total	Origin
Upstream (20%)	Computer Systems Design & Svc.	20.0	Imported
Downstream svc. (10%)	Computer Systems Design & Svc.	10.0	Domestic
Downstream compute (70%)	Internet & Telecom	21.0	Domestic
	Electricity	12.6	Domestic
	Other utilities	1.4	Domestic
	Machinery & equipment mfg.	35.0	Imported

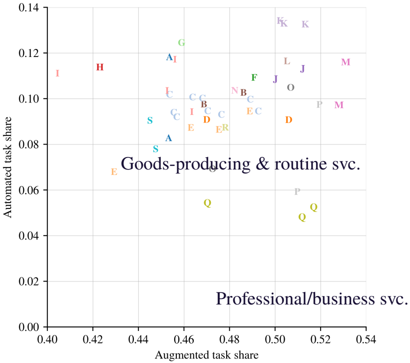
No separate AI industry: derived demand for ICT services & goods, electricity, utilities flows through existing markets.

Backup — key parameter values

Parameter	Description	Reference
α_o	Fréchet shape (tail thickness)	5
θ_o	Gumbel dependence (Kendall's $\tau = 0.6$)	2.5
ϵ	Task substitution elasticity	0.5
σ_v	Capital–task composite	0.5
σ_y, σ_n	VA vs. int.; int. composites	0 (Leontief)
σ_a	Armington (d vs. m)	2
σ_o, σ_q	Occupation, qualification choice	2, 2/3
η_g	Export demand: goods, business svc. / consumer svc.	4, 2
$\Delta \bar{E}_g$	Export-demand shift (reference)	$+10\%$

Sensitivity over $\alpha \in \{3, 5, 7\}$, $\theta \in \{5/3, 5/2, 5\}$, $\epsilon \in \{0.25, 0.5, 0.75\}$ in the longer paper (Lennox and Dixon, 2026).

Backup — Industries: heterogeneous task mix



- **Automation shares are well below augmentation shares** in every industry.
- Dispersion arises *endogenously* from occupational composition × equilibrium prices — no industry-specific technology imposed.

Backup — Wages: nearly universal real gains, modest dispersion

- Real-wage gains nearly universal — economy-wide productivity passes through via lower prices.
- Correlation of wage levels with wage changes weak (∼0.16).