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# Occupations, Tasks and Generative AI: A Computable General Equilibrium Analysis

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**Abstract**

This paper develops a task-based computable general equilibrium model to analyse the long-run economic effects of generative AI (GenAI) on the Australian economy. Each occupation performs a continuum of tasks executed in three modes: with raw labour; with AI-augmented labour; or automated using equipment and AI services. Task-level productivities in AI-using modes are draws from correlated Fréchet distributions, capturing heterogeneous within-occupation exposure. The model covers 45 industries and 97 occupations, calibrated to occupation-level GenAI exposure scores.

The reference simulation yields a 29.8% real GDP increase: roughly one third from task-level productivity gains, the rest from capital deepening and general equilibrium reallocation. Real consumption—our long-run welfare metric—rises by 16.2%, substantially less because additional investment is required to equip automated tasks. Augmentation accounts for more tasks than automation in nearly all industries and occupations.

Labour-market adjustment is dominated by within-occupation change—extensive-margin task reallocation equivalent to two thirds of current work—rather than net employment shifts between occupations. Losses concentrate in clerical, administrative, and sales roles, while most blue-collar occupations gain. Real wage effects are weakly correlated with initial wages; the rising capital share of income may matter more for distribution.

Sensitivity analysis shows aggregate outcomes hinge on the distribution of task-level productivity gains: fatter tails roughly double the GDP gain while preserving the adjustment pattern, whereas variation in the dependence parameter shifts the augmentation–automation balance and the incidence of adjustment. Conventional substitution elasticities matter less.

**Keywords:** Generative artificial intelligence; Computable general equilibrium; Task-based production; Occupational reallocation; Augmentation; Automation

**JEL classification:** C68; J23; J24; O33

## 1 Introduction

Generative AI (GenAI)—primarily large language models (LLMs)—exhibits the core characteristics of a general-purpose technology: pervasiveness, technical dynamism, and the capacity to catalyse complementary innovations (Gmyrek et al., 2023; Felten et al., 2023; Eloundou et al., 2024; Bresnahan and Trajtenberg, 1995). Unlike earlier waves of automation that mainly affected routine tasks (Autor et al., 2003), GenAI's applicability extends to non-routine cognitive work and the processing of unstructured data across diverse industries. A central economic distinction is whether GenAI is used to *automate* tasks—substituting directly for labour—or to *augment* workers, raising the productivity of labour that continues to perform the task (Brynjolfsson, 2023; Acemoglu, 2025). These features motivate the framework developed below.

Understanding the long-run structural implications of GenAI is a general-equilibrium problem: task-level cost changes alter factor demands, investment incentives, and the allocation of labour across occupations and industries. We address these interactions with a task-based computable general equilibrium (CGE) model calibrated to Australia, treating occupations as bundles of heterogeneous activities and linking labour supply to education. The model delivers internally consistent predictions for wages, occupational employment, and industry composition, disciplined by exposure indices that separately quantify augmentation and automation potential. Within occupations, heterogeneity is represented by correlated Fréchet draws, an extreme-value structure that yields closed-form aggregation and mode shares and maps the exposure indices into the key distributional parameters.

Recent experimental evidence suggests substantial productivity gains from GenAI in specific applications: time savings of 26–40% for coding and writing tasks (Noy and Zhang, 2023; Cui et al., 2026), with effects varying by worker skill and task type (Brynjolfsson et al., 2025b; Jia et al., 2024). Yet while adoption has been rapid (Hartley et al., 2024), aggregate employment effects appear limited and heterogeneous: Humlum and Vestergaard (2025) find small net effects on employment and earnings in highly exposed occupations; Dominski and Lee (2025) and Brynjolfsson et al. (2025a) report effects concentrated among entry-level workers and in occupations relying on complex reasoning; and Liu et al. (2025) find negative effects on job postings for roles most susceptible to automation. Aldasoro et al. (2026) find that adoption of AI in EU firms increases productivity 4% on average, with insignificant effects on employment in the short run. Such patterns are consistent with early-stage adoption of general-purpose technologies (Crafts, 2021; Brynjolfsson et al., 2021) and provide limited guidance on how task-level productivity changes will translate into wages, employment, and industry structure after technologies have matured and diffused.

Macroeconomic assessments adopt different strategies and interpret microeconomic evidence differently to estimate aggregate productivity impacts of GenAI. Applying Hulten's theorem to a task-based analysis, Acemoglu (2025) estimates that GenAI will boost aggregate productivity by 0.66% over one decade. With a more optimistic interpretation of the micro-econometric evidence, Aghion and Bunel (2024) estimate an effect ten times that, while they find that historical analogues suggest growth effects could be larger still.[1] The OECD, using a detailed micro-to-macro approach, estimates annualised productivity gains over a decade of 0.4–1.3% in countries with the most favourable conditions (United Kingdom and United States), depending on the speed of adoption (Filippucci et al., 2025).[2] Whereas these contributions focus on aggregate impacts over a medium-run horizon, our interest is in both aggregate and structural outcomes in the long run—the composition of the economy that these technologies imply, rather than the pace of diffusion. We also abstract from the possibility that GenAI accelerates innovation itself, with compounding effects on economic growth (Jones, 2025), but uncertain structural implications.

Characterising longer-run outcomes requires a labour demand representation capturing within-occupation task heterogeneity. Building on the task-based production literature (e.g. Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2022), we model each occupation as performing a continuum of tasks that can be executed in three modes: with raw labour; with labour *augmented* by AI services; or *automated* using equipment and AI services. Augmentation and automation thus compete as endogenous modes of task production, with the utilised mode determined task by task—capturing the choice between human–AI collaboration and full automation rather than imposing mode assignments *ex ante*. A third margin, which we abstract from here, is the generation of new tasks—and potentially, entirely new occupations.[3]

Capturing substitution across task execution modes while preserving within-occupation heterogeneity in a general-equilibrium setting requires a tractable distributional representation of task-level productivity. We assume that productivities in each mode are drawn from correlated Fréchet distributions, an extreme-value specification that delivers closed-form aggregation: the implied unit cost of the occupational task composite takes a CES-type form and the shares of tasks assigned to raw labour, augmented labour, and automation are explicit functions of relative prices and the distributional parameters. This tractability makes it feasible to embed endogenous mode choice within a multi-sector CGE model and to discipline the key scale parameters using the separate augmentation and automation exposure indices. A correlated Fréchet distribution is considered in Acemoglu et al. (2025) and applied in Cubas et al. (2024) to occupation-specific abilities in a Roy framework. Correlation across distributions allows that many tasks well-suited to augmentation may also be well-suited to automation, consistent with empirical exposure measures.

Our approach makes three contributions to the literature on general equilibrium analyses of AI and automation. First, we model augmentation and automation as endogenous, competing modes in a multi-sector framework.

[1]Their Hulten's theorem estimate for average annual growth over one decade is 0.68% while they obtain a range of 0.8–1.3% using historical analogues.

[2]The estimated range for Italy and Japan, assessed to have the least favourable conditions of the G7 countries, is 0.2–0.8% per annum.

[3]Acemoglu (2025) outlines four ways in which AI can affect production: (i) extensive-margin automation, (ii) new task complementarities, (iii) deepening of automation, and (iv) creation of new, labour-intensive tasks. Task automation and augmentation in our framework correspond to (i) and (ii) respectively. We also allow for (iii) but abstract from (iv).

Second, we extend this structure to previously automated activities (e.g., industrial robotics), allowing GenAI to enhance these tasks analogously to occupational labour. Third, we apply our framework to 97 detailed occupations, linking labour supply to educational qualifications and allowing for occupation-specific exposure to augmentation and automation. A distinctive feature of the data is that Jobs and Skills Australia (2025a) provide *separate* scores for augmentation potential and automation potential at the occupational level, derived from detailed task-level analysis. Most published exposure indices yield a single composite measure that conflates the two modes. These data allow us to calibrate the model's distributional scale parameters empirically.

Among the most closely related papers, Bekkers et al. (2025) analyse GenAI in a multi-sector model with task-based production and international trade, allowing GenAI to affect both production automation and trade costs. However, they impose automation shares rather than allowing them to respond endogenously to technology and relative prices. Filippucci et al. (2024) instead represent GenAI as sectoral productivity shocks. Both papers construct shocks using detailed occupational exposure indices. However, within each industry, indices are aggregated up into three broad skill groups in Bekkers et al. (2025) and into a single industry shock in Filippucci et al. (2024). In contrast, our framework (i) distinguishes augmentation from automation as separate margins and (ii) determines automation and augmentation task shares endogenously in general equilibrium, which allows us to characterise occupational reallocation and industry adjustment mechanisms that are masked by more aggregated representations. At the same time, these studies complement our contribution by exploring explicitly dynamic diffusion and adoption paths.

We calibrate task productivity distributions using occupation-level exposure scores for Australian occupations (Jobs and Skills Australia, 2025b,a), interpreting these as characterising the long-run technological potential of GenAI. These task-level mechanisms are embedded within a multi-sector model where industries combine occupational and equipment tasks with capital and intermediate inputs. The AI services used in tasks are composites of ICT goods and services, electricity, and utilities, so that price feedbacks and trade effects are captured endogenously.

Our reference case simulation yields a 29.8% increase in real GDP in the long run—which we interpret as being roughly two decades—although the welfare gain, at 16.2%, is substantially smaller because of the higher investment required. Of this GDP gain, roughly one third is attributable to task-level productivity improvements; the remainder arises through capital deepening and general equilibrium reallocation. Of all tasks originally performed by labour, 46.7% are augmented and 9.1% are fully automated. Employment shifts between occupations are moderate, with losses concentrated in lower-skilled white-collar roles and gains more widespread across blue-collar occupations. However, changes in task composition within occupations are large—equivalent to roughly two thirds of current work.

Given the deep uncertainties surrounding GenAI's capabilities, sensitivity analyses are important. Aggregate outcomes depend critically on the distributional characterisation of AI at the task level: moving from thinner tails ($\alpha = 7$) to fatter tails ($\alpha = 3$) roughly doubles the GDP gain, while strong tail dependence ($\theta = 5$) increases augmentation at the expense of automation. Importantly, changes in $\theta$ affect not only aggregate outcomes but also the incidence of adjustment across industries and occupations, whereas changes in $\alpha$ primarily rescale magnitudes. Varying conventional substitution elasticities within plausible ranges has comparatively modest effects.

The remainder of this paper is organised as follows. Section 2 provides an overview of the model structure, emphasising the task-based representation and its integration into the multi-sector framework. Section 3 summarises the calibration approach and data sources. Section 4 presents the results of our simulations: Section 4.1 reports macroeconomic results from our reference case; Section 4.2 considers the underlying task-level mechanisms and the role of the parameters governing distributional shape and tail dependence; Sections 4.3 and 4.4 show how impacts at task level translate into effects on industries, occupational employment, and wages; and Sections 4.5 and 4.6 study the sensitivity of aggregate and employment results to the distributional parameters. Section 5 discusses limitations and concludes.

## 2 Model

The model is comparative static and represents the economy in long-run equilibrium. This section provides an overview of the model and briefly presents its novel elements. We focus on the embedding of the task structure into production functions. As most other features of the model are standard in the literature, we present these more briefly in the main text, with further details provided in appendices.

## 2.1 Overview

We begin with the household and labour supply blocks that close the model, and then turn to the production structure where the task-based innovation enters.

Firms in 45 industries ($i \in \mathbb{I} \equiv \{1, 2, \dots, N_i\}$) produce using intermediate inputs, other capital and equipment capital, and up to 97 types of occupational labour ($o \in \mathbb{O} \equiv \{1, 2, \dots, N_o\}$). Each industry produces a corresponding good. The key innovation is a task-based representation of occupational labour embedded within the value-added nest. Within each occupation–industry pair, a continuum of tasks can be performed using non-AI, AI-augmented, or AI-automated modes. AI services are modelled as a composite of imported and domestic information and communications technology (ICT) services and goods, electricity, and other utilities, capturing price feedbacks and trade impacts.

Tasks within an occupation differ in their suitability for augmentation and automation. We model this heterogeneity explicitly by assuming that task-level productivities for AI-augmented and AI-automated modes are drawn from continuous joint distributions, allowing for dispersion and correlation across tasks. Given equilibrium input prices, firms compare mode-specific unit costs task by task, choosing the least-cost mode. Aggregation over the task continuum yields smooth, price-responsive mode shares within occupations and a tractable reduced-form representation of occupation-specific task costs and input requirements.

Aggregate labour supply is fixed, as is common in the CGE literature. This allows us to focus squarely on the long-run reallocation of labour within the economy, abstracting from potential responses of hours, participation and equilibrium unemployment. Workers are allocated first across qualifications (field × level) and then across occupations using a nested multinomial logit structure. The shifters in this block are calibrated to match baseline qualification and occupation shares, while the elasticities ($\sigma_{\mathrm{q}}, \sigma_{\mathrm{o}}$) govern the long-run responsiveness of qualification and occupational choices to relative wages. We set these elasticities to be modest, reflecting the empirical persistence of educational investments and greater mobility across occupations conditional on qualifications.

Market clearing requires that labour supply equals labour demand in each occupation, capital supply equals capital demand in each industry, and goods supply equals goods demand in each market. There are no commodity taxes, so domestic and import prices are uniform across purchasers. The rate of return to capital is assumed to be fixed in the long run, although relative prices of investment goods—and hence capital rental prices—are endogenous. This closure is consistent with standard long-run treatments in representative-agent neoclassical growth models. The balance of trade relative to GDP is held constant, while the terms of trade are endogenous. Export demand schedules are shifted outward exogenously to reflect global adoption of GenAI, with export volumes and prices adjusting endogenously in equilibrium.

## 2.2 Consumption

There is a single representative household that maximises a nested CES utility function

$$U = \left[ \sum_{g \in \mathbb{I}} \varkappa_{\mathrm{c},g}^{\frac{1}{\sigma_{\mathrm{u}}}} C_{\mathrm{c},g}^{\frac{\sigma_{\mathrm{u}}-1}{\sigma_{\mathrm{u}}}} \right]^{\frac{\sigma_{\mathrm{u}}}{\sigma_{\mathrm{u}}-1}} \tag{1}$$

where $C_{\mathrm{c},g}$ is an Armington composite of domestic $C_{\mathrm{d},g}$ and imported $C_{\mathrm{m},g}$ varieties of commodity $g$,

$$C_{\mathrm{c},g} = \left[ \varkappa_{\mathrm{d},g}^{\frac{1}{\sigma_{\mathrm{c}}}} C_{\mathrm{d},g}^{\frac{\sigma_{\mathrm{c}}-1}{\sigma_{\mathrm{c}}}} + \left(1 - \varkappa_{\mathrm{d},g}\right)^{\frac{1}{\sigma_{\mathrm{c}}}} C_{\mathrm{m},g}^{\frac{\sigma_{\mathrm{c}}-1}{\sigma_{\mathrm{c}}}} \right]^{\frac{\sigma_{\mathrm{c}}}{\sigma_{\mathrm{c}}-1}}. \tag{2}$$

The parameters $\varkappa_{\mathrm{c},g}$ and $\varkappa_{\mathrm{d},g}$ are CES distribution parameters, $\sigma_{\mathrm{u}}$ is the elasticity of substitution across commodity composites, and $\sigma_{\mathrm{c}}$ is the common Armington elasticity between domestic and imported varieties. Aggregate household expenditure equals factor income net of savings; the savings rate adjusts endogenously in the long-run closure so that the economy-wide rate of return on capital equals its exogenous level.

### 2.3 Labour supply and occupational choice

The economy is endowed with a fixed mass $N$ of persons, each supplying one unit of labour inelastically. There is no labour–leisure margin and no unemployment. Workers are mobile across industries within each occupation, but wages may differ across industries. We denote by $w_{o,i}$ the wage paid to occupation $o$ in industry $i$. The occupational wage relevant for labour supply, $w_o$, is defined as the average wage in occupation $o$,

$$w_o = \frac{\sum_{i\in\mathbb{I}} w_{o,i} N_{o,i}}{\sum_{i\in\mathbb{I}} N_{o,i}}. \tag{3}$$

With a single CPI numeraire common to all households, occupational wages $w_o$ act as relative prices that reallocate workers across qualifications and occupations. Let $\mathbb{Q}$ denote the set of qualifications (field × level, plus no post-school qualification). Conditional on their chosen qualification, workers choose an occupation. We represent these choices using a two-level nested logit structure, interpreted as a reduced-form representation of allocations in the long-run steady state.[4]

Let $\mathbb{O}$ denote the set of occupations. For each qualification–occupation pair $(q, o)$ let $\chi_{o,q} \geq 0$ denote a reduced-form feasibility/amenity weight. Setting $\chi_{o,q} = 0$ rules out a qualification–occupation match (e.g. because of legal minimum qualification requirements). Let $\sigma_{\mathrm{o}} > 0$ govern the responsiveness of occupational shares to relative wages within a qualification. The conditional share of qualification-$q$ workers employed in occupation $o$ is

$$\pi_{o|q} = \frac{\chi_{o,q}\, w_o^{\sigma_{\mathrm{o}}}}{\sum_{o'\in\mathbb{O}} \chi_{o',q}\, w_{o'}^{\sigma_{\mathrm{o}}}}. \tag{4}$$

Let $N_q$ denote the mass of persons holding qualification $q$. The mass of qualification-$q$ workers employed in occupation $o$ is then

$$N_{o,q} = \pi_{o|q} N_q. \tag{5}$$

Define the qualification-level value index

$$W_q = \left( \sum_{o\in\mathbb{O}} \chi_{o,q}\, w_o^{\sigma_{\mathrm{o}}} \right)^{1/\sigma_{\mathrm{o}}}. \tag{6}$$

Let $\xi_q > 0$ denote a qualification-specific weight capturing persistent barriers, costs, and non-pecuniary attributes of acquiring/holding qualification $q$. Let $\sigma_{\mathrm{q}} > 0$ govern the responsiveness of qualification shares to relative qualification values. The population share holding qualification $q$ is

$$\Pi_q = \frac{\xi_q\, W_q^{\sigma_{\mathrm{q}}}}{\sum_{q'\in\mathbb{Q}} \xi_{q'}\, W_{q'}^{\sigma_{\mathrm{q}}}} \tag{7}$$

and

$$N_q = \Pi_q N. \tag{8}$$

Total labour supplied to occupation $o$ is obtained by summing across qualifications,

$$N_o = \sum_{q\in\mathbb{Q}} N_{o,q}. \tag{9}$$

The shifters $\chi_{o,q}$ and $\xi_q$ are calibrated to match baseline employment shares by qualification and by qualification–occupation cell. The elasticities $\sigma_{\mathrm{o}}$ and $\sigma_{\mathrm{q}}$ govern the long-run responsiveness of occupational and qualification allocations to relative wage differentials.

### 2.4 Production

Figure 1 shows the nesting structure of the production function for industry $i$, which we describe in turn below.

[4] Qualifications take time and resources to acquire, and occupation-specific human capital accumulates on the job. Thus, the parameters in this block should be interpreted as capturing long-run steady-state allocations.

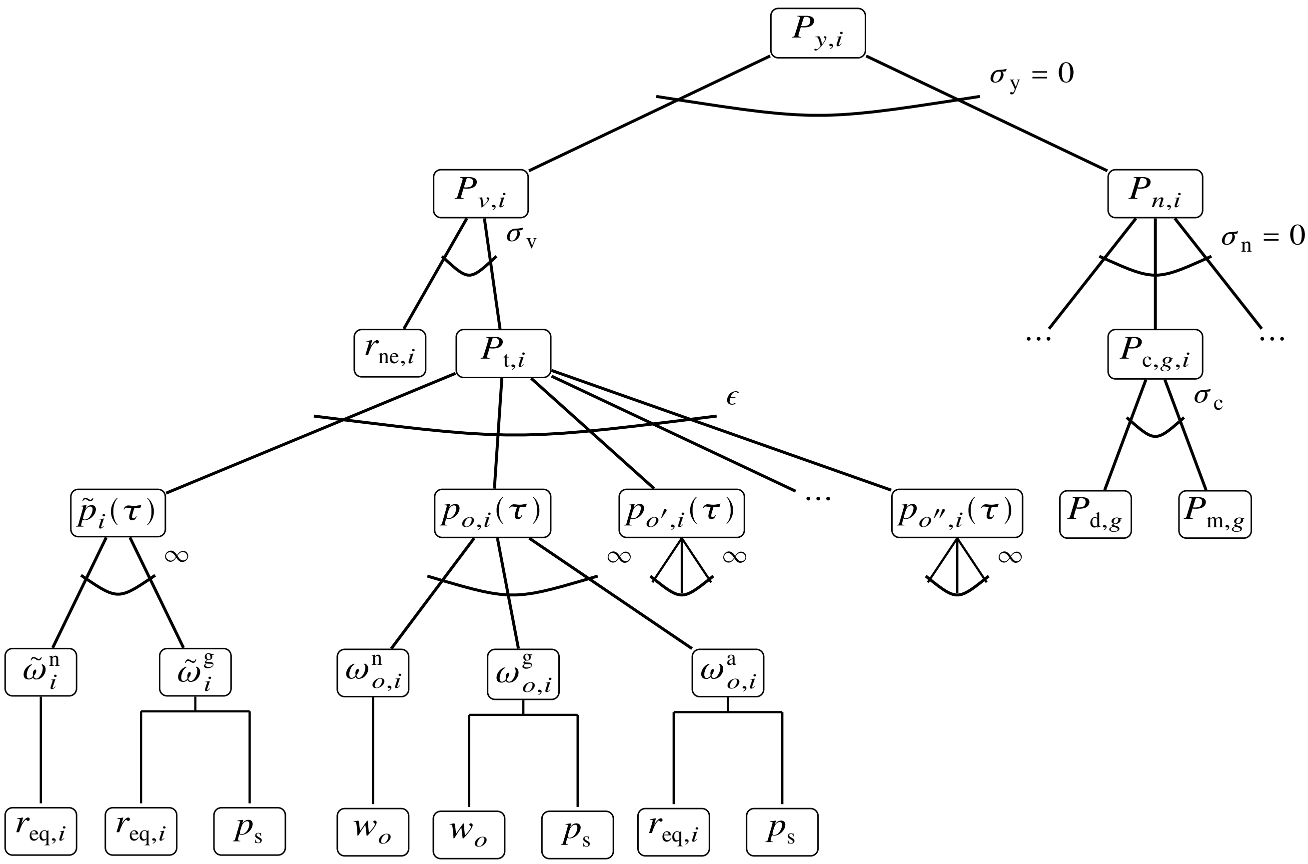


Figure 1: Illustration of the nested dual cost function for industry $i$. Leaves are prices for goods ($P_{c,g,i}$), non-equipment capital ($r_{ne,i}$), equipment capital ($r_{eq,i}$), labour ($w_o$) and AI services ($p_s$) inputs. Intermediate nodes show prices for composites of these inputs. The relevant substitution elasticities are shown for CES sub-nests. The two levels of nesting below $P_{t,i}$ represent the task-based structure. The elasticity of substitution between all individual tasks is $\epsilon$, while modes are perfectly substitutable within tasks. The lowest level shows the Leontief technologies for augmented and automated task modes.

As inputs to production, each industry uses intermediates, occupational labour, equipment capital and other capital. For generality, we specify a nested CES production function, although in simulations we set $\sigma_y$ and $\sigma_n$ to zero.[5] At the top level, a value added composite is combined with an intermediate composite

$$Y_i = \left[ \varsigma_v^{\frac{1}{\sigma_y}} X_{va,i}^{\frac{\sigma_y - 1}{\sigma_y}} + (1 - \varsigma_v)^{\frac{1}{\sigma_y}} X_{int,i}^{\frac{\sigma_y - 1}{\sigma_y}} \right]^{\frac{\sigma_y}{\sigma_y - 1}} \tag{10}$$

Value added is a composite of other capital and an aggregate task output

$$X_{va,i} = \left[ \varsigma_k^{\frac{1}{\sigma_v}} K_{ne,i}^{\frac{\sigma_v - 1}{\sigma_v}} + (1 - \varsigma_k)^{\frac{1}{\sigma_v}} T_i^{\frac{\sigma_v - 1}{\sigma_v}} \right]^{\frac{\sigma_v}{\sigma_v - 1}}. \tag{11}$$

Different intermediate goods $g \in \mathbb{I}$ are combined as

$$X_{int,i} = \left[ \sum_{g \in \mathbb{I}} \varsigma_{c,g,i}^{\frac{1}{\sigma_n}} X_{c,g,i}^{\frac{\sigma_n - 1}{\sigma_n}} \right]^{\frac{\sigma_n}{\sigma_n - 1}}. \tag{12}$$

These intermediates are Armington composites of domestic and imported inputs,

$$X_{c,g,i} = \left[ \varsigma_{d,g,i}^{\frac{1}{\sigma_c}} X_{d,g,i}^{\frac{\sigma_c - 1}{\sigma_c}} + \left(1 - \varsigma_{d,g,i}\right)^{\frac{1}{\sigma_c}} X_{m,g,i}^{\frac{\sigma_c - 1}{\sigma_c}} \right]^{\frac{\sigma_c}{\sigma_c - 1}}. \tag{13}$$

[5] Leontief and Cobb-Douglas nests are limiting cases of the CES production function as elasticities of substitution go to zero and unity, respectively: the Cobb-Douglas production function is obtained from this one by applying L'Hôpital's rule.

where $\varsigma_{\mathrm{c},g,i}$ and $\varsigma_{\mathrm{d},g,i}$ are CES distribution parameters, $\sigma_{\mathrm{n}}$ is the elasticity of substitution across intermediate composites, and $\sigma_{\mathrm{c}}$ is the Armington elasticity between domestic and imported varieties. Cost-minimising demands and composite price indices for all CES nests in the model are collected in Appendix A.1.

The task composite $T_i$ aggregates 'equipment tasks' (which are previously automated activities) and occupational tasks (tasks initially performed by occupational labour):

$$T_i = \left[\tilde{\varphi}_i^{1/\epsilon} \int_0^1 \tilde{x}_i(\tau)^{(\epsilon-1)/\epsilon}\, \mathrm{d}\tau + \sum_{o\in\mathbb{O}} \varphi_{o,i}^{1/\epsilon} \int_0^1 x_{o,i}(\tau)^{(\epsilon-1)/\epsilon}\, \mathrm{d}\tau\right]^{\epsilon/(\epsilon-1)} \tag{14}$$

where $\tilde{x}_i(\tau)$ denotes equipment task outputs, $x_{o,i}(\tau)$ denotes occupational task outputs, and $\epsilon$ is the elasticity of substitution between tasks. The weights $\tilde{\varphi}_i$ and $\varphi_{o,i}$ capture industry-specific differences in the quantities of each task type required. Unlike models with a fixed automation cutoff (e.g. Acemoglu and Restrepo, 2022), mode assignment here is not determined by a threshold on the task index $\tau$ but by the realised productivity draw $\psi^{\mathrm{g}}_{o,i}$ or $\psi^{\mathrm{a}}_{o,i}$ relative to input price ratios. Consequently the integrals in (14) run from 0 to 1 for all modes, with the effective task shares determined endogenously through the productivity distributions derived in Section 2.4.2.

### 2.4.1 Task production and mode competition

While occupational labour tasks are initially performed by raw labour, with the advent of GenAI, they may alternatively be performed by labour augmented by AI services, or automated using equipment and AI services. The task production function for occupation $o$ in industry $i$ is:

$$x_{o,i}(\tau) = x^{\mathrm{n}}_{o,i}(\tau) + \psi^{\mathrm{g}}_{o,i}(\tau)\, x^{\mathrm{g}}_{o,i}(\tau) + \psi^{\mathrm{a}}_{o,i}(\tau)\, x^{\mathrm{a}}_{o,i}(\tau) \tag{15}$$

where the superscripts n, g, and a denote non-AI, augmented, and automated modes respectively. The task-specific productivity parameters $\psi^{\mathrm{g}}_{o,i}(\tau)$ and $\psi^{\mathrm{a}}_{o,i}(\tau)$ reflect variation in the productivity of labour and equipment across tasks in the AI-using modes.

Production in each mode combines primary inputs with AI services in fixed proportions:

$$\begin{aligned} x^{\mathrm{n}}_{o,i}(\tau) &= A^{L}_{o,i}\, n^{\mathrm{n}}_{o,i}(\tau) \\ x^{\mathrm{g}}_{o,i}(\tau) &= \min\left\{A^{L}_{o,i}\, n^{\mathrm{g}}_{o,i}(\tau),\; A^{G}_{o,i}\, s^{\mathrm{g}}_{o,i}(\tau)\right\} \\ x^{\mathrm{a}}_{o,i}(\tau) &= \min\left\{A^{K}_{i}\, k^{\mathrm{a}}_{o,i}(\tau),\; A^{S}_{o,i}\, s^{\mathrm{a}}_{o,i}(\tau)\right\} \end{aligned} \tag{16}$$

where $n^{\mathrm{n}}_{o,i}(\tau)$ and $n^{\mathrm{g}}_{o,i}(\tau)$ denote labour inputs in the non-AI and augmented modes, $k^{\mathrm{a}}_{o,i}(\tau)$ denotes equipment input in the automated mode, and $s^{\mathrm{g}}_{o,i}(\tau)$ and $s^{\mathrm{a}}_{o,i}(\tau)$ denote AI-services inputs in the augmented and automated modes. The parameters $A^{L}_{o,i}$, $A^{K}_{i}$, $A^{G}_{o,i}$, and $A^{S}_{o,i}$ are factor-augmenting productivity terms that allow for industry- and occupation-specific calibration; they are held fixed in our simulations.

The distinction between the augmented and automated modes reflects the nature of the primary input. In the augmented mode, a human worker remains the primary input and AI services ($s^{\mathrm{g}}_{o,i}(\tau)$) raise the productivity of labour ($n^{\mathrm{g}}_{o,i}(\tau)$), with no dedicated capital required. In the automated mode, a machine—industrial robots, computer-controlled equipment, or data-centre infrastructure—replaces labour as the primary input, and AI services ($s^{\mathrm{a}}_{o,i}(\tau)$) raise the productivity of equipment ($k^{\mathrm{a}}_{o,i}(\tau)$). Equipment thus represents dedicated automation capital, while AI services represent inference compute and related ICT inputs consumed in proportion to task volume.

With task modes being perfect substitutes, each task is allocated to the mode with lowest unit cost. Given the wage $w_o$, equipment rental $r_{\mathrm{eq},i}$, and AI services price $p_{\mathrm{s}}$, the unit cost for occupational task $\tau$ is:

$$p_{o,i}(\tau) = \min\left\{\omega^{\mathrm{n}}_{o,i},\; \frac{\omega^{\mathrm{g}}_{o,i}}{\psi^{\mathrm{g}}_{o,i}(\tau)},\; \frac{\omega^{\mathrm{a}}_{o,i}}{\psi^{\mathrm{a}}_{o,i}(\tau)}\right\} \tag{17}$$

$$\omega^{\mathrm{n}}_{o,i} \equiv w_o/A^{L}_{o,i}, \qquad \omega^{\mathrm{g}}_{o,i} \equiv w_o/A^{L}_{o,i} + p_{\mathrm{s}}/A^{G}_{o,i}, \qquad \omega^{\mathrm{a}}_{o,i} \equiv r_{\mathrm{eq},i}/A^{K}_{i} + p_{\mathrm{s}}/A^{S}_{o,i}.$$

The cost ratios that determine mode thresholds are

$$\hat{\omega}^{\mathrm{g}}_{o,i} \equiv \omega^{\mathrm{g}}_{o,i}/\omega^{\mathrm{n}}_{o,i} = 1 + \frac{p_{\mathrm{s}}\, A^{L}_{o,i}}{A^{G}_{o,i}\, w_o}, \qquad \hat{\omega}^{\mathrm{a}}_{o,i} \equiv \omega^{\mathrm{a}}_{o,i}/\omega^{\mathrm{n}}_{o,i} = \frac{r_{\mathrm{eq},i}\, A^{L}_{o,i}}{A^{K}_{i}\, w_o} + \frac{p_{\mathrm{s}}\, A^{L}_{o,i}}{A^{S}_{o,i}\, w_o}. \tag{18}$$

Equipment tasks—activities already performed by automated equipment prior to GenAI—may also be enhanced by AI services embodied in that equipment.[6] The production function for equipment task $\tau$ in industry $i$ is

$$\begin{aligned}\tilde{x}_i(\tau) &= \tilde{x}_i^{\mathrm{n}}(\tau) + \tilde{\psi}_i^{\mathrm{g}}(\tau)\,\tilde{x}_i^{\mathrm{g}}(\tau) \\ \tilde{x}_i^{\mathrm{n}}(\tau) &\equiv A_i^K\,\tilde{k}_i^{\mathrm{n}}(\tau) \\ \tilde{x}_i^{\mathrm{g}}(\tau) &\equiv \min\left\{A_i^K\,\tilde{k}_i^{\mathrm{g}}(\tau),\ \tilde{A}_i^S\,\tilde{s}_i^{\mathrm{g}}(\tau)\right\}\end{aligned} \tag{19}$$

where $\tilde{k}_i^{\mathrm{n}}(\tau)$ and $\tilde{k}_i^{\mathrm{g}}(\tau)$ are equipment inputs in the non-AI and AI-enhanced modes, $\tilde{s}_i^{\mathrm{g}}(\tau)$ is AI services input, $A_i^K$ is an equipment productivity parameter common to both modes, and $\tilde{\psi}_i^{\mathrm{g}}(\tau)$ is the task-specific productivity draw. Unlike automation of occupational tasks, the AI-enhanced equipment mode does not substitute a new primary input: it raises the productivity of equipment already in use, requiring AI services in fixed proportions. In our main simulations we set AI enhancement of equipment tasks to zero, since our empirical exposure estimates are limited to occupational tasks; a supplementary simulation illustrates the effects of allowing this channel.

The unit cost per equipment task is

$$\tilde{p}_i(\tau) = \min\left\{\tilde{\omega}_i^{\mathrm{n}},\ \frac{\tilde{\omega}_i^{\mathrm{g}}}{\tilde{\psi}_i^{\mathrm{g}}(\tau)}\right\} \tag{20}$$

$$\tilde{\omega}_i^{\mathrm{n}} \equiv r_{\mathrm{eq},i}/A_i^K, \qquad \tilde{\omega}_i^{\mathrm{g}} \equiv r_{\mathrm{eq},i}/A_i^K + p_{\mathrm{s}}/\tilde{A}_i^S.$$

Note that $\tilde{\omega}_i^{\mathrm{n}}$ equals the equipment component of $\omega_{o,i}^{\mathrm{a}}$ and $\tilde{\omega}_i^{\mathrm{g}}$ has the same structure—equipment plus AI services—but with equipment-specific AI productivity $\tilde{A}_i^S$. An equipment task is AI-enhanced if and only if $\tilde{\psi}_i^{\mathrm{g}}(\tau) > \hat{\tilde{\omega}}_i^{\mathrm{g}} \equiv \tilde{\omega}_i^{\mathrm{g}}/\tilde{\omega}_i^{\mathrm{n}}$, i.e. the AI productivity gain exceeds the ratio of combined (equipment plus AI) to pure-equipment unit costs.

Cost minimisation over the task composite (14) yields demand for each individual task output. Letting $P_{\mathrm{t},i}$ denote the unit cost of the task composite, the demand for occupational task $\tau$ of type $(o, i)$ is

$$x_{o,i}(\tau) = \varphi_{o,i}\left(\frac{P_{\mathrm{t},i}}{p_{o,i}(\tau)}\right)^{\epsilon} T_i, \tag{21}$$

and the demand for equipment task $\tau$ in industry $i$ is

$$\tilde{x}_i(\tau) = \tilde{\varphi}_i\left(\frac{P_{\mathrm{t},i}}{\tilde{p}_i(\tau)}\right)^{\epsilon} T_i. \tag{22}$$

Since unit costs $p_{o,i}(\tau)$ and $\tilde{p}_i(\tau)$ depend on task-specific productivity draws, these demand schedules are heterogeneous across tasks and must be integrated over the productivity distributions to obtain aggregate factor demands.

### 2.4.2 Task productivity distributions

To derive aggregate mode shares and task share weights, we specify distributions for task productivities $\psi_{o,i}^{\mathrm{g}}(\tau)$ and $\psi_{o,i}^{\mathrm{a}}(\tau)$. Our data suggest that these productivities are positively correlated within occupations: tasks with high potential for augmentation also tend to have high potential for automation.[7] To capture this pattern, we assume $\psi_{o,i}^{\mathrm{g}}$ and $\psi_{o,i}^{\mathrm{a}}$ follow a correlated Fréchet distribution—Fréchet marginals linked by a Gumbel copula.[8]

[6] We label the AI-using mode for equipment tasks g, reserving a for tasks that switch their primary input from labour to equipment. The AI-using mode here augments equipment already in use rather than automating anything further.

[7] The underlying task-level analysis suggests substantial overlap in the tasks that are augmentable and automatable within occupations (Jobs and Skills Australia, personal communication, May 2025.).

[8] The Fréchet distribution with scale $\kappa$ and shape $\alpha$ is a heavy-tailed continuous probability distribution on $(0, \infty)$ with CDF $F_X(x) = \exp[-(\kappa/x)^{\alpha}]$ and PDF $f_X(x) = (\alpha/\kappa)(\kappa/x)^{1+\alpha}\exp[-(\kappa/x)^{\alpha}]$. The two-dimensional Gumbel copula $C(U, V) = \exp[-[(-\ln U)^{\theta} + (-\ln V)^{\theta}]^{1/\theta}]$ exhibits upper-tail dependence, capturing the tendency for large values of both variables to occur jointly. A joint CDF with given marginals is obtained by substituting their CDFs into the copula.

The joint CDF of productivities is:

$$F(\bar{\psi}^{\mathrm{g}}_{o,i}, \bar{\psi}^{\mathrm{a}}_{o,i}) = \exp\left[-\left(\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\bar{\psi}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\bar{\psi}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}\right)^{1/\theta_o}\right] \tag{23}$$

where $\kappa^{\mathrm{g}}_{o,i}$ and $\kappa^{\mathrm{a}}_{o,i}$ are occupation–industry-specific scale parameters, $\alpha_o$ is the shape parameter (smaller values imply heavier tails), and $\theta_o \in [1, \infty)$ governs the strength of upper-tail dependence (Kendall's tau equals $1-1/\theta_o$). In our reference case, $\alpha_o$ and $\theta_o$ are set to common values across occupations.

This distributional specification yields closed-form expressions for the endogenously-determined task share weights that enter the reduced-form CES production function. The weights for tasks performed without AI are

$$\Gamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i}) = \exp\left[-\left(\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}\right)^{1/\theta_o}\right] \tag{24}$$

where $\hat{\omega}^{\mathrm{g}}_{o,i}$ and $\hat{\omega}^{\mathrm{a}}_{o,i}$ are the cost ratios defined in (18). Augmented task share weights are given by

$$\Gamma^{\mathrm{g}}_{o,i}(\boldsymbol{\omega}_{o,i}) = \Omega_{o,i}(\boldsymbol{\omega}_{o,i})\ \left(\kappa^{\mathrm{g}}_{o,i}\right)^{\epsilon-1}\left[\frac{\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o}}{\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}}\right]^{1+\frac{1-\epsilon}{\alpha_o\theta_o}}. \tag{25}$$

with[9]

$$\Omega_{o,i}(\boldsymbol{\omega}_{o,i}) \equiv \mathrm{Gamma}\left[1+\frac{1-\epsilon}{\alpha_o}\right] - \mathrm{Gamma}\left[1+\frac{1-\epsilon}{\alpha_o},\ -\log\Gamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i})\right]. \tag{26}$$

The expression for automated task share weights is analogous—i.e. swapping the g and a superscripts in (25). Derivations and related expressions for task shares (i.e. the unweighted fraction of tasks performed in each mode) are given in Appendices A.2 and A.3.

Equipment tasks follow an analogous but simpler structure, since there is only one AI-using mode. The AI-enhanced productivity $\tilde{\psi}^{\mathrm{g}}_i$ is assumed to follow a univariate Fréchet distribution with scale $\tilde{\kappa}^{\mathrm{g}}_i$ and shape $\tilde{\alpha}_i$, independently of occupational task productivities. Equipment task $\tau$ in industry $i$ is AI-enhanced if and only if $\tilde{\psi}^{\mathrm{g}}_i(\tau) > \hat{\tilde{\omega}}^{\mathrm{g}}_i \equiv \tilde{\omega}^{\mathrm{g}}_i/\tilde{\omega}^{\mathrm{n}}_i$. The non-AI task share weight is the Fréchet CDF evaluated at this threshold:

$$\tilde{\Gamma}^{\mathrm{n}}_i = \exp\left[-\left(\frac{\tilde{\kappa}^{\mathrm{g}}_i}{\hat{\tilde{\omega}}^{\mathrm{g}}_i}\right)^{\tilde{\alpha}_i}\right]. \tag{27}$$

For the AI-enhanced mode, evaluating the analogous integral gives

$$\tilde{\Gamma}^{\mathrm{g}}_i(\tilde{\boldsymbol{\omega}}_i) = \tilde{\Omega}_i(\tilde{\boldsymbol{\omega}}_i)\ (\tilde{\kappa}^{\mathrm{g}}_i)^{\epsilon-1} \tag{28}$$

where

$$\tilde{\Omega}_i(\tilde{\boldsymbol{\omega}}_i) \equiv \mathrm{Gamma}\left[1+\frac{1-\epsilon}{\tilde{\alpha}_i}\right] - \mathrm{Gamma}\left[1+\frac{1-\epsilon}{\tilde{\alpha}_i},\ -\log\tilde{\Gamma}^{\mathrm{n}}_i\right]. \tag{29}$$

The equipment task weights have the same mathematical structure as their occupational counterparts, with the univariate case reflecting the absence of a competing AI mode.

Using these weights, the explicit task production function (15) can be expressed in a reduced form as

$$T_i = \left[\tilde{\varphi}_i^{1/\epsilon}\sum_{m\in\{\mathrm{n,g}\}}\left(\tilde{\Gamma}^m_i\right)^{1/\epsilon}\left(\tilde{x}^m_i\right)^{(\epsilon-1)/\epsilon} + \sum_{o\in\mathbb{O}}\varphi_{o,i}^{1/\epsilon}\sum_{m\in\{\mathrm{n,g,a}\}}\left(\Gamma^m_{o,i}\right)^{1/\epsilon}\left(x^m_{o,i}\right)^{(\epsilon-1)/\epsilon}\right]^{\epsilon/(\epsilon-1)} \tag{30}$$

This is a CES production function of the composite inputs used in each mode in which the weights are endogenous functions of both the underlying technology parameters (given exogenously) and prices (determined endogenously in general equilibrium). The corresponding dual cost function—the unit cost of the task composite—is

$$P_{\mathrm{t},i} = \left[\tilde{\varphi}_i\sum_{m\in\{\mathrm{n,g}\}}\tilde{\Gamma}^m_i\,(\tilde{\omega}^m_i)^{1-\epsilon} + \sum_{o\in\mathbb{O}}\varphi_{o,i}\sum_{m\in\{\mathrm{n,g,a}\}}\Gamma^m_{o,i}\,(\omega^m_{o,i})^{1-\epsilon}\right]^{1/(1-\epsilon)}. \tag{31}$$

[9] $\mathrm{Gamma}(\cdot)$ is the Gamma function and $\mathrm{Gamma}(\cdot,\cdot)$ is the upper incomplete Gamma function.

### 2.4.3 Aggregate task input demands

To complete the specification of industry cost minimisation, we integrate individual task demands over the sets of tasks assigned to each mode. Combining (21) with the definitions of the task share weights yields mode-level aggregate task outputs for occupational tasks,[10]

$$x^{m}_{o,i} = \varphi_{o,i}\, \Gamma^{m}_{o,i} \left( \frac{P_{\mathrm{t},i}}{\omega^{m}_{o,i}} \right)^{\epsilon} T_i, \qquad m \in \{\mathrm{n}, \mathrm{g}, \mathrm{a}\}, \tag{32}$$

and for equipment tasks:

$$\tilde{x}^{m}_{i} = \tilde{\varphi}_{i}\, \tilde{\Gamma}^{m}_{i} \left( \frac{P_{\mathrm{t},i}}{\tilde{\omega}^{m}_{i}} \right)^{\epsilon} T_i, \qquad m \in \{\mathrm{n}, \mathrm{g}\}. \tag{33}$$

These have the standard CES demand form, with the endogenous weights $\Gamma^{m}_{o,i}$ and $\tilde{\Gamma}^{m}_{i}$ introducing a price-responsiveness beyond what fixed CES distribution parameters alone would imply.

Factor demands follow from the Leontief structure of each mode. For occupation $o$ in industry $i$, labour input demand is

$$N_{o,i} = \frac{x^{\mathrm{n}}_{o,i} + x^{\mathrm{g}}_{o,i}}{A^{L}_{o,i}}, \tag{34}$$

since both the non-AI and augmented modes employ labour. Equipment capital is demanded by the automated mode of occupational tasks and by both modes of equipment tasks. Summing over occupations, total equipment capital demand in industry $i$ is

$$K_{\mathrm{eq},i} = \frac{1}{A^{K}_{i}} \left[ \tilde{x}^{\mathrm{n}}_{i} + \tilde{x}^{\mathrm{g}}_{i} + \sum_{o \in \mathbb{O}} x^{\mathrm{a}}_{o,i} \right]. \tag{35}$$

Non-equipment capital $K_{\mathrm{ne},i}$ is determined by cost minimisation over the value-added CES nest and does not enter the task structure directly.

AI services demand in industry $i$ aggregates over all AI-using modes:

$$S_i = \sum_{o \in \mathbb{O}} \left( \frac{x^{\mathrm{g}}_{o,i}}{A^{G}_{o,i}} + \frac{x^{\mathrm{a}}_{o,i}}{A^{S}_{o,i}} \right) + \frac{\tilde{x}^{\mathrm{g}}_{i}}{\tilde{A}^{S}_{i}}. \tag{36}$$

The first two terms capture AI services consumed in augmented and automated occupational tasks respectively; the third captures AI services in AI-enhanced equipment tasks. Total AI services demand is $S = \sum_{i \in \mathbb{I}} S_i$, from which domestic and imported good demands are determined in Section 2.5. Note that these demands scale with task-level factor inputs rather than with gross output $Y_i$, reflecting the fixed input proportions in task production (16) and their aggregation across tasks (36). As a result, the AI cost share in total production cost is endogenous and responds to changes in relative input prices, distinguishing AI services from conventional intermediate inputs.

## 2.5 AI services

AI services used in task production are represented as a Leontief composite of existing domestic and imported goods rather than a separately produced output, with fixed expenditure shares $a_{\mathrm{d},g}$ and $a_{\mathrm{m},g}$ for domestic and imported varieties of each good $g$ respectively, as specified in Table 2. The price of one unit of AI services follows directly from the Leontief cost function:

$$p_{\mathrm{s}} = \sum_{g \in \mathbb{G}_s} \left( a_{\mathrm{d},g}\, P_{\mathrm{d},g} + a_{\mathrm{m},g}\, P_{\mathrm{m},g} \right), \tag{37}$$

where $\mathbb{G}_s \subseteq \mathbb{I}$ denotes the set of goods with positive expenditure shares in AI services. Domestic and import demands arising from AI services are

$$S_{\mathrm{d},g} = a_{\mathrm{d},g}\, S, \qquad S_{\mathrm{m},g} = a_{\mathrm{m},g}\, S, \qquad g \in \mathbb{G}_s, \tag{38}$$

[10]Since we use $X$ to denote inputs of the aggregate industry production functions, we use lower case $x$ without a $\tau$ index to indicate task aggregates. However, for aggregate inputs to tasks, we use upper case symbols.

where $S = \sum_{i \in \mathbb{I}} S_i$ is total AI services demand across all tasks, modes, and industries, with industry-level demand $S_i$ given by (36), and these demands enter the market-clearing equations (44)–(45). Unlike ordinary intermediate demands, which are proportional to output, AI service demands scale with task-level factor inputs—specifically, with the quantities of labour and equipment engaged in AI-using modes (see (17)). Expanded AI adoption therefore generates endogenous price feedbacks through the markets for ICT services, electricity, and equipment that are captured in the general-equilibrium solution.

## 2.6 Capital and investment

Each industry uses two types of capital indexed by $k \in \{\text{ne}, \text{eq}\}$: non-equipment capital (e.g. structures, vehicles) and equipment capital (machines used in automated tasks, as described in Section 2.4.1). Gross capital formation of each type is a CES composite of investment goods, mirroring the structure of intermediates in equations (12)–(13):

$$I_{k,i} = \left[ \sum_{g \in \mathbb{I}} \zeta_{\text{c},g,k,i}^{\frac{1}{\sigma_\text{i}}} I_{\text{c},g,k,i}^{\frac{\sigma_\text{i}-1}{\sigma_\text{i}}} \right]^{\frac{\sigma_\text{i}}{\sigma_\text{i}-1}}, \tag{39}$$

where the Armington composites $I_{\text{c},g,k,i}$ have the same structure as (13):

$$I_{\text{c},g,k,i} = \left[ \zeta_{\text{d},g,k,i}^{\frac{1}{\sigma_\text{c}}} I_{\text{d},g,k,i}^{\frac{\sigma_\text{c}-1}{\sigma_\text{c}}} + \left(1 - \zeta_{\text{d},g,k,i}\right)^{\frac{1}{\sigma_\text{c}}} I_{\text{m},g,k,i}^{\frac{\sigma_\text{c}-1}{\sigma_\text{c}}} \right]^{\frac{\sigma_\text{c}}{\sigma_\text{c}-1}}. \tag{40}$$

The parameters $\zeta_{\text{c},g,k,i}$ and $\zeta_{\text{d},g,k,i}$ are CES distribution parameters and $\sigma_\text{i}$ is the elasticity of substitution across investment goods. In the long-run balanced-growth equilibrium, relative prices are constant, so the rental price of type-$k$ capital in industry $i$ is

$$r_{k,i} = (\rho + \mu_{k,i} + \delta_{k,i})\, P_{k,i}, \tag{41}$$

where $\rho$ is the common net rate of return, $\mu_{k,i}$ is an industry- and asset-specific risk premium, $\delta_{k,i}$ is the depreciation rate, and $P_{k,i}$ is the investment price index dual to (39) (see Appendix A.1). Endogenous changes in relative investment goods prices therefore feed directly into rental prices and factor demands.

Capital stocks adjust freely to satisfy demand: $K_{k,i} = I_{k,i}/\delta_{k,i}$. Since $\rho$, $\mu_{k,i}$, and $\delta_{k,i}$ are fixed, the rental price $r_{k,i}$ moves only with the endogenous investment price $P_{k,i}$, and supply of each capital type is perfectly elastic at the implied rental price. The aggregate capital stock is determined by the household savings rate, which adjusts endogenously to maintain $\rho$ at its exogenous level.

## 2.7 Market clearance and external closure

Factor market clearing is as described in the overview. Labour market clearing requires, for each occupation $o$, that the sum of labour demands across industries equals the supply of workers to that occupation:

$$\sum_{i \in \mathbb{I}} N_{o,i} = N_o, \qquad o \in \mathbb{O}, \tag{42}$$

where $N_{o,i}$ is given by (34) and $N_o$ by (9). Wages $w_o$ adjust endogenously to clear each occupational labour market. Capital market clearing requires, for each capital type $k \in \{\text{ne}, \text{eq}\}$, that supply equals demand in every industry. The long-run required rate of return, $\rho$, is fixed exogenously, while investment-good prices—and hence rental rates $r_{k,i}$—are determined endogenously. Capital quantities adjust to satisfy these conditions.

Capital market clearing requires that supply equals demand for each capital type in every industry. The long-run rate of return is fixed exogenously, while investment-good prices—and thus rental rates—are determined endogenously, with capital quantities adjusting accordingly.

For goods markets, industry $g$ produces a single domestic variety at price $P_{\text{d},g}$. In the absence of commodity taxes, $P_{\text{d},g}$ and $P_{\text{m},g}$ are the same for all purchasers, so a single set of Armington price indices $P_g$ enters the demand equations of all users (see Appendix A.1). Imported varieties of good $g$ carry an exogenous foreign-currency price $P_{\text{w},g}$. The domestic-currency import price is

$$P_{\text{m},g} = e\, P_{\text{w},g}, \tag{43}$$

where $e$ is a real exchange rate (domestic price level relative to foreign) that adjusts endogenously. The consumer price index $P_{\mathrm{c}} \equiv [\sum_{g\in\mathbb{I}} \varkappa_{\mathrm{c},g} P_{\mathrm{c},g}^{1-\sigma_{\mathrm{u}}}]^{1/(1-\sigma_{\mathrm{u}})}$ serves as numéraire and is normalised to unity; movements in $e$ therefore represent real appreciation or depreciation relative to the foreign price level. Market clearing for the domestic variety requires that output equals the sum of domestic uses plus exports:

$$Y_g = \sum_{i\in\mathbb{I}} X_{\mathrm{d},g,i} + \sum_{i\in\mathbb{I}} \sum_{k\in\{\mathrm{ne,eq}\}} I_{\mathrm{d},g,k,i} + C_{\mathrm{d},g} + S_{\mathrm{d},g} + E_g, \qquad g \in \mathbb{I} \tag{44}$$

where $E_g$ denotes exports and $S_{\mathrm{d},g}$ denotes demand for the domestic variety of good $g$ arising from AI services, whose composition across goods follows the fixed-coefficient structure of Table 2. Total imports equal the sum of import demands across all users:

$$M_g = \sum_{i\in\mathbb{I}} X_{\mathrm{m},g,i} + \sum_{i\in\mathbb{I}} \sum_{k\in\{\mathrm{ne,eq}\}} I_{\mathrm{m},g,k,i} + C_{\mathrm{m},g} + S_{\mathrm{m},g}, \qquad g \in \mathbb{I}. \tag{45}$$

Exports of good $g$ face a downward-sloping rest-of-world demand schedule,

$$E_g = \bar{E}_g \left(\frac{P_{\mathrm{d},g}}{P_{\mathrm{w},g}}\right)^{-\eta_g}, \tag{46}$$

where $P_{\mathrm{w},g}$ is the world price of competing goods (in foreign currency), $\eta_g > 0$ is the export demand elasticity, and $\bar{E}_g$ is an exogenous demand shifter. This specification allows the terms of trade to respond endogenously to domestic cost changes.

Nominal GDP is reported on both the expenditure and income sides. In the absence of commodity taxes and subsidies, the two measures coincide in equilibrium. We denote expenditure-side GDP by $\mathrm{GDP}^{(E)}$ and income-side GDP by $\mathrm{GDP}^{(I)}$. Expenditure-side GDP is

$$\mathrm{GDP}^{(E)} \equiv \sum_{g\in\mathbb{I}} P_{\mathrm{c},g} C_{\mathrm{c},g} + \sum_{i\in\mathbb{I}} \sum_{k\in\{\mathrm{ne,eq}\}} P_{k,i} I_{k,i} + \sum_{g\in\mathbb{I}} P_{\mathrm{d},g} E_g - \sum_{g\in\mathbb{I}} P_{\mathrm{m},g} M_g. \tag{47}$$

Income-side GDP is

$$\mathrm{GDP}^{(I)} \equiv \sum_{o\in\mathbb{O}} w_o N_o + \sum_{i\in\mathbb{I}} \sum_{k\in\{\mathrm{ne,eq}\}} r_{k,i} K_{k,i}. \tag{48}$$

In equilibrium, $\mathrm{GDP}^{(E)} = \mathrm{GDP}^{(I)}$. Corresponding indices of real GDP and associated price deflators are constructed as Divisia indices along the GEMPACK solution path (Dixon et al., 1982; Horridge, 2000).

The external closure imposes a fixed ratio of the trade balance to nominal GDP:

$$\sum_{g\in\mathbb{I}} P_{\mathrm{d},g} E_g - \sum_{g\in\mathbb{I}} P_{\mathrm{m},g} M_g = \phi \cdot \mathrm{GDP}^{(E)} \tag{49}$$

where $\phi$ is held at its baseline value and nominal GDP is measured by $\mathrm{GDP}^{(E)}$ in (47) (at basic prices, given the absence of commodity taxes and subsidies). The real exchange rate $e$ adjusts endogenously to satisfy (49), with import prices $P_{\mathrm{m},g}$ responding via (43) and the terms of trade adjusting accordingly.

# 3 Calibration and Data

## 3.1 Data and baseline projection

Australian input–output and employment data for 2019 are first projected to 2050 using the dynamic CGE model VUEF (Victoria University Employment Forecasting model). These projections (Dixon, 2022) focus on the evolution of qualifications in the labour force and the allocation of qualified labour among occupations and industries, so provide a natural starting point for the long-run comparative-static simulations we present here. The baseline projection used does not incorporate impacts of GenAI.[11] Besides its dynamic components, VUEF has a broadly

[11] A more limited version of the task-based features presented here is incorporated in VUEF and is used to generate dynamic projections of GenAI impacts in Jobs and Skills Australia (2025b).

similar structure to the model presented here. However, to simplify exposition of the model and analysis of our results, we suppress some detailed features of VUEF that are less relevant to the questions at hand.[12]

VUEF itself is calibrated using input–output data from the Australian Bureau of Statistics (ABS) national accounts. These provide the industry-level structure of intermediate demands, value added, and final demands required to calibrate production function parameters and market clearing conditions. Employment data by occupation and industry are drawn from the ABS Labour Force Survey and Census, providing the initial allocation of workers across the 97 three-digit ANZSCO (Australian and New Zealand Standard Classification of Occupations) occupations and 121 production industries. From the VUEF projection, we disaggregate capital and investment by industry into equipment capital and non-equipment capital, as required for the present model. As the VUEF database already features industry-specific investment and capital stocks, we do this by defining as 'equipment' the investment goods produced by four industries, and competing imports: (i) professional, scientific, computer and electronic equipment manufacturing; (ii) electrical equipment manufacturing; (iii) domestic appliance manufacturing; and (iv) specialised and other machinery and equipment manufacturing.[13] Finally, to facilitate analysis, we aggregate the VUEF-projected database from 121 to 45 production industries and from three to one tourism sectors.

### 3.2 Parameters

The shape parameter $\alpha_o$ and dependence parameter $\theta_o$ are set to common values across occupations in the reference case: $\alpha_o = 5$ and $\theta_o = 2.5$ (corresponding to Kendall's tau of 0.6). These values imply moderately heavy tails and moderate upper-tail dependence. Given the limited empirical basis for these parameters, the sensitivity analysis explores a wide range: $\alpha_o \in \{3, 5, 7\}$ and $\theta_o \in \{5/3, 5/2, 5\}$.

The elasticity of substitution between tasks $\epsilon$ is set to 0.5 in the reference case, consistent with estimates in the task-based literature (e.g. Humlum and Vestergaard, 2025; Acemoglu and Restrepo, 2022). Sensitivity analysis considers values of 0.25 and 0.75. The elasticity between capital and the task composite $\sigma_{\mathrm{v}}$ is also set to 0.5.

Table 1 summarises the key model parameters and their values in the reference case and sensitivity simulations. For simplicity, a common Armington elasticity $\sigma_{\mathrm{c}} = 2$ is applied to all goods in all uses; in practice, estimates of Armington elasticities vary considerably across commodities, and this simplification may affect results for industries where trade responses are important, notably machinery and equipment.

### 3.3 GenAI exposure scores

Task productivity distributions are calibrated using task-based measures of exposure to generative AI for 97 three-digit ANZSCO occupations (Jobs and Skills Australia, 2025a). These measures build on the methodology developed by the International Labour Organization (ILO) for assessing generative AI exposure at the task level (Gmyrek et al., 2023). The approach evaluates the technical feasibility of applying generative AI to detailed occupational tasks rather than assigning exposure directly at the occupation level. In the ILO framework, task descriptions associated with each occupation are assessed using large language models to determine whether generative AI systems could plausibly perform the task or assist a human worker in carrying it out. Each task is assigned a score between zero and one representing its potential exposure to generative AI, and occupation-level exposure measures are obtained by aggregating these task-level scores across all tasks associated with the occupation (Gmyrek et al., 2023).

Jobs and Skills Australia (JSA) adapts this framework to the Australian labour market using the Australian and New Zealand Standard Classification of Occupations (ANZSCO). Task descriptions associated with each ANZSCO four-digit occupation are evaluated using a similar procedure, producing task-level exposure measures that are subsequently aggregated to the occupational level. In contrast to the original ILO implementation, the JSA methodology distinguishes explicitly between two channels through which generative AI may affect work tasks: augmentation, where AI tools assist human workers in performing a task more effectively, and automation, where the task may potentially be carried out by AI systems with minimal human input. The resulting occupational

[12] Apart from omitting all dynamic features, our simplifications include collapsing transport and other margin demands into the general intermediate inputs nest, and combining public and private consumption.

[13] Our intention is to focus narrowly on computers and other types of equipment that may be used to automate the tasks of occupations. We therefore exclude those industries producing transport equipment.

Table 1: Summary of key model parameters

| Parameter | Description | Reference value | Sensitivity range |
|---|---|---|---|
| *Task productivity distributions* | | | |
| $\alpha_o$ | Fréchet shape (tail thickness) | 5 | {3, 5, 7} |
| $\theta_o$ | Gumbel dependence | 2.5 | {5/3, 5/2, 5} |
| $\kappa^{\mathrm{g}}_{o,i}$, $\kappa^{\mathrm{a}}_{o,i}$ | Fréchet scale (occupation- and industry-specific) | Calibrated | — |
| *Production nests* | | | |
| $\epsilon$ | Task substitution elasticity | 0.5 | {0.25, 0.5, 0.75} |
| $\sigma_{\mathrm{v}}$ | Capital–task composite elasticity | 0.5 | {0.25, 0.5, 0.75} |
| $\sigma_{\mathrm{y}}$ | Output (VA vs. intermediates) | 0 | — |
| $\sigma_{\mathrm{n}}$ | Intermediate goods composite | 0 | — |
| $\sigma_{\mathrm{c}}$ | Armington (domestic vs. imported) | 2 | — |
| $\sigma_{\mathrm{u}}$ | Consumption composite | 0.9 | — |
| $\sigma_{\mathrm{i}}$ | Investment goods composite | 0 | — |
| *Labour supply* | | | |
| $\sigma_{\mathrm{o}}$ | Occupational choice elasticity | 2 | — |
| $\sigma_{\mathrm{q}}$ | Qualification choice elasticity | 2/3 | — |
| *Trade and external closure* | | | |
| $\eta_g$ | Export demand elasticity: goods & business services | 4 | — |
| $\eta_{\underline{g}}$ | Export demand elasticity: consumer services | 2 | — |
| $\Delta\bar{E}_g$ | Export demand shift | +10% | {0, 10, 20 } |
| $\phi$ | Trade balance / GDP ratio | Baseline value | Fixed |
| *Capital market* | | | |
| $\rho$ | Net rate of return | Exogenous | Fixed |

indices therefore report separate augmentation and automation exposure scores for each occupation (Jobs and Skills Australia, 2025a). These exposure scores measure the technical potential for generative AI to affect tasks within an occupation rather than the probability of adoption. For convenience, we reproduce the scores, aggregated to the three-digit occupations of the model, in Table D.3.

Figure 2 shows empirical cumulative distribution functions (ECDFs) of augmentation and automation exposure across occupations. Solid lines report employment-weighted ECDFs (interpreting occupational scores as applying to individual workers), while dotted lines treat each occupation equally. Automation exposure is mildly right-skewed: the employment-weighted mean (0.383) exceeds the median (0.357), indicating that a small number of highly automatable occupations raise the average. Augmentation exposure exhibits the opposite pattern: the mean (0.638) lies below the median (0.661), consistent with a small set of low-augmentation occupations pulling down an otherwise broadly higher level of exposure.

We interpret these exposure scores as describing the long-run technological potential of each mode in isolation and in partial equilibrium. This interpretation abstracts from competition between augmentation and automation, the costs of AI services, and relative input price changes—factors that are accounted for when we simulate the model. Specifically, given the benchmark input prices (including wages $w_{o,i}$) we calibrate the scale parameters $\kappa^{\mathrm{g}}_{o,i}$ and $\kappa^{\mathrm{a}}_{o,i}$ so that, in the absence of the competing mode and at zero AI services cost, the share of tasks suitable for augmentation or automation matches the corresponding exposure score.

## 3.4 AI services

We represent AI services as a composite of existing modelled domestic and imported goods, rather than as a fully-fledged production industry. This simplifying device reflects the considerable uncertainty surrounding both the current cost structure of GenAI and its future evolution. Algorithmic efficiency gains alone have reduced inference costs on AI benchmarks by roughly a factor of three per year (Gundlach et al., 2025), and specialised smaller language models may out-compete very large generalist models (Wang et al., 2024), further lowering costs. Although graphics processing unit (GPU)-based data centres are particularly energy- and water-intensive, improvements in chip design and cooling technologies are likely to mitigate these costs over time (OECD, 2025). The assumed cost structure is summarised in Table 2.

We distinguish between 'upstream' and 'downstream' AI activities. Upstream activities encompass funda-

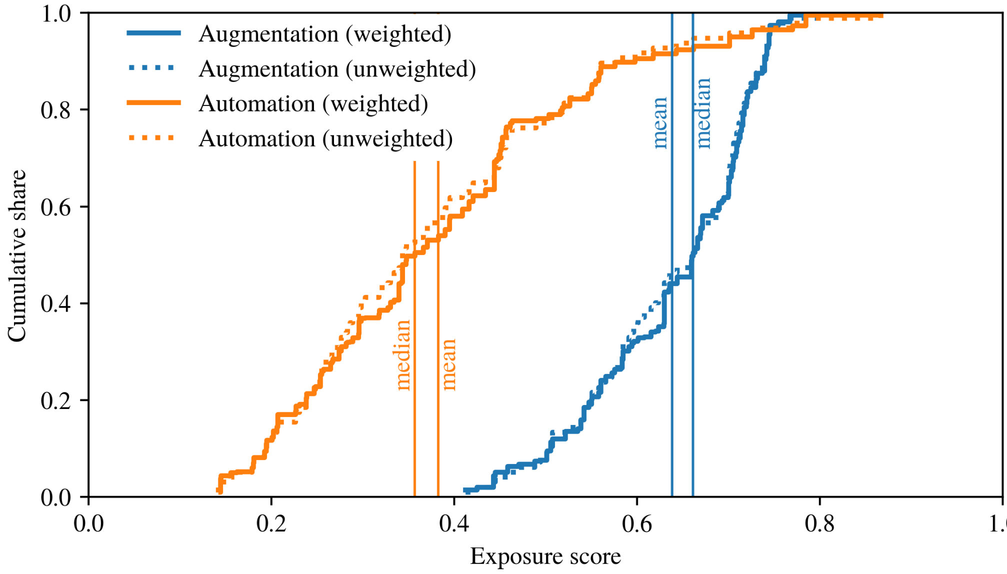


Figure 2: Empirical cumulative distribution functions of augmentation and automation exposure across occupations, unweighted and weighted by initial occupational employment. Vertical lines indicate the employment-weighted mean and median for each series.

| Division | Subdivisions | Industry name | Share within block (%) | Share of total (%) | Origin |
|---|---|---|---|---|---|
| *Upstream AI development and training (20% of total)* | | | | | |
| M | 70 | Computer Systems Design & Services | 100 | 20.0 | Imported |
| *Downstream services (10% of total)* | | | | | |
| M | 70 | Computer Systems Design & Services | 100 | 10.0 | Domestic |
| *Downstream compute and storage (70% of total)* | | | | | |
| J | 58–59 | Internet & Telecommunications | 30 | 21.0 | Domestic |
| D | 26 | Electricity | 18 | 12.6 | Domestic |
| D | 27–29 | Other Utilities | 2 | 1.4 | Domestic |
| C | 24 | Machinery & Equipment Manufacturing | 50 | 35.0 | Imported |
| **Total** | | | | **100.0** | |

Table 2: Cost structure of AI services represented as a composite of existing modelled industries.

mental AI research, the development of large language models such as ChatGPT, and internationally marketed AI services. Downstream activities comprise the adaptation and application of these products to firm-specific needs, as well as the compute and storage required to support inference. We assume that upstream activities remain dominated by large foreign firms, while downstream services are domestically provided, including AI data centres supporting inference. Downstream AI services also require imported inputs, notably GPUs and other ICT equipment, which are largely imported into Australia; as we do not model stocks of AI-specific capital, these imported investment goods are treated as intermediate inputs.[14] A more complete treatment of AI services supply is left for future research.

# 4 Results

The results reported below describe a long-run equilibrium in which GenAI—characterised by occupational exposure scores and associated modelling assumptions—is fully integrated into production. The model captures the economic structure implied by the technology's technical potential, abstracting from diffusion dynamics, transitional adjustment, and institutional constraints that may limit specific applications even in the long run. Examples include direct regulation of occupational work practices, compliance with professional legal duties (fiduciary obligations, duties of care, etc.), and intellectual property or data privacy laws constraining AI training and deploy-

[14]This treatment slightly understates GDP, as expenditures on AI-related ICT capital are omitted from aggregate investment and the associated returns are omitted from domestic income.

ment. Such factors could materially reduce realised exposure in affected occupations relative to our calibration.

In addition to the domestic technology shocks informed by the exposure indices, we allow for a uniform outward shift in export demand curves to reflect GenAI adoption in other countries. In the reference case simulation we assume a +10% shift in all export demands. We also consider the sensitivity of our results to higher (+20%) or lower (0%) shifts and to other key parameters (Table 1).

Our presentation emphasises mechanisms, focusing on how task-level adoption of GenAI propagates through production, capital accumulation, and labour-market reallocation in general equilibrium.

## 4.1 Reference case simulation

The reference case simulation yields a 29.8% increase in GDP, but only a 16.2% increase in welfare, as measured by the long run change in the real consumption composite. Annualising the GDP gain over a twenty year adoption period yields 1.31%. In the medium speed adoption scenario of Filippucci et al. (2025), Canada (the most similar G7 economy to Australia) achieves 49% adoption over a decade and GenAI contributes 0.86% to annualised productivity growth. However, they assume maximum adoption of 80%, whereas we use our full exposure scores, with task-level adoption determined endogenously by cost minimisation. As a rough benchmark, linearly scaling their estimate to full adoption implies a growth rate of approximately 1.1%.

Table 3 decomposes the GDP gain on both the income and expenditure sides. The gain reflects the interaction of three mechanisms: task-level productivity improvements from augmentation and automation; capital deepening amplified by shifts in relative input prices; and general equilibrium reallocation across industries, driven by changes in the level and composition of demand including the assumed +10% outward shift in export demand curves. We view this as a conservative benchmark relative to Bekkers et al. (2025), who, under scenarios with incomplete GenAI adoption, model real exports increasing in the order of  10% for primary goods and  30% for ‘other services’.[15]

Table 3: Income- and expenditure-side decomposition of real GDP in the reference GenAI simulation

| **Income-side decomposition** | | **Expenditure-side decomposition** | |
|---|---|---|---|
| Component | pp contribution | Component | pp contribution |
| Labour (composition) | 0.0 | Real consumption | 10.8 |
| Non-AI tasks | -31.3 | Real investment | 16.5 |
| Augmented tasks | 31.3 | Other capital goods | 10.3 |
| Capital | 19.7 | Equipment goods | 6.2 |
| Non-equipment capital | 12.3 | Net trade | 2.5 |
| Equipment: previously automated tasks | 1.2 | Real exports | 11.4 |
| Equipment: occupational tasks | 6.1 | Real imports | -8.9 |
| Technical change (GenAI) | 10.1 | | |
| Real GDP (income) | 29.8 | Real GDP (expenditure) | 29.8 |

*Notes:* Each table entry gives a contribution in percentage points to the overall change in GDP. Figures are rounded. Consequently, individual entries may not sum to subtotals, and subtotals may not sum to totals.

On the income side, task-level technical change—the direct productivity gains associated with augmentation and automation, as captured by the distributional scale parameters $\kappa^{\mathrm{g}}_{o,i}$ and $\kappa^{\mathrm{a}}_{o,i}$—accounts for roughly one third of the GDP gain (10.1 pp). The remainder reflects capital deepening: more intensive use of non-equipment capital (12.3 pp), in previously automated tasks (1.2 pp), and equipment capital used in newly automated occupational tasks (6.1 pp). With a fixed workforce, labour reallocation contributes negligibly to aggregate GDP, although the underlying gross flows are large: the value of labour shifting from non-AI to augmented tasks is roughly equal to the GDP gain.

Equipment capital deepening is driven directly by task automation, in which equipment displaces labour, and reinforced by substitution higher in the production structure. GenAI raises wages relative to the prices of equipment and AI services, encouraging further automation. Equipment and AI services prices in turn rise relative to non-equipment capital, inducing broader capital deepening via the value-added nest. Compositional

[15] These correspond to Australia’s main sources of export income: agricultural and mineral commodities, inbound international tourism and tertiary education provision to international students.

effects—shifts in industry mix toward capital-intensive activities—amplify these within-industry mechanisms, as documented in Section 4.3.

On the expenditure side, consumption contributes only 10.8 pp of the 29.8% GDP gain, whereas investment contributes 16.5 pp and net trade 2.5 pp. The rising import intensity of production is driven primarily by demand for machinery and equipment, used both as investment goods and to deliver AI services.[16] With the trade-balance-to-GDP ratio held fixed, export volumes must expand, and by more than import volumes since finite export demand elasticities imply a deterioration in the terms of trade.

The nominal investment share of GDP in basic prices[17] rises from 34.5% to 40.7%. Under the long-run closure, in which the balance of trade is fixed relative to GDP, the substantially higher saving rate required to finance this investment diverts resources from consumption, explaining the gap between output and welfare impacts. The labour share of income falls from 60.0% to 52.4% of GDP.[18]

## 4.2 Task-level mechanisms

The aggregate productivity gains reported in Table 3 arise from firms' task-by-task decisions to adopt AI-augmented or AI-automated production modes. We first document the resulting task allocation patterns at the industry level and then examine their occupational structure.

### 4.2.1 Task mode competition by industry

Figure 3 shows the relationship between augmented and automated task shares across industries under three distributional parameterisations: the reference case ($\alpha = 5$, $\theta = 2.5$), thinner-tailed distributions ($\alpha = 7$), and stronger tail dependence ($\theta = 5$). Each point represents one industry, with dispersion primarily reflecting differences in occupational composition.

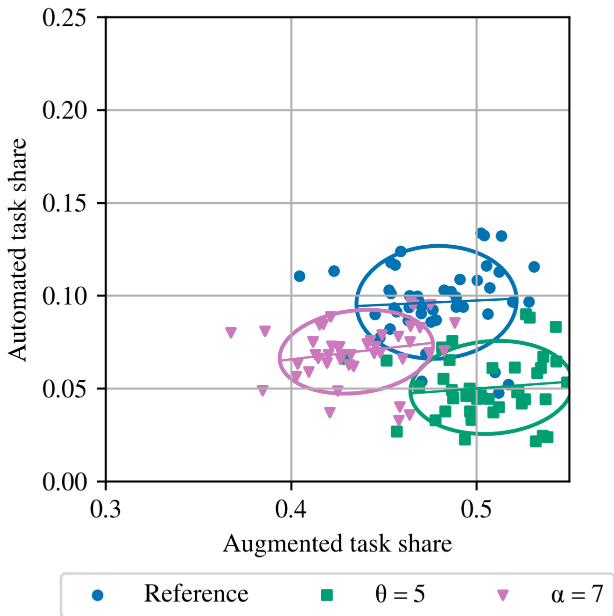


Figure 3: Augmented versus automated task shares by industry in the reference case and under alternative distributional assumptions. Each point represents one industry. Ellipses show one-standard-deviation intervals.

Across nearly all industries, augmentation shares (horizontal axis) exceed automation shares (vertical axis), reflecting the systematically higher augmentation exposure in the source data (Jobs and Skills Australia, 2025a).

[16]We model imported machinery for AI services as intermediates rather than investment. Treating these flows as investment in AI-specific capital would raise measured real investment and GDP but would not substantively alter the results.

[17]Netting out final indirect taxes reduces GDP and increases the investment share in the model database.

[18]For comparison, Coelli and Borland (2023) reports the Australian labour share rising over the 1960s and 70s, reaching an average of around 70%. In the 1980s, it fell sharply and then more slowly, averaging around 60% in the 2010s. Another sharp fall (~5 pp in six years) preceded the COVID-19 pandemic.

At the same time, equilibrium price adjustments—declining equipment prices relative to wages—work in the opposite direction, partially offsetting this calibrated advantage and generating the mode competition observed in the figure. Importantly, heterogeneity in adoption across industries arises endogenously from occupational composition rather than from industry-specific technology assumptions.

With thinner tails ($\alpha = 7$), both augmentation and automation shares decline because fewer tasks achieve productivity gains large enough to justify the costs of AI services and equipment capital. This shift toward the origin is approximately uniform across industries, indicating that the tail parameter mainly scales adoption. By contrast, stronger tail dependence ($\theta = 5$) increases augmentation shares while reducing automation shares. When the same tasks tend to have high productivity in both modes, augmentation more often dominates because of its calibrated productivity advantage.

### 4.2.2 Task mode patterns by occupation

Figure 4 shows industry-weighted[19] average task shares for each of the 97 three-digit occupations, organised by ANZSCO Major Group.[20] Occupational task shares may differ across industries because both the task productivity distributions and relative input costs may vary at the occupation–industry level, through the scale parameters and through industry-specific labour costs $w_{o,i}$ and equipment price differentials. Weighted averages over both occupations and industries are shown in Table 4 for both low and high Fréchet parameter values.

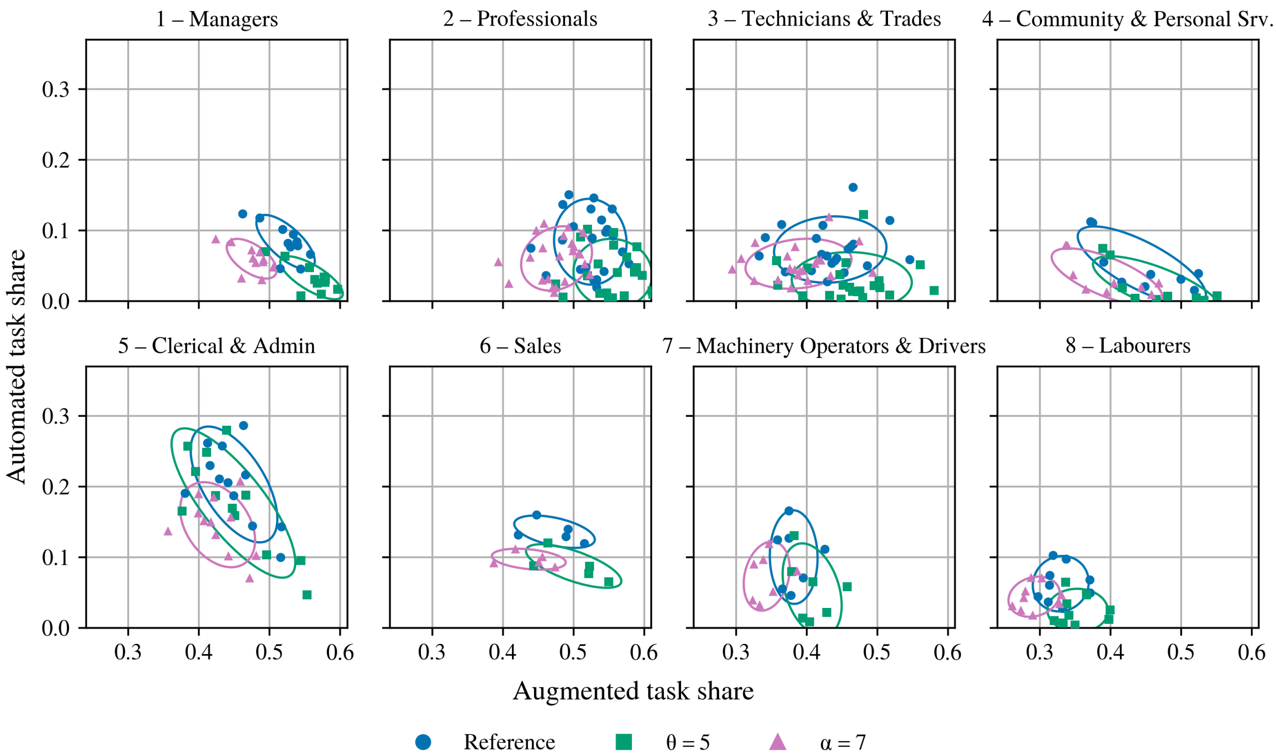


Figure 4: Industry-weighted average task shares by occupation, organised by ANZSCO major group, in the reference case and under alternative distributional assumptions. Each point represents one occupation. Ellipses show one-standard-deviation intervals within each major group. Reference case shown as circles; $\alpha = 7$ (thinner tails) as triangles; $\theta = 5$ (stronger dependence) as squares.

Substantial heterogeneity is evident across occupations. Clerical and administrative roles (group 5) exhibit the highest automation shares, while managerial and professional occupations (groups 1 and 2) are dominated by augmentation. Blue-collar occupations generally display lower automation shares and moderate augmentation. These differences reflect the interaction between occupation- and industry-specific task characteristics and the relative costs of labour, equipment, and AI services. Overall, 46.7% of tasks are augmented and 9.1% automated in the reference case.

[19] Task shares for an occupation in each industry are weighted by initial industry shares of occupational labour input.

[20] The 97 three-digit occupations are grouped into 43 Sub-Major Groups, which are grouped in turn into 8 Major Groups.

Table 4: Overall occupational task allocations

| | Reference | $\alpha = 7$ | $\alpha = 3$ | $\theta = 5$ | $\theta = 5/3$ |
|---|---|---|---|---|---|
| Non-AI | 44.2 | 50.9 | 39.8 | 45.7 | 41.9 |
| Augmented | 46.7 | 42.5 | 48.4 | 49.4 | 45.6 |
| Automated | 9.1 | 6.5 | 11.7 | 4.9 | 12.5 |

Variation in the distributional parameters affects occupations in systematic but distinct ways. Thinner tails ($\alpha = 7$) reduce both augmentation and automation shares across all occupation groups, with reductions roughly proportional to reference-case adoption rates. This confirms that $\alpha$ primarily controls the scale of GenAI adoption. By contrast, stronger tail dependence ($\theta = 5$) generates heterogeneous responses across and within groups. Automation shares decline in all major groups, but the magnitude of the decline varies substantially, and augmentation responses may differ even within major groups. This heterogeneity arises because occupations differ in their exposure scores, and hence in the balance of competition between augmented and automated modes; occupational wage adjustments further differentiate the responses.

## 4.3 Output and productivity effects by industry

This section examines industry-level results from two complementary perspectives: a supply-side decomposition into factor contributions and technical change, and a demand-side attribution using the Leontief inverse.

### 4.3.1 Supply-side decomposition

Figure 5 shows percentage changes in industry value added, decomposed into the contributions of labour, other capital, equipment, and technical change. Bar widths are proportional to initial industry value added, so that bar areas represent each industry's contribution to the aggregate percentage-point change in GDP. The horizontal axis reports the 19 ANZSIC (Australian and New Zealand Standard Industrial Classification) Divisions (A–S), together with a separate Dwellings sector (W).[21]

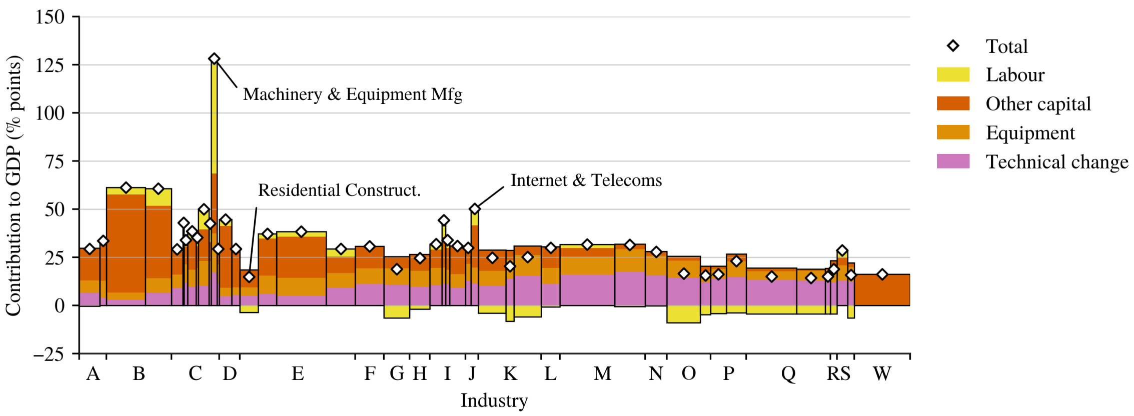


Figure 5: Industry-level changes in value added, decomposed into contributions from technical change and factor inputs. Bar widths are proportional to initial industry value added. These data are tabulated in D.1.

All industries experience positive long-run gains, but there is substantial heterogeneity in both the magnitude and the sources of these gains. Capital-intensive and export-oriented industries exhibit the strongest increases in value added, reflecting a combination of capital deepening and demand expansion. Mining industries (Division B), for example, benefit from both their initial factor intensities and the outward shift in export demand. Industries supplying AI-related services, such as Internet and Telecommunications within Division J, also expand strongly. The very large percentage gain for Machinery and Equipment Manufacturing reflects its small initial base combined with strong demand for equipment investment; this result is sensitive to the assumption that the

[21] Dwellings is classified within Division L under ANZSIC, but is separated here because it represents imputed rather than actual production and uses no labour.

equipment needed to automate occupational tasks has a similar composition to equipment currently used for other purposes.

The relative contribution of technical change varies considerably across industries and is not simply proportional to overall value-added gains. In several consumption-oriented industries (Divisions P to S) and in residential construction, the technical-change contribution is large relative to value added, yet overall gains are modest. This pattern arises because these industries have high exposure to GenAI through their occupational composition but face relatively weak demand growth. The result is that labour is reallocated away from these industries to those that have lower GenAI exposure and/or stronger demand growth. Output prices rise in the latter industries relative to the former. This is an instance of Baumol's cost disease (Baumol, 1967): when productivity gains are concentrated in sectors facing inelastic or saturating demand, resources shift toward lower-productivity activities, moderating aggregate growth. The effect is present but modest in our results, consistent with the relatively even distribution of GenAI exposure across occupational compositions compared with, for example, the ICT boom of the 1990s (Filippucci et al., 2024).

### 4.3.2 Demand-side decomposition

The demand side is clearly important to the heterogeneity of industry responses. To elucidate demand-side drivers, we perform a shift-share decomposition of changes in industry outputs, and consequently, in industry value added. We attribute output changes to changes in final demands by using a Leontief inverse matrix. This matrix changes from the initial to the final equilibrium due to changes in intermediate input intensities and intermediate import substitution effects. We further decompose changes in both final demands and the Leontief inverse matrix using a shift-share method. A description of this method is given in Appendix B.

Figure 6 shows the decomposition of value added changes by shift-share component (i.e. summing over the four categories of final demand: equipment investment, non-equipment investment, consumption, exports). For most industries, the dominant demand-side driver is the general expansion of economic activity. Changes in the composition of final demand make significant positive contributions to the change in value added of many export-oriented (mining industries in Division B) or investment-oriented industries (some manufacturing industries in Division C and non-residential construction industries in Division E). For heavily consumption-oriented industries (Divisions O, P, Q, R, W), there are significant negative contributions. This reflects the higher savings rate and strong trade growth discussed above. Alternative decompositions by final demand category are presented in Appendix C.

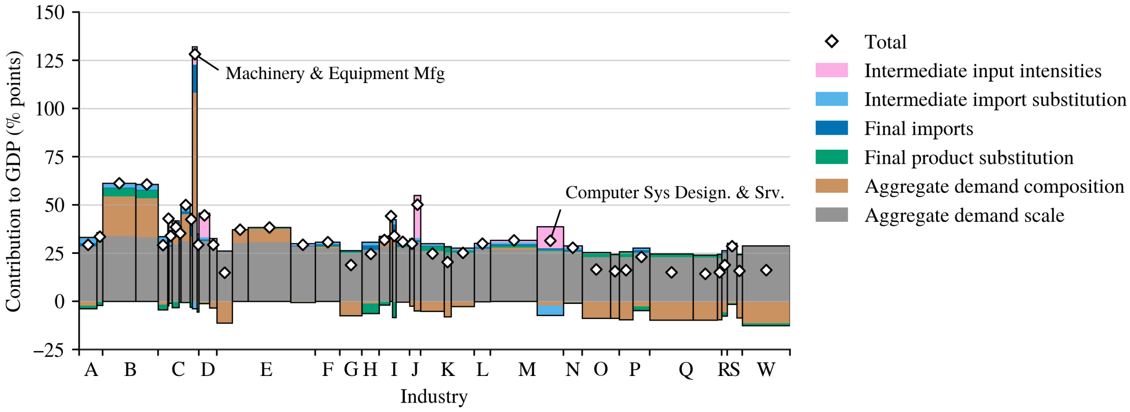


Figure 6: Industry-level changes in value added, decomposed into contributions from demand and supply-side (i.e. input-output) effects. Bar widths are proportional to initial industry value added. These data are tabulated in D.2.

Final and intermediate import substitution effects and intermediate input intensity effects play an important role only for those industries supplying equipment and/or AI services.[22] For instance, in the Machinery & Equipment Manufacturing industry, the largest positive contribution is associated with the changing composition of

[22]For simplicity, we do not separate ordinary from AI services intermediate inputs. Consequently, intermediate substitution effects encompass not only direct price-driven substitution within the Armington sub-nests (13), but compositional effects associated with AI services inputs.

aggregate demand: equipment investment increases strongly. In the Computer Systems Design & Services industry, intermediate input intensities make a strong positive contribution while intermediate imports partly offset this. In the Computer Systems Design & Services industry, intermediate input intensities make a strong positive contribution, while intermediate imports partly offset this. This pattern reflects the role of this industry's output in the composition of AI services and the assumed two-thirds import share in AI services (see Table 2, rows one and two).

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### 4.4 Occupational reallocation and wages

We now examine how the task-level mechanisms documented in Section 4.2 translate into occupational employment changes. Figure 7 compares the modelled long-run impacts of GenAI on employment (i.e. employment in the reference GenAI simulation relative to employment in the VUEF database projection) with observed employment changes over the past decade.[23] Net reallocation due to GenAI is largest in blue-collar occupations (up to +13%) and most negative in lower-skilled white-collar occupations (down to −22%), where exposure to GenAI—particularly automation—is highest. Relative to historical experience, these changes are moderate: employment declined by more than 15% in seven occupations and increased by more than 50% in twenty-one occupations in the decade to 2024. A notable exception is delivery drivers, a blue-collar occupation that has grown strongly in recent years but is modelled as contracting under GenAI. Based on the exposure scores, this occupation is among the most automatable blue-collar jobs.

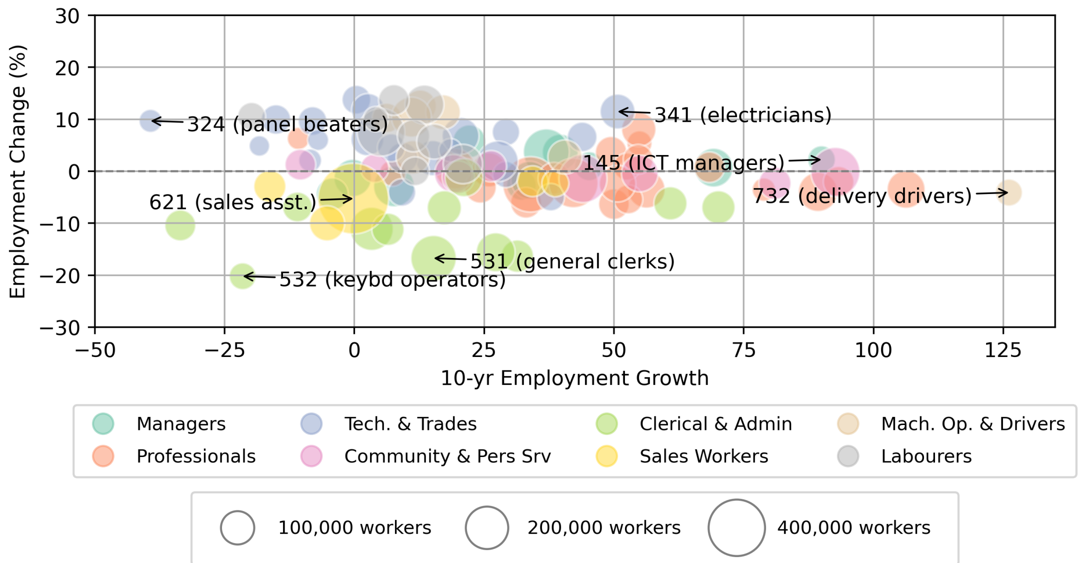


Figure 7: Modelled employment growth due to GenAI (vertical axis) versus observed employment growth 2014–24 (horizontal axis) in 97 3-digit ANZSCO occupations. Bubble sizes reflect 2019 employment.

To link micro-level task substitution to macro labour-market outcomes, we additively decompose occupational employment changes into their underlying drivers. Table 5 reports this decomposition for the eight 'major groups' of occupations in the ANZSCO classification. Results for the 97 ANZSCO three-digit occupations are reported in Table D.4 in Appendix D. All values are reported in thousands of worker equivalents; the total workforce comprises 17.3 million persons.

In the first five columns, changes in industry labour demand are decomposed. The 'Non-AI' and 'Augmented' columns capture the effects of task-mode substitution on labour demand, including both the extensive margin (tasks shifting between modes) and the intensive margin (changes in the intensity with which remaining non-AI or augmented tasks are used).[24] 'Other Input Substitution' captures changes in labour demand arising from

[23] Data are from the ABS Labour Force Survey Feb 2015 and Feb 2025. Note that the total labour force grew 25% over this decade. In the Gen AI simulation, the total labour force is held constant.

[24] Automated tasks use no labour directly, so there is no separate automation contribution in the table. Instead, automation affects labour demand indirectly through the overall effect of task-mode substitution on the labour required per unit of the task composite.

Table 5: Decomposition of occupational employment changes ('000 worker equivalents).

| | Labour demand | | | | | | Industry output | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Non-AI* | | *Augmented* | | | | | | | |
| | Extensive margin | Intensive margin | Extensive margin | Intensive margin | Other input substitution | Subtotal | Output shares | Output scale | Subtotal | |
| Managers | -2398 | -193 | 1691 | -69 | 20 | -949 | 57 | 934 | 992 | 42 |
| Professionals | -4470 | -345 | 3121 | -130 | 31 | -1792 | 17 | 1696 | 1713 | -78 |
| Tech. & Trades | -1199 | -130 | 847 | -34 | 3 | -513 | 81 | 556 | 638 | 124 |
| Services | -603 | -65 | 453 | -16 | 3 | -228 | -82 | 307 | 224 | -4 |
| Clerical & Admin | -1303 | -54 | 740 | -22 | 10 | -629 | 3 | 438 | 441 | -187 |
| Sales | -401 | -29 | 256 | -9 | 5 | -177 | -1 | 155 | 154 | -23 |
| Operators & Drivers | -531 | -66 | 348 | -14 | 4 | -259 | 67 | 267 | 334 | 75 |
| Labourers | -269 | -47 | 190 | -7 | 1 | -133 | 10 | 174 | 185 | 52 |
| Total | -11178 | -933 | 7650 | -305 | 82 | -4684 | 154 | 4530 | 4684 | 0 |

substitution between the task composite and non-task capital as relative prices adjust. The remaining columns decompose changes in labour demand arising from output changes into an industry output-share effect and an aggregate-demand-scale effect.[25]

With aggregate labour supply fixed, the overall total is zero. The net changes in major occupation groups ('Total' column) reflect the balance of several large, offsetting forces. Most importantly, GenAI induces substantial direct labour savings as tasks are reallocated from non-AI to augmented or automated modes. This extensive-margin reallocation amounts to around 11.4 million worker equivalents, or roughly two thirds of all work currently performed in the economy. This effect is modestly reinforced on the intensive margin, as tasks that remain non-AI are used less intensively in production of the task composite. Some displaced work is reallocated to augmented tasks within the same occupational groups, while declining equipment prices increase competition from task automation. These large gross reallocations associated with task substitution are primarily offset by growth in aggregate demand. However, input substitution and demand composition effects are large relative to the net employment changes observed across occupations. Taken together, the results indicate that the dominant labour-market effect of GenAI in the model is a reconfiguration of work within occupations, with changes in occupational employment levels playing a secondary role.

Figure 8 plots the modelled long-run effects of GenAI on real wages against full-time weekly wages in 2025.[26] The correlation is weak (16%) and dispersion is particularly high among lower-wage occupations. Clerical and administrative occupations experience the weakest wage gains—with Keyboard Operators seeing a slight decline—while blue-collar occupations experience the strongest. Applying the modelled wage changes to 2025 wages, the Gini index between-occupation average wages rises from 0.155 to 0.163.

The near-universal real wage increase reflects the economy-wide productivity gain: lower production costs reduce the price level relative to nominal wages, raising real purchasing power even in occupations with little direct AI exposure. The dispersion in wage outcomes arises from heterogeneity in task-level outcomes within occupations, as determined by the Fréchet–Gumbel productivity distributions. In the long-run comparative-static framework, occupational allocations adjust through a discrete-choice structure governed by the elasticities $\sigma_o$ and $\sigma_q$. The non-linear mapping from calibrated exposure scores to equilibrium task-mode shares—via productivity draws relative to input price ratios—generates wage responses that are not proportional to initial exposure. Occupations where augmentation dominates benefit from the productivity premium of AI-assisted work; those where automation is more prevalent face competitive displacement of labour from many tasks, moderating wage growth even as aggregate productivity rises. Although there are clear winners and losers across occupations, these results suggest that the rise in the capital share of income may be more consequential than the modest increase in between-occupation wage dispersion.

Taken together, the employment and wage results indicate that the dominant labour-market effect of GenAI

[25] To do this, we normalise the output decompositions described in Section 4.3.2. The 'output shares' include all demand-side contributions other than aggregate demand scale.

[26] Data are from the Australian Bureau of Statistics, 'Employee Earnings and Hours, Australia', May 2025. The first occupation, Legislators and General Managers, is omitted because the weekly wage statistic is unavailable.

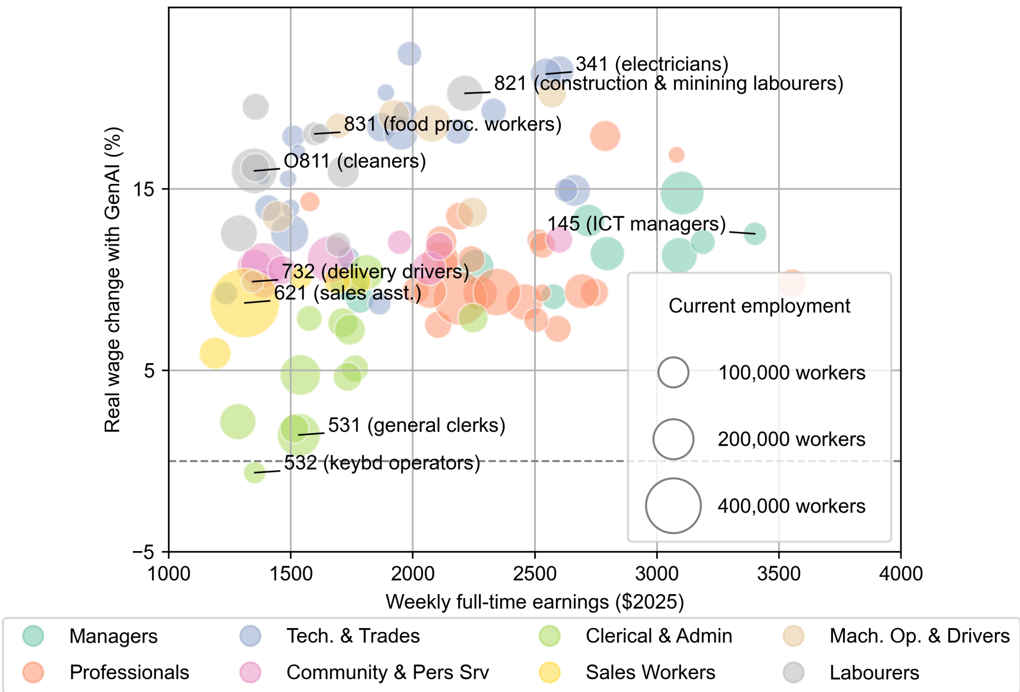


Figure 8: Modelled real wage changes due to GenAI (vertical axis) versus full-time wages 2025 (horizontal axis) in 97 3-digit ANZSCO occupations. Bubble sizes reflect 2019 employment.

in the model is a reconfiguration of work within occupations, with net employment changes across occupations playing a secondary role. Extensive-margin task reallocation is equivalent to roughly two thirds of current work, yet headline employment and wage changes are moderate by historical standards. This implies that changes in the nature of work—what tasks are performed and how—are central to understanding GenAI's labour-market effects. The direct effect on wage dispersion across occupations is modest; the more consequential distributional channel is likely the rising capital share of income, which benefits asset owners disproportionately.

### 4.5 Sensitivity of aggregate impacts

The top panel of Figure 9 reports the percentage increase in real GDP in the reference case (29.8%) and nine sensitivity simulations, which span a wide range from 18.3% to 45.9%. Aggregate output is most sensitive to the distributional characterisation of AI-augmented and AI-automated task productivities. Thinner tails ($\alpha = 7$) imply fewer tasks with exceptionally high productivity gains, while strong upper-tail dependence ($\theta = 5$) implies that the same tasks tend to be highly productive in both modes, making augmentation and automation closer substitutes. Either condition substantially reduces GDP gains. Conversely, fatter tails ($\alpha = 3$) allow a larger mass of tasks to generate large productivity improvements, while weak dependence ($\theta = 5/3$) means the two AI modes function more as complements.

These aggregate sensitivities reflect changes in task-mode adoption. As documented in Section 4.2, thinner tails reduce both augmentation and automation shares in a broadly proportional manner across occupations, whereas stronger tail dependence shifts tasks toward augmentation at the expense of automation, with heterogeneous effects across occupation groups. The resulting differences in task allocation propagate through capital accumulation and reallocation to generate the observed variation in aggregate outcomes.

Moving from $\alpha = 7$ to $\alpha = 3$ more than doubles the GDP gain, illustrating both the flexibility of the Fréchet–Gumbel framework in representing different technological environments and the importance of empirically grounding these distributional assumptions. By comparison, aggregate results are relatively insensitive to variation in factor and task substitution elasticities: changing elasticities from 0.25 to 0.75 alters the GDP gain by only 2.6 percentage points. Extending GenAI to previously automated equipment tasks raises GDP by 1.3 percentage points, reflecting the modest initial share of equipment—as already-automated tasks—in GDP.

The middle panel of Figure 9 decomposes GDP gains into contributions from task-level technical change and

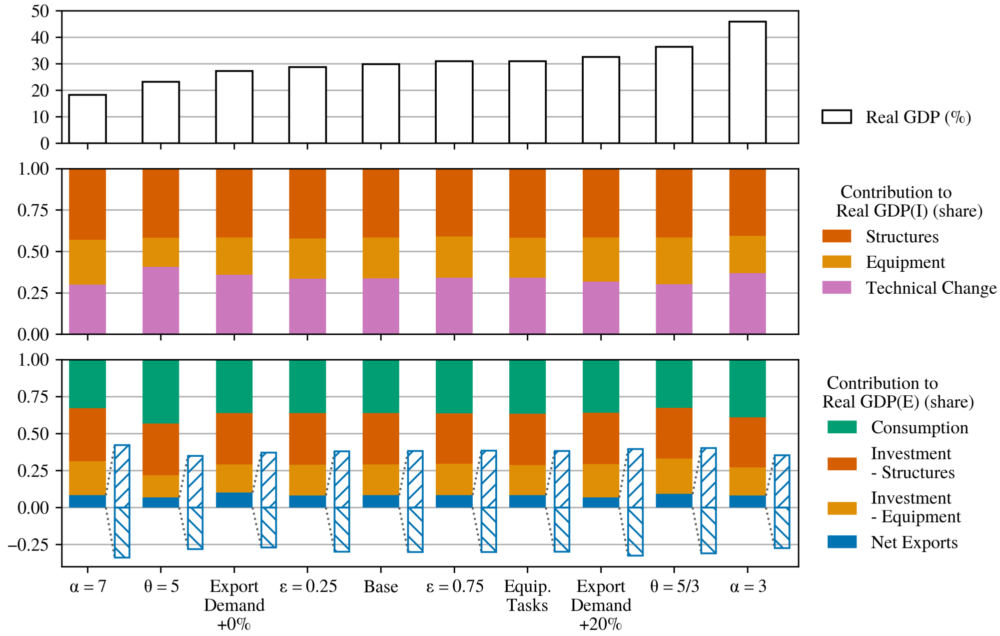


Figure 9: Decomposition of GDP contributions across sensitivity simulations. Top: aggregate GDP change. Middle: income-side contributions from technical change and capital deepening. Bottom: expenditure components.

capital deepening in other capital and equipment. With thinner tails ($\alpha = 7$), technical change plays a smaller role relative to capital—particularly equipment—deepening, as average productivity gains in augmented and automated tasks are modest. In this case, automation displaces labour while generating relatively small productivity improvements, an instance of what Acemoglu and Restrepo (2018a) term 'so-so automation'. With fatter tails ($\alpha = 3$), technical change accounts for a larger share of GDP growth. Strong tail dependence ($\theta = 5$) similarly shifts the composition toward technical change and away from equipment deepening, as augmentation more often dominates automation and relative equipment price declines are smaller.

The lower panel of Figure 9 reports the expenditure-side decomposition. Variations in aggregate outcomes are mirrored primarily in equipment investment, which contributes between 14.9% of the GDP gain under $\theta = 5$ and 24.0% under $\alpha = 7$.[27] Consumption absorbs most remaining variation. Overall, the sensitivity analysis highlights that uncertainty about the long-run impact of GenAI is driven primarily by uncertainty over the distribution of task-level productivity gains and the interaction between augmentation and automation, rather than by conventional substitution elasticities or demand assumptions.

These results underscore that the largest quantitative uncertainties concern the shape of task-level technological opportunities. Better empirical characterisation of the direct productivity gains from adopting GenAI in different occupations and industries—which in the model are summarised by the shape and tail-dependence parameters—will therefore be important to understanding eventual economic impacts. In practice, these characteristics are likely to vary systematically across occupations and industries, generating an additional source of heterogeneity that is abstracted from in the present analysis.

### 4.6 Employment by industry and occupation

The top panel of Figure 10 reports changes in employment, measured in units of effective labour, by industry in the reference-case simulation. Bar widths are proportional to initial industry employment shares. Employment gains are concentrated in capital-intensive and goods-producing industries, particularly mining and manufacturing (Divisions B and C), as well as in industries that support these sectors or provide AI-related services. These include utilities (Division D), non-residential construction (most of Division E), transport (Division I), internet and telecommunications (within Division J), professional and scientific services (Division M), and repair and maintenance services (within Division S). Employment changes are generally modest in magnitude.

The middle and lower panels report industry employment sensitivities to changes in $\alpha$ and $\theta$, respectively,

[27] N.B. these are percentages of the total, not percentage point contributions.

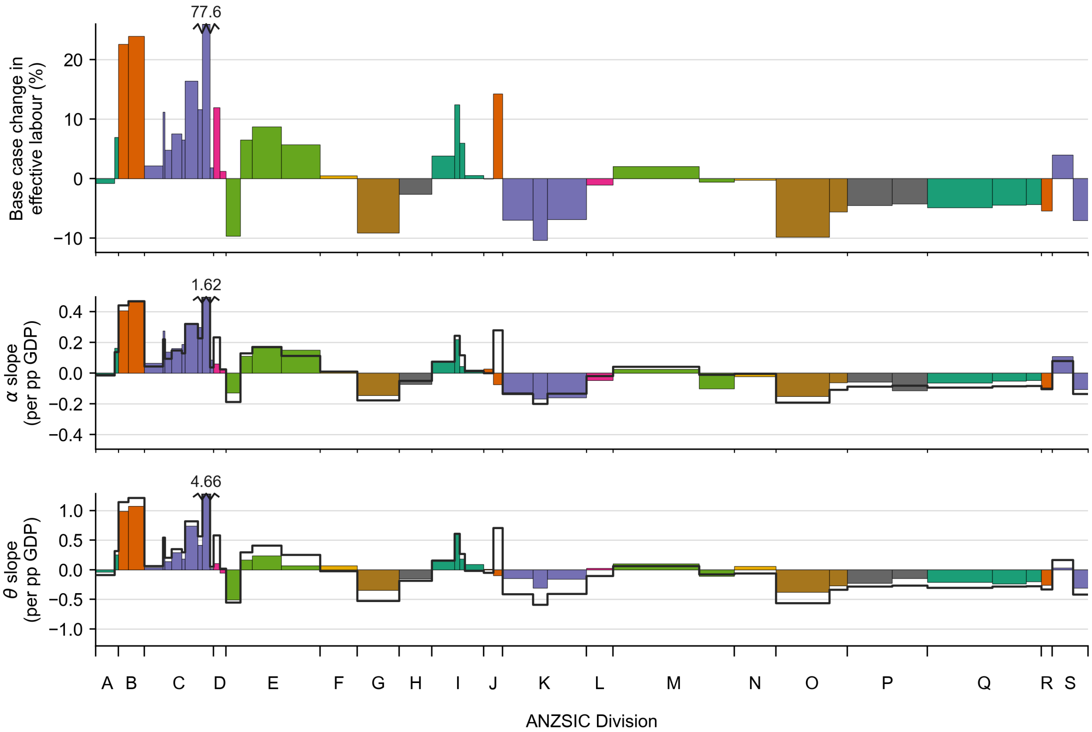


Figure 10: Changes due to GenAI in effective labour by industry (top panel) and sensitivity to Fréchet–Gumbel parameters (lower panels). Bar widths are proportional to initial allocation of labour. Bar heights in the lower panels show percentage changes in effective labour per percentage-point increase in GDP. Step lines indicate the component explained by the common pattern, obtained from a linear projection on the top-panel employment changes. Deviations from the step line reflect parameter-specific heterogeneity beyond the common pattern.

expressed as the percentage-point change in effective labour associated with a parameter variation calibrated to deliver a one-percentage-point increase in GDP. Deviations from the step line are limited for $\alpha$, indicating that changes in tail thickness primarily scale the magnitude of industry employment responses with little effect on their relative pattern. By contrast, variation in $\theta$ generates more systematic deviations, implying greater heterogeneity across industries beyond simple rescaling. Thus, changes in dependence affect not only how much adjustment occurs, but also where it occurs.

Figure 11 reports corresponding results for occupational employment measured in persons. In the reference case (top panel), employment changes are heterogeneous within managerial and professional groups, reflecting dispersion in occupational exposure to GenAI. By contrast, employment changes are more uniform across the remaining major groups. Employment gains occur in most occupations within groups 3 (technicians and trades), 4 (community and personal service workers), 7 (machinery operators and drivers), and 8 (labourers), while employment declines are concentrated in groups 5 (clerical and administrative workers) and 6 (sales workers). Group 5 is particularly notable, as it combines high exposure to automation with a large initial share of total employment.

As with industries, changes in $\alpha$ mainly rescale occupational employment responses, leaving their relative ordering largely unchanged. Changes in $\theta$, by contrast, generate substantial heterogeneity. Although lower $\theta$ increases adjustment overall, it mitigates employment losses in some occupations—most notably within clerical and administrative roles—relative to what would be implied by a simple rescaling of the reference-case pattern. This confirms that variation in dependence affects not only the intensity but also the incidence of employment adjustment across occupations.

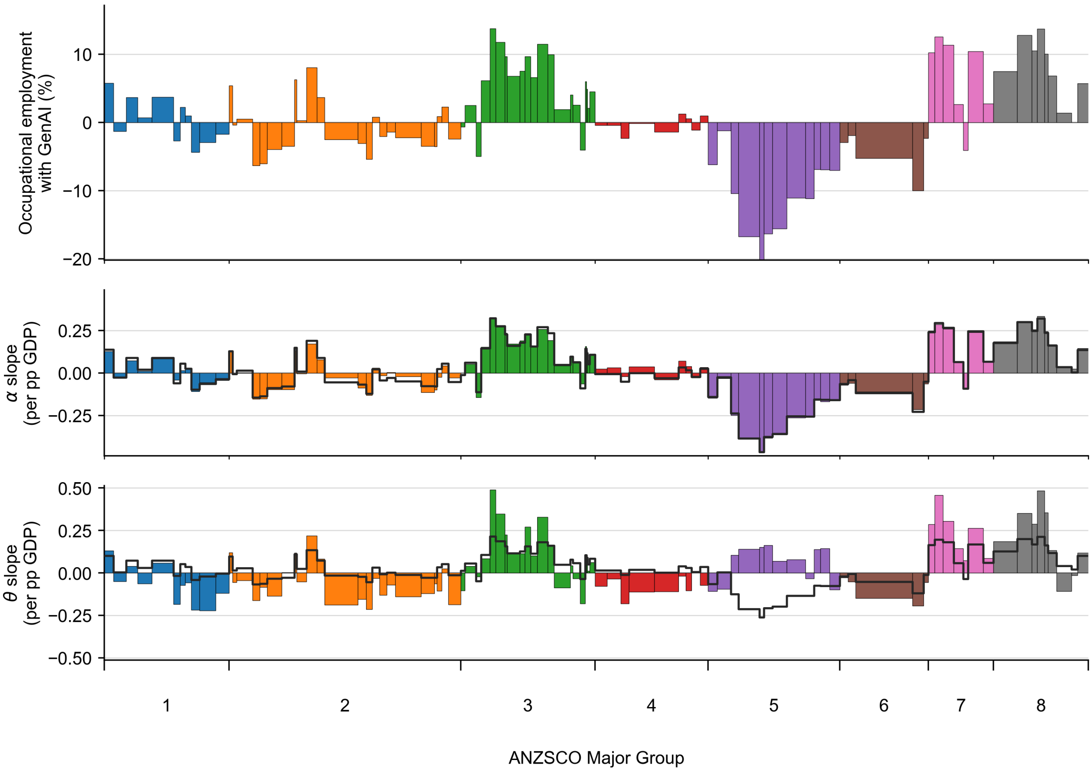


Figure 11: Changes due to GenAI in employed persons by occupation (top panel) and sensitivity to Fréchet–Gumbel parameters (lower panels). Bar widths are proportional to initial allocation of workers.

## 5 Concluding remarks

This paper develops a task-based CGE framework to analyse the long-run economic effects of generative AI. The model explicitly represents competition between non-AI, AI-augmented, and AI-automated task modes within occupations, allowing adoption decisions at the task level to propagate through industry structure, capital accumulation, and labour demand in general equilibrium. By embedding this mechanism in a 45-industry, 97-occupation model calibrated using separate augmentation and automation exposure scores, the framework provides a coherent account of how GenAI reshapes production, occupational employment, and relative wages.

Three conclusions emerge from the analysis. First, large aggregate gains from GenAI need not arise primarily from direct labour productivity improvements. In the reference case, around two thirds of the GDP gain reflects capital deepening and reallocation triggered by task-level adoption rather than direct technical change at the task level. The long-run welfare gain is substantially smaller than the long-run GDP gain because the more capital-intensive structure of the GenAI-equipped economy requires a permanently higher investment share. This divergence between output and welfare, together with the associated shift in factor income toward capital, suggests that the distributional consequences of GenAI may be as important as its aggregate productivity effects.

Second, labour-market adjustment occurs primarily within occupations rather than between them. Extensive-margin task reallocation affects roughly two thirds of all work in the economy, even though changes in occupational employment and wages remain moderate. This implies that changes in the nature of work within occupations are central to understanding the labour-market effects of GenAI. Where net employment shifts do occur, they favour blue-collar occupations and disadvantage lower-skilled white-collar roles, but these movements are modest relative to the scale of within-occupation restructuring and to historical patterns of structural change.

Third, long-run outcomes depend critically on the distributional properties of task-level productivity gains. The tail thickness and dependence structure of augmentation and automation potentials play a decisive role in determining both the magnitude of aggregate gains and their incidence across industries and occupations, whereas conventional substitution elasticities matter considerably less. Changes in tail thickness primarily scale the magnitude of outcomes, while changes in dependence alter the balance between augmentation and automation and therefore the pattern of adjustment across the economy. Empirically grounding these distributional parameters—

through micro-level measurement of the productivity gains that GenAI delivers across diverse tasks—is therefore an important priority for future research.

The analysis also assumes a fixed global rate of return to capital. While this assumption is consistent with standard neoclassical modelling, global saving may not adjust sufficiently to sustain the increase in the investment share implied by the simulations, from 34.5% to 40.7%. Within the framework of the model, our results do not depend on how this investment is financed. Australia has a relatively small technology sector and will most likely rely heavily on foreign direct investment and imported AI hardware, with the returns on FDI flowing to foreign owners. What matters is the implicit assumption that, in the long run, the ratio of the net international investment position to GDP is unchanged—which amounts to assuming that Australians increase their rate of saving commensurately with the increased capital intensity of the economy.[28]

A further set of limitations concerns the exposure data on which our calibration rests. The JSA scores are derived from LLM-based assessments of task descriptions—a method whose accuracy and consistency have not been systematically validated against observed adoption outcomes. It is therefore possible that the indices mischaracterise the relative potential for augmentation and automation across occupations, or that the underlying task descriptions do not adequately capture what workers actually do. More fundamentally, the analysis characterises GenAI entirely in terms of its exposure to existing occupational tasks, and so cannot account for the emergence of entirely new tasks or occupations (Acemoglu and Restrepo, 2018b; Acemoglu, 2025), nor for the possibility that GenAI accelerates technological progress itself (Jones, 2025). Even modest increases in the rate of idea generation could compound over time and potentially dwarf the static reallocation effects examined here.

## Data availability, acknowledgements and declarations

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### Funding, prior work and disclaimer

No specific grant from funding agencies was received to support the development and application of the model reported in this paper. However, the research reported builds on earlier work undertaken under contract for Jobs and Skills Australia (JSA), which analysed generative AI adoption using dynamic simulations of the VUEF model (Jobs and Skills Australia, 2025b). The present paper uses the GenAI exposure scores published by JSA (Jobs and Skills Australia, 2025a) and extends our original methodology within the comparative-static framework reported here. The analysis and conclusions in this paper are those of the authors and do not necessarily reflect the views of Jobs and Skills Australia.

The authors declare no competing interests.

### Data and code availability

Occupation-level GenAI exposure scores are publicly available from Jobs and Skills Australia (Jobs and Skills Australia, 2025a). Australian input–output data and labour force statistics are published by the Australian Bureau of Statistics. The model database is derived from projections of these data using the VUEF model (Dixon, 2022) and is not publicly available. Python scripts and inputs used to generate figures and tables are available from the corresponding author on request.

[28]For context, Australia's NIIP has been relatively stable at around −50% of GDP for three decades. There are nonetheless reasons to expect long-run saving to adjust. If AI adoption raises the capital share of income globally—as our results suggest it does domestically—standard neoclassical theory implies that the equilibrium saving rate rises endogenously: in the Ramsey model, the steady-state saving rate is increasing in the capital share, with no change in preferences required. Australia's compulsory superannuation system provides a further automatic channel, since higher labour income translates mechanically into higher mandated saving.

### Use of generative AI and AI-assisted technologies

During the preparation of this paper, the authors used ChatGPT and Claude to support literature review, to draft or adapt Python code for figures and tables, and to review, critique, and copy-edit text. The authors reviewed and edited the resulting material and take full responsibility for the content of the paper.

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# A Further mathematical details of the model

## A.1 CES demand and cost equations

The model uses nested CES functions throughout. Every nest takes the same generic form: a composite $Q$ assembled from inputs $q_g$ indexed by $g \in \mathcal{G}$ with distribution parameters $\delta_g$ and substitution elasticity $\sigma$,

$$Q = \left[ \sum_{g \in \mathcal{G}} \delta_g^{1/\sigma} \, q_g^{(\sigma-1)/\sigma} \right]^{\sigma/(\sigma-1)} . \tag{A.1}$$

The distribution parameters satisfy the normalisation $\sum_{g \in \mathcal{G}} \delta_g = 1$, which is equivalent to requiring that $\delta_g$ equals the cost or expenditure share of input $g$ when all input prices are equal, and which fixes the units of the composite $Q$. Cost minimisation yields the demand equations

$$q_g = \delta_g \left( \frac{P_g}{P} \right)^{-\sigma} Q \tag{A.2}$$

and the dual price index

$$P = \left[ \sum_{g \in \mathcal{G}} \delta_g \, P_g^{1-\sigma} \right]^{1/(1-\sigma)} . \tag{A.3}$$

These equations apply to every nest in the model; they differ only in the identity of the composite $Q$, the inputs $q_g$, the share parameters $\delta_g$, and the elasticity $\sigma$, as mapped out in Table A.1. In the intermediate, consumption, and investment nests, each input $q_g$ is itself a CES composite of domestic and imported varieties—an Armington nest with a common elasticity $\sigma_{\mathrm{c}}$—obtained by applying (A.1)–(A.3) at the inner level.

Table A.1: CES structure: mapping of generic notation to each application. Generic CES equations are (A.1)–(A.3).

| Application | $Q$ | $P$ (dual) | $q_g$ | $p_g$ | $\delta_g$ | $\sigma$ | |
|---|---|---|---|---|---|---|---|
| *Utility* | | | | | | | |
| Consumption utility | $U$ | $P_{\mathrm{c}}$ | $C_{\mathrm{c},g}$ | $P_g$ | $\varkappa_{\mathrm{c},g}$ | $\sigma_{\mathrm{u}}$ | (1) |
| *Production* | | | | | | | |
| Industry output | $Y_i$ | $P_{\mathrm{y},i}$ | $X_{\mathrm{va},i}$, $X_{\mathrm{int},i}$ | $P_{\mathrm{v},i}$, $P_{\mathrm{m},i}$ | $\varsigma_{\mathrm{v}}$, $1-\varsigma_{\mathrm{v}}$ | $\sigma_{\mathrm{y}}$ | (10) |
| Value added | $X_{\mathrm{va},i}$ | $P_{\mathrm{v},i}$ | $K_{\mathrm{ne},i}$, $T_i$ | $P_{k,i}$, $P_{T,i}$ | $\varsigma_{\mathrm{k}}$, $1-\varsigma_{\mathrm{k}}$ | $\sigma_{\mathrm{v}}$ | (11) |
| Intermediate composite | $X_{\mathrm{int},i}$ | $P_{\mathrm{m},i}$ | $X_{\mathrm{c},g,i}$ | $P_g$ | $\varsigma_{\mathrm{c},g,i}$ | $\sigma_{\mathrm{n}}$ | (12) |
| *Investment* | | | | | | | |
| Investment composite | $I_{k,i}$ | $P_{k,i}$ | $I_{\mathrm{c},g,k,i}$ | $P_g$ | $\zeta_{\mathrm{c},g,k,i}$ | $\sigma_{\mathrm{i}}$ | (39) |
| *Armington nests (inner CES level)* | | | | | | | |
| Consumption Armington | $C_{\mathrm{c},g}$ | $P_g$ | $C_{\mathrm{d},g}$, $C_{\mathrm{m},g}$ | $P_{\mathrm{d},g}$, $P_{\mathrm{m},g}$ | $\varkappa_{\mathrm{d},g}$ | $\sigma_{\mathrm{c}}$ | (2) |
| Investment Armington | $I_{\mathrm{c},g,k,i}$ | $P_g$ | $I_{\mathrm{d},g,k,i}$, $I_{\mathrm{m},g,k,i}$ | $P_{\mathrm{d},g}$, $P_{\mathrm{m},g}$ | $\zeta_{\mathrm{d},g,k,i}$ | $\sigma_{\mathrm{c}}$ | (40) |
| Intermediate Armington | $X_{\mathrm{c},g,i}$ | $P_g$ | $X_{\mathrm{d},g,i}$, $X_{\mathrm{m},g,i}$ | $P_{\mathrm{d},g}$, $P_{\mathrm{m},g}$ | $\varsigma_{\mathrm{d},g,i}$ | $\sigma_{\mathrm{c}}$ | (13) |

## A.2 Derivation of task share weights

This appendix derives the closed-form expressions for the task share weights presented in Section 2. The derivation proceeds in three steps: identifying the regions of the productivity space assigned to each mode, integrating over the joint distribution to obtain the non-AI weight, and evaluating the conditional integrals for the AI-using weights.

### A.2.1 Mode assignment regions

Given the task unit costs (17), occupational task $\tau$ of type $(o,i)$ is performed without AI if and only if the non-AI mode has the lowest unit cost, i.e.

$$\psi^{\mathrm{g}}_{o,i}(\tau) \le \hat{\omega}^{\mathrm{g}}_{o,i} \qquad \text{and} \qquad \psi^{\mathrm{a}}_{o,i}(\tau) \le \hat{\omega}^{\mathrm{a}}_{o,i} \tag{A.4}$$

where $\hat{\omega}^{\mathrm{g}}_{o,i}$ and $\hat{\omega}^{\mathrm{a}}_{o,i}$ are the cost ratios defined in (18). The automated mode is least-cost if and only if

$$\psi^{\mathrm{a}}_{o,i}(\tau) > \hat{\omega}^{\mathrm{a}}_{o,i} \qquad \text{and} \qquad \psi^{\mathrm{g}}_{o,i}(\tau) \le \frac{\hat{\omega}^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}} \, \psi^{\mathrm{a}}_{o,i}(\tau). \tag{A.5}$$

The augmented mode is least-cost when $\psi^{\mathrm{g}}_{o,i}(\tau) > \hat{\omega}^{\mathrm{g}}_{o,i}$ and $\psi^{\mathrm{a}}_{o,i}(\tau) \le (\hat{\omega}^{\mathrm{a}}_{o,i}/\hat{\omega}^{\mathrm{g}}_{o,i}) \, \psi^{\mathrm{g}}_{o,i}(\tau)$.

### A.2.2 Non-AI task share weight

The weight for non-AI tasks equals the probability that (A.4) holds, which is simply the joint CDF (23) evaluated at $(\hat{\omega}^{\mathrm{g}}_{o,i}, \hat{\omega}^{\mathrm{a}}_{o,i})$:

$$\varGamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i}) = F(\hat{\omega}^{\mathrm{g}}_{o,i}, \hat{\omega}^{\mathrm{a}}_{o,i}) = \exp\left[-\left(\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}\right)^{1/\theta_o}\right]. \tag{A.6}$$

The weights $\varGamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i})$ depend on both occupation and industry through the industry-specific input prices and efficiency terms in (18).

### A.2.3 Automated task share weight

Consider the automated task share weight. By definition,

$$\varGamma^{\mathrm{a}}_{o,i}(\boldsymbol{\omega}_{o,i}) \equiv \int_{\mathcal{T}^{\mathrm{a}}_{o,i}} \psi^{\mathrm{a}}_{o,i}(\tau)^{\,\epsilon-1}\,\mathrm{d}\tau. \tag{A.7}$$

The set $\mathcal{T}^{\mathrm{a}}_{o,i}$ is defined by conditions (A.5). Changing variables from $\tau$ to $\psi^{\mathrm{a}}_{o,i}$ (using the marginal Fréchet density $f_{\mathrm{a}}$) and conditioning on $\psi^{\mathrm{a}}_{o,i} = z_o$, the integral becomes

$$\begin{aligned}\varGamma^{\mathrm{a}}_{o,i}(\boldsymbol{\omega}_{o,i}) &= \int_{\hat{\omega}^{\mathrm{a}}_{o,i}}^{\infty} z_o^{\epsilon-1}\,\mathbb{P}\left[\psi^{\mathrm{g}}_{o,i} \le \frac{\hat{\omega}^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}} z_o \,\middle|\, \psi^{\mathrm{a}}_{o,i} = z_o\right] f_{\mathrm{a}}(z_o)\,\mathrm{d}z_o \\ &= \int_{\hat{\omega}^{\mathrm{a}}_{o,i}}^{\infty} z_o^{\epsilon-1}\,\frac{\partial F(\bar{\psi}^{\mathrm{g}}_{o,i}, \bar{\psi}^{\mathrm{a}}_{o,i})}{\partial \bar{\psi}^{\mathrm{a}}_{o,i}}\bigg|_{\frac{\hat{\omega}^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}} z_o,\, z_o}\,\mathrm{d}z_o.\end{aligned} \tag{A.8}$$

The partial derivative of the Gumbel–Fréchet CDF is

$$\begin{aligned}\frac{\partial F}{\partial \bar{\psi}^{\mathrm{a}}_{o,i}}\bigg|_{\frac{\hat{\omega}^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}} z_o,\, z_o} &= \left[\left(\kappa^{\mathrm{g}}_{o,i}\frac{\hat{\omega}^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + (\kappa^{\mathrm{a}}_{o,i})^{\alpha_o\theta_o}\right]^{\frac{1-\theta_o}{\theta_o}} (\kappa^{\mathrm{a}}_{o,i})^{\alpha_o\theta_o} \\ &\quad \times \alpha_o\, z_o^{-\alpha_o-1}\,\exp\left[-z_o^{-\alpha_o}\left(\left(\kappa^{\mathrm{g}}_{o,i}\frac{\hat{\omega}^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + (\kappa^{\mathrm{a}}_{o,i})^{\alpha_o\theta_o}\right)^{1/\theta_o}\right].\end{aligned} \tag{A.9}$$

Substituting into (A.8) and applying the change of variables $\tilde{z}_o = z_o^{-\alpha_o}$ (so that $\mathrm{d}\tilde{z}_o = -\alpha_o z_o^{-\alpha_o-1}\mathrm{d}z_o$ and the integral runs from $(\hat{\omega}^{\mathrm{a}}_{o,i})^{-\alpha_o}$ to zero), the integrand takes the form of an incomplete Gamma function. After simplification,

$$\varGamma^{\mathrm{a}}_{o,i}(\boldsymbol{\omega}_{o,i}) = \varOmega_{o,i}(\boldsymbol{\omega}_{o,i})\,\left(\kappa^{\mathrm{a}}_{o,i}\right)^{\epsilon-1}\left[\frac{\left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}}{\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}}\right]^{1+\frac{1-\epsilon}{\alpha_o\theta_o}} \tag{A.10}$$

where

$$\varOmega_{o,i}(\boldsymbol{\omega}_{o,i}) \equiv \mathrm{Gamma}\left[1 + \frac{1-\epsilon}{\alpha_o}\right] - \mathrm{Gamma}\left[1 + \frac{1-\epsilon}{\alpha_o},\, -\log \varGamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i})\right], \tag{A.11}$$

Gamma[$\cdot$] is the Gamma function, and Gamma[$\cdot,\cdot$] is the upper incomplete Gamma function.

The augmented weight follows by symmetry—swapping the g and a superscripts in (A.10)—yielding equation (25) in the main text.

### A.2.4 Equipment task share weights

For equipment tasks, the derivation is simpler because only one AI-using mode exists. Equipment task $\tau$ is performed without AI if $\tilde{\psi}^{\mathrm{g}}_i(\tau) \le \hat{\tilde{\omega}}^{\mathrm{g}}_i$. Since $\tilde{\psi}^{\mathrm{g}}_i$ follows a univariate Fréchet distribution with scale $\tilde{\kappa}^{\mathrm{g}}_i$ and shape $\tilde{\alpha}_i$, the non-AI weight is

$$\tilde{\varGamma}^{\mathrm{n}}_i(\tilde{\boldsymbol{\omega}}_i) = F(\hat{\tilde{\omega}}^{\mathrm{g}}_i) = \exp\left[-\left(\frac{\tilde{\kappa}^{\mathrm{g}}_i}{\hat{\tilde{\omega}}^{\mathrm{g}}_i}\right)^{\tilde{\alpha}_i}\right], \tag{A.12}$$

as given by (27). For the AI-enhanced weight, the integral

$$\tilde{\varGamma}^{\mathrm{g}}_i(\tilde{\boldsymbol{\omega}}_i) = \int_{\hat{\tilde{\omega}}^{\mathrm{g}}_i}^{\infty} z_i^{\epsilon-1}\tilde{f}(z_i)\,\mathrm{d}z_i, \tag{A.13}$$

where $\tilde{f}$ is the Fréchet density, reduces via the same change of variables to

$$\tilde{\varGamma}^{\mathrm{g}}_i(\tilde{\boldsymbol{\omega}}_i) = \tilde{\varOmega}_i(\tilde{\boldsymbol{\omega}}_i)\,(\tilde{\kappa}^{\mathrm{g}}_i)^{\epsilon-1} \tag{A.14}$$

with $\tilde{\varOmega}_i(\tilde{\boldsymbol{\omega}}_i)$ as defined in (29).

## A.3 Task shares and average productivities

### A.3.1 Task shares

While the task share weights $\Gamma^m_{o,i}$ suffice to characterise the equilibrium, we also derive unweighted task shares $\Theta^m_{o,i} \equiv \mu(\mathcal{T}^m_{o,i})$ for $m \in \{\mathrm{n},\mathrm{g},\mathrm{a}\}$ and $\tilde{\Theta}^m_i \equiv \mu(\tilde{\mathcal{T}}^m_i)$ for $m \in \{\mathrm{n},\mathrm{g}\}$, in order to link the model to the calibration data. Specifically, we interpret the estimated share of occupational tasks that may potentially be augmented as the $\Theta^{\mathrm{g}}_{o,i}$ that results when (i) $\kappa^{\mathrm{a}}_{o,i} = 0$; (ii) $p_{\mathrm{s}} = 0$; and (iii) the price per unit of effective labour or equipment equals its normalised value in the initial equilibrium. The same logic applies to potentially automated task shares.

Integrating over each mode region yields

$$\Theta^{\mathrm{n}}_{o,i} = \exp\left[-\left(\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}\right)^{1/\theta_o}\right] = \Gamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i}), \tag{A.15}$$

$$\Theta^{\mathrm{g}}_{o,i} = \left(1 - \Theta^{\mathrm{n}}_{o,i}\right) \frac{\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o}}{\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}}, \tag{A.16}$$

and

$$\Theta^{\mathrm{a}}_{o,i} = \left(1 - \Theta^{\mathrm{n}}_{o,i}\right) \frac{\left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}}{\left(\frac{\kappa^{\mathrm{g}}_{o,i}}{\hat{\omega}^{\mathrm{g}}_{o,i}}\right)^{\alpha_o\theta_o} + \left(\frac{\kappa^{\mathrm{a}}_{o,i}}{\hat{\omega}^{\mathrm{a}}_{o,i}}\right)^{\alpha_o\theta_o}}. \tag{A.17}$$

Thus the non-AI task share equals the non-AI task share weight, while the augmented and automated shares divide the remaining mass in proportion to their respective Fréchet–Gumbel survival terms.

### A.3.2 Average task productivity

We define the average productivity of augmented occupational tasks as the ratio of augmented task outputs to augmented task inputs:

$$\bar{\psi}^{\mathrm{g}}_{o,i} \equiv \frac{\int_{\mathcal{T}^{\mathrm{g}}_{o,i}} \psi^{\mathrm{g}}_{o,i}(\tau)\, x^{\mathrm{g}}_{o,i}(\tau)\,\mathrm{d}\tau}{\int_{\mathcal{T}^{\mathrm{g}}_{o,i}} x^{\mathrm{g}}_{o,i}(\tau)\,\mathrm{d}\tau} = \left(\frac{\mathrm{Gamma}\left[\frac{\alpha_o-1-\epsilon}{\alpha_o}\right] - \mathrm{Gamma}\left[\frac{\alpha_o-1-\epsilon}{\alpha_o},\, -\log\Gamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i})\right]}{\mathrm{Gamma}\left[\frac{\alpha_o-\epsilon}{\alpha_o}\right] - \mathrm{Gamma}\left[\frac{\alpha_o-\epsilon}{\alpha_o},\, -\log\Gamma^{\mathrm{n}}_{o,i}(\boldsymbol{\omega}_{o,i})\right]}\right) \times \left(\frac{\Theta^{\mathrm{g}}_{o,i} + \Theta^{\mathrm{a}}_{o,i}}{\Theta^{\mathrm{g}}_{o,i}}\right)^{\frac{1}{\alpha_o\theta_o}} \kappa^{\mathrm{g}}_{o,i}. \tag{A.18}$$

The expression for the average productivity of automated tasks is analogous, with superscripts g and a swapped and $\kappa^{\mathrm{g}}_{o,i}$ replaced by $\kappa^{\mathrm{a}}_{o,i}$.

# B Demand-side decomposition of industry output

This appendix describes the shift-share decomposition used to attribute changes in industry output to demand-side and supply-side drivers in Figures 6, C.1, and C.2.

## B.1 Input–output decomposition

For any set of quantities and prices satisfying the equilibrium defined by the model equations, let $\mathbf{y}$ denote the vector of industry gross outputs, i.e. with element $i$ equal $Y_i$. Let $\mathbf{F}_{\mathrm{d}}$ denote the matrix with elements $(g,h)$ corresponding to the quantity of the $h$th final demand for the $g$th domestic good, with $h \in \{\mathrm{c},\mathrm{e},\mathrm{eq},\mathrm{ne}\}$ (consumption, exports, equipment investment, non-equipment investment). Finally, let $\mathbf{A}_{\mathrm{d}}$ be a matrix of domestic input–output (IO) coefficients: element $(g,i)$ is the quantity of domestic commodity $g$ used—as ordinary intermediates and AI services—to produce one unit of output in industry $i$. At this equilibrium, the balance (in quantity units) between domestic output and absorption of domestic goods can be written

$$\mathbf{y} = \mathbf{A}_{\mathrm{d}}\,\mathbf{y} + \mathbf{F}_{\mathrm{d}}\mathbf{1}, \tag{B.1}$$

where $\mathbf{1}$ denotes a conformable vector of ones.

To account for intermediate import substitution effects, we rewrite the balance as

$$\mathbf{y} = (\mathbf{S}_{\mathrm{d}} \odot \mathbf{A}_{\mathrm{t}})\,\mathbf{y} + \mathbf{F}_{\mathrm{d}}\,\mathbf{1}, \tag{B.2}$$

where $\mathbf{A}_{\mathrm{t}}$ is a matrix of composite (i.e. imported and domestic) intermediate input coefficients, $\mathbf{S}_{\mathrm{d}}$ is corresponding matrix of domestic shares and $\odot$ denotes the Hadamard product.

The Leontief inverse matrix is

$$\mathbf{L} \equiv (\mathbf{I} - \mathbf{S}_{\mathrm{d}} \odot \mathbf{A}_{\mathrm{t}})^{-1} \tag{B.3}$$

and allows us to construct a decomposition of the output vector in the manner of input-output analyses, i.e.

$$\mathbf{Y} = \mathbf{L}\mathbf{F}. \tag{B.4}$$

From this, it can be seen that the element $(i, j)$ of the Leontief inverse gives the direct plus indirect output of industry $i$ required to deliver one unit of final demand for good $j$. Accordingly, column $k$ of the decomposed output $\mathbf{Y}$ is that required to deliver column $k$ of final demand $\mathbf{F}$. The decomposition is exact, so summing the columns of $\mathbf{Y}$ recovers $\mathbf{y}$.

## B.2 Decomposing changes

Comparative statics involves comparing the final and initial equilibria—in this case, with vs without GenAI. The IO coefficients as defined above are not fixed parameters, but the equilibrium outcome of producers' cost-minimising decisions, so differ in the initial and final equilibria. Producers substitute between domestic and imported intermediates ((13)) and use AI services intermediates as tasks are augmented and automated. Thus, changes in $\mathbf{F}$ and $\mathbf{L}$ cause changes in $\mathbf{Y}$.

The model is solved by linearisation and homotopy-continuation (Horridge et al., 2018), so we can work with the total differential of (B.4):

$$\mathrm{d}\mathbf{Y} = \mathrm{d}\mathbf{L}\,\mathbf{F} + \mathbf{L}\,\mathrm{d}\mathbf{F}. \tag{B.5}$$

The first term captures supply-side effects operating through changes in the Leontief inverse; the second captures demand-side effects. Using (B.3), $\mathrm{d}\mathbf{L}$ can be expressed in terms of import substitution effects and input intensity effects.[29]

The two matrices of derivatives can be further decomposed. Firstly, the change in the Leontief inverse is decomposed as

$$\mathrm{d}\mathbf{L} = \underbrace{\mathbf{L}\mathrm{d}\mathbf{S}_{\mathrm{d}} \odot \mathbf{A}_{\mathrm{t}}\mathbf{L}}_{\substack{\text{substitution against}\\ \text{intermediate imports}}} + \underbrace{\mathbf{L}\mathbf{S}_{\mathrm{d}} \odot \mathrm{d}\mathbf{A}_{\mathrm{t}}\mathbf{L}}_{\substack{\text{changes in}\\ \text{input intensities}}}. \tag{B.6}$$

Secondly, a shift-share analysis is used to model changes in final demands. Let matrix $\mathbf{S}_{\mathrm{f}}$ give domestic shares in total (domestic plus imported) final demands $\mathbf{F}_t$. Let $\mathbf{S}_{\mathrm{c}}$ give the commodity shares of each of the four components of aggregate final demand (i.e. each column sums to one). Let $\mathbf{D}$ denote a diagonal matrix of dimension four, where the diagonal elements are the share of each aggregate in real GDP, which we denote $\Upsilon$. Then

$$\mathbf{F}_d = (\mathbf{S}_{\mathrm{f}} \odot \mathbf{S}_{\mathrm{c}})\,\mathbf{D}\,\Upsilon \tag{B.7}$$

Totally differentiating B.7 gives

$$\mathrm{d}\mathbf{F}_d = \underbrace{(\mathrm{d}\mathbf{S}_{\mathrm{f}} \odot \mathbf{S}_{\mathrm{c}})\,\mathbf{D}\,\Upsilon}_{\substack{\text{substitution against}\\ \text{final imports}}} + \underbrace{(\mathbf{S}_{\mathrm{f}} \odot \mathrm{d}\mathbf{S}_{\mathrm{c}})\,\mathbf{D}\,\Upsilon}_{\substack{\text{composition of}\\ \text{demand aggregates}}} + \underbrace{(\mathbf{S}_{\mathrm{f}} \odot \mathbf{S}_{\mathrm{c}})\,\mathrm{d}\mathbf{D}\,\Upsilon}_{\text{aggregate composition}} + \underbrace{(\mathbf{S}_{\mathrm{f}} \odot \mathbf{S}_{\mathrm{c}})\,\mathbf{D}\,\mathrm{d}\Upsilon}_{\text{aggregate scale}}. \tag{B.8}$$

In Figure C.1, the four components correspond to the four columns of $\mathrm{d}\mathbf{Y}$, summing over the four shift-share components of $\mathrm{d}\mathbf{F}_d$. Figure C.2 does the same except that it sums over only the first three shift-share components, omitting the aggregate scale term.

[29]With $\sigma_{\mathrm{y}} = 0$ and $\sigma_{\mathrm{n}} = 0$, changes in $\mathbf{A}_{\mathrm{t}}$ are due entirely to increasing use of AI services inputs. If these substitution elasticities are non-zero, $\mathbf{A}_{\mathrm{t}}$ also captures associated substitution effects.

## C Supplementary figures

This appendix presents two additional decompositions of industry value-added changes that complement the shift-share decomposition in Figure 6.

Figure C.1 shows the raw demand-side decomposition, attributing each industry's value-added change to the four final-demand categories (consumption, exports, equipment investment, non-equipment investment) that ultimately absorb its output. This decomposition is dominated by the general expansion of aggregate demand, which obscures the structural reallocation across industries.

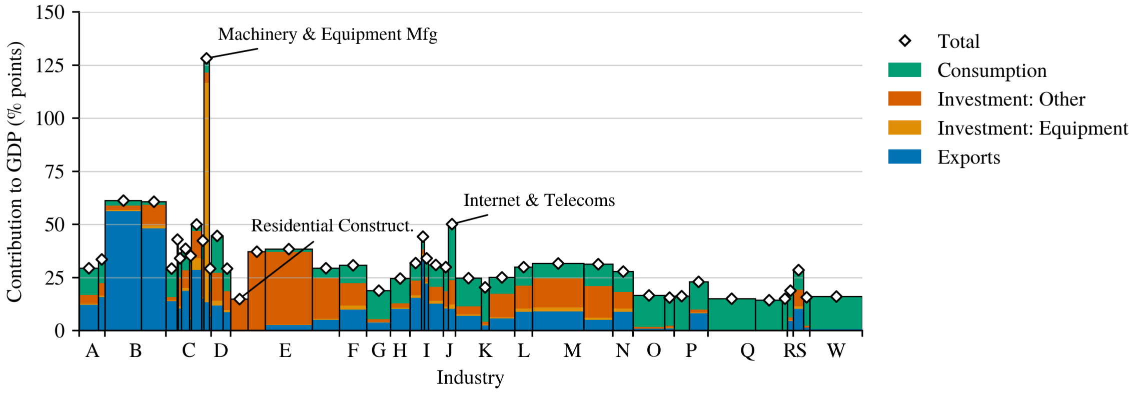


Figure C.1: Industry-level changes in value added, decomposed by final demand category. Bar widths are proportional to initial industry value added.

Figure C.2 strips out the aggregate expansion component to reveal the structural shifts in demand composition across industries.

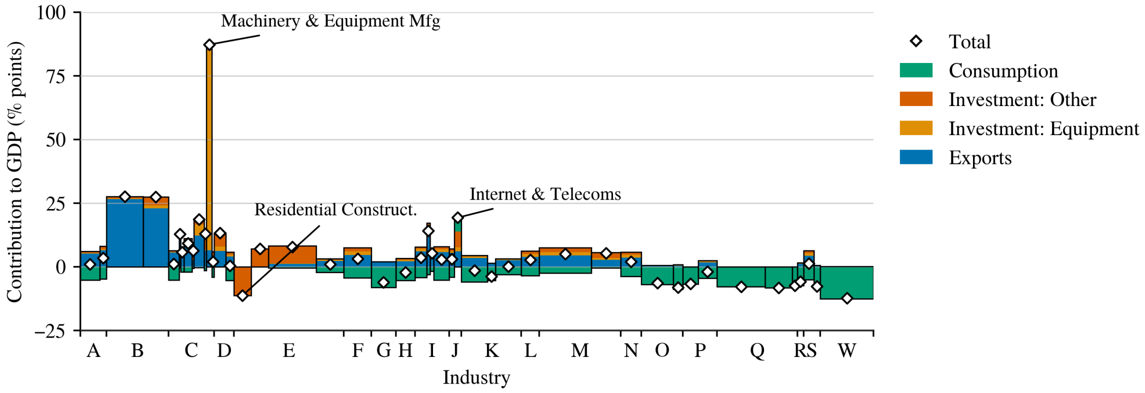


Figure C.2: Industry-level changes in value added net of aggregate demand effects, decomposed by final demand category. Bar widths are proportional to initial industry value added.

# D Supplementary tables

Table D.1: Industry contributions to GDP and value added (reference case)

| | Labour | Other capital | Equipment | Technical change | Value added |
|---|---|---|---|---|---|
| Agriculture | −0.3 | 16.9 | 6.5 | 6.5 | 192.9 |
| Forestry & Fishing | 1.8 | 19.0 | 9.0 | 3.8 | 65.5 |
| Fossil Fuel Mining | 3.7 | 51.0 | 3.7 | 2.9 | 363.6 |
| Other Mining | 9.1 | 37.4 | 7.8 | 6.4 | 246.4 |
| Food Prd. | 1.3 | 11.9 | 7.1 | 9.0 | 107.2 |
| Textile, Clothing, Footwear | 6.7 | 18.0 | 8.7 | 9.6 | 12.7 |
| Wood, Paper & Printing | 3.7 | 9.0 | 9.5 | 11.9 | 34.5 |
| Petroleum & Chemicals | 4.3 | 15.8 | 9.0 | 9.5 | 78.3 |
| Non-Metallic Mineral Prd. | 4.6 | 11.2 | 9.1 | 10.5 | 20.5 |
| Metal Prd. | 10.4 | 16.4 | 13.0 | 10.2 | 100.6 |
| Transport Equipment Mfg | 9.7 | 9.6 | 9.9 | 13.3 | 21.4 |
| Machinery & Equipment Mfg | 59.7 | 31.2 | 20.1 | 17.3 | 55.6 |
| Furniture & Other Mfg | 1.5 | 6.6 | 9.4 | 11.9 | 18.9 |
| Electricity | 3.4 | 32.1 | 4.3 | 4.9 | 116.8 |
| Other Utilities | 0.5 | 19.6 | 3.8 | 5.5 | 79.1 |
| Residential Construct. | −3.6 | 9.1 | 4.2 | 5.2 | 172.0 |
| Non-residential Construct. | 2.4 | 19.2 | 9.5 | 6.0 | 171.1 |
| Civil Construct. | 2.8 | 21.3 | 9.5 | 4.9 | 468.6 |
| Construct. Srv. | 4.0 | 8.6 | 7.5 | 9.2 | 274.0 |
| Wholesale Srv | 0.3 | 11.1 | 8.2 | 11.1 | 269.6 |
| Retail Srv | −6.5 | 6.1 | 8.6 | 10.7 | 241.3 |
| Accommodation & Food | −1.9 | 8.6 | 8.1 | 9.8 | 191.5 |
| Road Transport | 2.9 | 9.7 | 8.9 | 10.5 | 114.2 |
| Rail & Water Transport | 8.8 | 15.8 | 8.4 | 11.2 | 31.6 |
| Air Transport | 4.3 | 11.2 | 7.4 | 11.2 | 38.1 |
| Other Transport | 0.3 | 14.3 | 7.1 | 9.2 | 150.0 |
| Information & Media | 0.0 | 8.4 | 8.7 | 12.8 | 50.4 |
| Internet & Telecoms | 8.6 | 22.0 | 8.2 | 11.5 | 72.3 |
| Finance | −4.1 | 10.9 | 7.6 | 10.3 | 256.7 |
| Insurance & Superannuation | −8.2 | 5.0 | 9.9 | 13.7 | 77.0 |
| Auxiliary Fin. & Ins. Srv. | −5.8 | 4.7 | 11.0 | 15.2 | 256.4 |
| Rental, Hiring & Real Est. | −0.7 | 11.2 | 8.3 | 11.1 | 177.2 |
| Prof., Sci. & Tech. Srv. | 1.9 | 4.5 | 9.4 | 15.9 | 512.4 |
| Computer Sys Design. & Srv. | −0.5 | 2.7 | 11.6 | 17.7 | 290.0 |
| Admin & Support Srv | −0.2 | 2.2 | 10.2 | 15.7 | 204.2 |
| Public Admin | −8.9 | 2.3 | 8.6 | 14.6 | 313.9 |
| Public Safety & Defence | −4.8 | 3.0 | 5.5 | 12.0 | 94.6 |
| School Education | −4.2 | 1.6 | 5.1 | 13.9 | 151.2 |
| Tertiary Education | −3.7 | 3.8 | 8.2 | 14.7 | 186.0 |
| Health Care Srv | −4.4 | 1.8 | 4.6 | 13.2 | 474.8 |
| Aged & Disability Care | −4.4 | 0.9 | 4.9 | 13.1 | 269.0 |
| Child Care | −4.3 | 0.8 | 4.3 | 14.3 | 48.5 |
| Arts & Recreation | −4.4 | 4.5 | 6.7 | 12.1 | 60.9 |
| Repair & Maintenance | 3.7 | 4.1 | 7.9 | 13.0 | 102.0 |
| Personal & Other Srv | −6.4 | 2.3 | 7.6 | 12.3 | 62.1 |
| Dwellings | 0.0 | 16.2 | 0.0 | 0.0 | 525.6 |

Notes: Labour, other capital, equipment and technical change are the bar-segment contributions from the decomposition. Value added is the corresponding base-year industry value added. All figures are rounded to one decimal place.

Table D.2: Industry contributions to GDP and value added (reference case)

| | Aggregate demand scale | Aggregate demand composition | Final product substitution | Final imports | Intermedi-ate import substitution | Intermedi-ate input intensities | Value added |
|---|---|---|---|---|---|---|---|
| Agriculture | 28.5 | −2.2 | −1.6 | 1.7 | 2.8 | 0.3 | 192.9 |
| Forestry & Fishing | 30.2 | 0.3 | −2.1 | 1.4 | 3.4 | 0.4 | 65.5 |
| Fossil Fuel Mining | 33.8 | 20.6 | 4.3 | 0.3 | 1.8 | 0.6 | 363.6 |
| Other Mining | 33.2 | 20.2 | 4.0 | 0.4 | 2.5 | 0.3 | 246.4 |
| Food Prd. | 28.0 | −1.7 | −2.7 | 2.2 | 3.2 | 0.3 | 107.2 |
| Textile, Clothing, Footwear | 30.1 | 3.0 | −2.2 | 5.0 | 6.9 | 0.3 | 12.7 |
| Wood, Paper & Printing | 28.2 | −0.8 | −0.1 | 1.0 | 5.3 | 0.5 | 34.5 |
| Petroleum & Chemicals | 29.5 | 3.8 | −3.2 | 2.0 | 6.1 | 0.6 | 78.3 |
| Non-Metallic Mineral Prd. | 28.8 | −0.2 | −0.1 | 0.6 | 5.7 | 0.5 | 20.5 |
| Metal Prd. | 31.3 | 14.0 | −0.5 | 1.4 | 3.0 | 0.7 | 100.6 |
| Transport Equipment Mfg | 29.5 | 4.1 | −3.1 | 8.3 | 3.4 | 0.3 | 21.4 |
| Machinery & Equipment Mfg | 40.9 | 67.2 | −0.2 | 14.6 | −3.6 | 9.3 | 55.6 |
| Furniture & Other Mfg | 27.3 | −3.2 | −2.3 | 4.5 | 2.9 | 0.2 | 18.9 |
| Electricity | 31.3 | −0.7 | −0.4 | 0.8 | 1.0 | 12.6 | 116.8 |
| Other Utilities | 28.9 | −3.0 | −0.4 | 0.5 | 0.8 | 2.5 | 79.1 |
| Residential Construct. | 26.2 | −11.3 | 0.0 | 0.0 | 0.0 | 0.0 | 172.0 |
| Non-residential Construct. | 30.1 | 7.1 | 0.0 | 0.0 | 0.0 | 0.0 | 171.1 |
| Civil Construct. | 30.6 | 7.1 | 0.2 | 0.1 | 0.1 | 0.4 | 468.6 |
| Construct. Srv. | 28.4 | −0.6 | 0.2 | 0.3 | 0.4 | 0.7 | 274.0 |
| Wholesale Srv | 27.6 | 0.6 | 0.6 | 0.8 | 0.6 | 0.5 | 269.6 |
| Retail Srv | 24.9 | −7.5 | 0.9 | 0.3 | 0.2 | 0.1 | 241.3 |
| Accommodation & Food | 26.7 | −1.0 | −5.1 | 2.3 | 1.3 | 0.4 | 191.5 |
| Road Transport | 28.3 | 2.4 | −1.9 | 1.3 | 1.3 | 0.5 | 114.2 |
| Rail & Water Transport | 30.1 | 10.5 | 1.1 | 1.0 | 1.2 | 0.4 | 31.6 |
| Air Transport | 28.7 | 8.0 | −8.3 | 3.3 | 1.9 | 0.5 | 38.1 |
| Other Transport | 28.1 | −0.4 | 0.6 | 0.8 | 1.1 | 0.8 | 150.0 |
| Information & Media | 26.9 | −2.5 | 1.5 | 1.1 | 2.4 | 0.6 | 50.4 |
| Internet & Telecoms | 30.8 | −4.6 | −0.3 | 1.0 | 1.0 | 22.3 | 72.3 |
| Finance | 26.2 | −5.1 | 2.2 | 0.4 | 0.5 | 0.6 | 256.7 |
| Insurance & Superannuation | 24.2 | −8.0 | 3.5 | 0.3 | 0.4 | 0.2 | 77.0 |
| Auxiliary Fin. & Ins. Srv. | 25.0 | −2.5 | 1.1 | 0.4 | 0.6 | 0.6 | 256.4 |
| Rental, Hiring & Real Est. | 27.3 | −0.2 | 0.0 | 0.8 | 1.0 | 1.1 | 177.2 |
| Prof., Sci. & Tech. Srv. | 26.7 | 1.3 | 0.9 | 0.7 | 1.0 | 1.1 | 512.4 |
| Computer Sys Design. & Srv. | 26.1 | −2.0 | 0.7 | 0.7 | −5.3 | 11.3 | 290.0 |
| Admin & Support Srv | 25.8 | −0.5 | −0.5 | 1.0 | 1.0 | 1.0 | 204.2 |
| Public Admin | 23.0 | −8.8 | 2.2 | 0.1 | 0.1 | 0.1 | 313.9 |
| Public Safety & Defence | 23.7 | −8.8 | 0.4 | 0.1 | 0.1 | 0.2 | 94.6 |
| School Education | 23.0 | −9.6 | 2.9 | 0.0 | 0.0 | 0.0 | 151.2 |
| Tertiary Education | 24.9 | −2.6 | −2.1 | 1.6 | 0.9 | 0.3 | 186.0 |
| Health Care Srv | 22.8 | −9.6 | 1.8 | 0.1 | 0.0 | 0.0 | 474.8 |
| Aged & Disability Care | 22.7 | −9.6 | 1.4 | 0.0 | 0.0 | 0.0 | 269.0 |
| Child Care | 22.4 | −9.5 | 2.0 | 0.0 | 0.0 | 0.0 | 48.5 |
| Arts & Recreation | 24.6 | −5.8 | −1.8 | 1.0 | 0.6 | 0.2 | 60.9 |
| Repair & Maintenance | 27.3 | −0.9 | −0.6 | 0.8 | 0.9 | 1.1 | 102.0 |
| Personal & Other Srv | 23.5 | −8.5 | 0.5 | 0.2 | 0.1 | 0.1 | 62.1 |
| Dwellings | 28.5 | −11.5 | −1.1 | 0.2 | 0.1 | 0.0 | 525.6 |

Notes: Aggregate demand scale, Aggregate demand composition, Final product substitution', 'Final imports', 'Intermediate import substitution', 'Intermediate input intensities', 'Value added' are the bar-segment contributions from the decomposition. Value added is the corresponding base-year industry value added. All figures are rounded to one decimal place.

Table D.3: JSA exposure scores for ANZSCO 3-digit occupations

| Occupation | Augmentation | Automation | Occupation | Augmentation | Automation |
|---|---|---|---|---|---|
| 111 | 0.660 | 0.276 | 411 | 0.635 | 0.264 |
| 121 | 0.666 | 0.434 | 421 | 0.644 | 0.202 |
| 131 | 0.720 | 0.366 | 422 | 0.669 | 0.318 |
| 132 | 0.712 | 0.408 | 423 | 0.541 | 0.207 |
| 133 | 0.715 | 0.394 | 431 | 0.560 | 0.343 |
| 134 | 0.695 | 0.357 | 441 | 0.572 | 0.195 |
| 135 | 0.700 | 0.395 | 442 | 0.535 | 0.267 |
| 139 | 0.700 | 0.390 | 451 | 0.558 | 0.382 |
| 141 | 0.689 | 0.450 | 452 | 0.594 | 0.255 |
| 142 | 0.717 | 0.416 | 511 | 0.740 | 0.576 |
| 149 | 0.709 | 0.451 | 512 | 0.705 | 0.452 |
| 211 | 0.596 | 0.231 | 521 | 0.701 | 0.661 |
| 212 | 0.692 | 0.446 | 531 | 0.744 | 0.784 |
| 221 | 0.739 | 0.456 | 532 | 0.800 | 0.866 |
| 222 | 0.739 | 0.554 | 541 | 0.724 | 0.770 |
| 223 | 0.754 | 0.597 | 542 | 0.703 | 0.726 |
| 224 | 0.741 | 0.526 | 551 | 0.745 | 0.701 |
| 225 | 0.721 | 0.550 | 552 | 0.705 | 0.642 |
| 231 | 0.600 | 0.283 | 561 | 0.629 | 0.551 |
| 232 | 0.732 | 0.448 | 591 | 0.708 | 0.618 |
| 233 | 0.729 | 0.330 | 599 | 0.700 | 0.558 |
| 234 | 0.730 | 0.347 | 611 | 0.711 | 0.516 |
| 241 | 0.659 | 0.339 | 612 | 0.719 | 0.503 |
| 242 | 0.709 | 0.461 | 621 | 0.630 | 0.443 |
| 249 | 0.743 | 0.518 | 631 | 0.682 | 0.546 |
| 251 | 0.689 | 0.317 | 639 | 0.700 | 0.489 |
| 252 | 0.666 | 0.289 | 711 | 0.547 | 0.238 |
| 253 | 0.663 | 0.247 | 712 | 0.565 | 0.295 |
| 254 | 0.671 | 0.295 | 721 | 0.507 | 0.180 |
| 261 | 0.767 | 0.560 | 731 | 0.550 | 0.347 |
| 262 | 0.702 | 0.520 | 732 | 0.601 | 0.463 |
| 263 | 0.737 | 0.457 | 733 | 0.501 | 0.194 |
| 271 | 0.661 | 0.390 | 741 | 0.615 | 0.370 |
| 272 | 0.669 | 0.343 | 811 | 0.442 | 0.144 |
| 311 | 0.704 | 0.370 | 821 | 0.412 | 0.142 |
| 312 | 0.714 | 0.420 | 831 | 0.425 | 0.145 |
| 313 | 0.700 | 0.557 | 832 | 0.445 | 0.179 |
| 321 | 0.591 | 0.238 | 839 | 0.501 | 0.257 |
| 322 | 0.538 | 0.248 | 841 | 0.505 | 0.206 |
| 323 | 0.623 | 0.253 | 851 | 0.521 | 0.253 |
| 324 | 0.494 | 0.162 | 891 | 0.488 | 0.298 |
| 331 | 0.538 | 0.192 | 899 | 0.458 | 0.227 |
| 332 | 0.470 | 0.200 | | | |
| 333 | 0.550 | 0.155 | | | |
| 334 | 0.630 | 0.238 | | | |
| 341 | 0.584 | 0.180 | | | |
| 342 | 0.585 | 0.226 | | | |
| 351 | 0.583 | 0.274 | | | |
| 361 | 0.582 | 0.266 | | | |
| 362 | 0.575 | 0.281 | | | |
| 391 | 0.507 | 0.334 | | | |
| 392 | 0.620 | 0.286 | | | |
| 393 | 0.583 | 0.302 | | | |
| 394 | 0.608 | 0.342 | | | |
| 399 | 0.634 | 0.327 | | | |

Continued on next page

| | Labour demand | | | | | | Industry output | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Non-AI* | | *Augmented* | | | | | | | |
| | Extensive margin | Intensive margin | Extensive margin | Intensive margin | Other input substitution | Subtotal | Output shares | Output scale | Subtotal | |

Table D.4: Decomposition of ANZSCO three-digit occupational employment changes ('000 worker equivalents). Total workforce = 17.3 million persons.

| | Labour demand | | | | | | Industry output | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Non-AI* | | *Augmented* | | | | | | | |
| | Extensive margin | Intensive margin | Extensive margin | Intensive margin | Other input substitution | Subtotal | Output shares | Output scale | Subtotal | |
| 111 | -164.3 | -17.6 | 123.8 | -5.6 | 1.3 | -62.4 | 6.2 | 71.5 | 77.7 | 15.2 |
| 121 | -177.6 | -12.7 | 114.5 | -3.9 | 2.4 | -77.3 | 2.8 | 70.9 | 73.8 | -3.5 |
| 131 | -281.5 | -24.4 | 205.3 | -9.4 | 2.7 | -107.2 | 13.8 | 108.2 | 122.1 | 14.9 |
| 132 | -380.8 | -30.5 | 271.5 | -11.4 | 3.2 | -148.0 | 5.1 | 146.7 | 151.8 | 3.8 |
| 133 | -484.3 | -35.6 | 335.2 | -13.1 | 1.7 | -196.0 | 38.7 | 182.8 | 221.5 | 25.4 |
| 134 | -126.2 | -9.8 | 95.2 | -3.5 | 0.6 | -43.7 | -13.4 | 51.7 | 38.3 | -5.4 |
| 135 | -196.5 | -19.0 | 138.9 | -6.6 | 1.8 | -81.5 | 10.8 | 77.1 | 88.0 | 6.4 |
| 139 | -133.5 | -10.6 | 95.3 | -3.8 | 1.0 | -51.6 | 0.9 | 52.6 | 53.5 | 1.9 |
| 141 | -53.4 | -3.4 | 35.1 | -1.1 | 0.5 | -22.3 | -1.9 | 20.7 | 18.7 | -3.5 |
| 142 | -151.3 | -10.5 | 106.7 | -4.0 | 2.0 | -57.0 | -7.0 | 57.6 | 50.5 | -6.5 |
| 149 | -248.4 | -19.1 | 169.6 | -6.8 | 2.7 | -102.1 | 1.4 | 94.3 | 95.8 | -6.3 |
| 211 | -9.5 | -1.2 | 7.2 | -0.3 | 0.0 | -3.7 | 0.0 | 4.7 | 4.6 | 0.9 |
| 212 | -48.8 | -4.0 | 32.9 | -1.3 | 0.5 | -20.8 | 1.5 | 18.9 | 20.5 | -0.2 |
| 221 | -299.5 | -22.3 | 209.0 | -9.1 | 2.3 | -119.5 | 12.7 | 108.9 | 121.6 | 2.1 |
| 222 | -299.2 | -22.0 | 194.9 | -8.6 | 3.7 | -131.1 | -0.2 | 105.0 | 104.7 | -26.4 |
| 223 | -217.9 | -11.2 | 138.8 | -4.8 | 1.1 | -94.1 | 2.9 | 73.5 | 76.5 | -17.6 |
| 224 | -376.2 | -24.4 | 252.5 | -9.9 | 3.2 | -154.9 | 0.6 | 133.4 | 134.1 | -20.7 |
| 225 | -210.4 | -13.6 | 131.3 | -5.0 | 1.6 | -96.1 | 11.2 | 74.6 | 85.9 | -10.2 |
| 231 | -38.5 | -4.6 | 27.0 | -1.1 | 0.5 | -16.7 | 2.8 | 18.1 | 20.9 | 4.1 |
| 232 | -203.5 | -15.9 | 140.6 | -6.2 | 1.2 | -83.9 | 10.1 | 74.5 | 84.6 | 0.7 |
| 233 | -428.2 | -39.3 | 311.0 | -15.3 | 1.6 | -170.2 | 56.5 | 161.2 | 217.7 | 47.4 |
| 234 | -166.5 | -13.9 | 124.4 | -5.6 | 0.9 | -60.7 | 5.8 | 63.6 | 69.5 | 8.7 |
| 241 | -171.4 | -15.2 | 129.0 | -4.9 | 1.0 | -61.4 | -20.8 | 74.9 | 54.0 | -7.3 |
| 242 | -90.7 | -7.3 | 63.3 | -2.6 | 0.8 | -36.6 | -2.4 | 34.8 | 32.4 | -4.1 |
| 249 | -19.4 | -1.2 | 13.4 | -0.5 | 0.1 | -7.5 | -0.8 | 6.9 | 6.1 | -1.4 |
| 251 | -94.9 | -7.7 | 72.1 | -2.7 | 0.6 | -32.7 | -5.4 | 39.3 | 33.8 | 1.1 |
| 252 | -81.6 | -6.8 | 63.4 | -2.3 | 0.4 | -26.9 | -11.6 | 35.7 | 24.1 | -2.8 |
| 253 | -149.1 | -13.1 | 117.9 | -4.4 | 0.8 | -47.9 | -21.9 | 66.3 | 44.4 | -3.5 |
| 254 | -381.2 | -30.8 | 295.5 | -10.5 | 1.8 | -125.2 | -54.4 | 165.2 | 110.7 | -14.4 |
| 261 | -485.4 | -32.7 | 319.0 | -14.3 | 3.3 | -210.1 | 25.0 | 163.0 | 188.0 | -22.1 |
| 262 | -249.1 | -18.5 | 158.6 | -6.3 | 1.9 | -113.4 | 8.2 | 92.4 | 100.7 | -12.7 |
| 263 | -159.2 | -13.3 | 109.3 | -5.2 | 1.3 | -67.0 | 11.3 | 57.7 | 69.0 | 1.9 |
| 271 | -124.3 | -12.0 | 86.3 | -3.8 | 0.9 | -52.8 | 5.4 | 51.9 | 57.3 | 4.4 |
| 272 | -164.6 | -13.1 | 123.5 | -4.4 | 0.8 | -57.9 | -19.1 | 70.4 | 51.3 | -6.5 |
| 311 | -58.3 | -4.6 | 43.0 | -1.7 | 0.3 | -21.3 | -2.4 | 23.1 | 20.7 | -0.5 |
| 312 | -183.6 | -13.8 | 122.5 | -4.9 | 0.4 | -79.3 | 17.5 | 68.2 | 85.8 | 6.4 |
| 313 | -85.4 | -6.0 | 51.8 | -2.0 | 0.6 | -41.1 | 3.9 | 31.0 | 35.0 | -6.0 |
| 321 | -114.6 | -13.3 | 83.1 | -3.4 | 0.4 | -47.9 | 4.8 | 55.6 | 60.5 | 12.5 |
| 322 | -44.0 | -6.5 | 27.8 | -1.3 | 0.0 | -24.1 | 12.6 | 22.3 | 34.9 | 10.8 |
| 323 | -117.9 | -15.0 | 82.9 | -4.1 | 0.4 | -53.6 | 23.0 | 52.9 | 75.9 | 22.3 |
| 324 | -12.5 | -1.9 | 9.3 | -0.3 | 0.0 | -5.5 | 0.6 | 7.5 | 8.1 | 2.6 |
| 331 | -74.8 | -8.8 | 55.8 | -1.9 | -0.2 | -30.0 | -0.7 | 41.0 | 40.3 | 10.2 |
| 332 | -30.5 | -3.9 | 21.2 | -0.6 | -0.1 | -14.1 | 0.3 | 18.9 | 19.3 | 5.2 |
| 333 | -22.3 | -2.5 | 17.3 | -0.6 | -0.1 | -8.2 | 0.3 | 12.1 | 12.5 | 4.2 |
| 334 | -45.3 | -3.9 | 33.7 | -1.1 | -0.1 | -16.8 | 1.2 | 20.6 | 21.8 | 5.0 |
| 341 | -168.0 | -21.4 | 127.3 | -5.4 | -0.1 | -67.7 | 18.4 | 84.0 | 102.5 | 34.7 |
| 342 | -50.4 | -6.8 | 36.7 | -1.7 | 0.3 | -21.8 | 5.9 | 24.8 | 30.8 | 8.9 |
| 351 | -56.2 | -6.2 | 40.3 | -1.5 | 0.7 | -23.0 | -2.8 | 27.8 | 25.0 | 1.9 |
| 361 | -22.2 | -2.7 | 16.3 | -0.6 | 0.1 | -9.2 | -0.1 | 11.1 | 10.9 | 1.6 |
| 362 | -38.9 | -4.5 | 27.7 | -1.0 | 0.1 | -16.6 | -0.9 | 19.4 | 18.4 | 1.8 |

Continued on next page

| | Labour demand | | | | | | Industry output | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | *Non-AI* | | *Augmented* | | | | | | | |
| | Extensive margin | Intensive margin | Extensive margin | Intensive margin | Other input substitution | Subtotal | Output shares | Output scale | Subtotal | |
| 391 | -19.3 | -2.0 | 12.6 | -0.3 | 0.1 | -9.0 | -3.4 | 10.7 | 7.3 | -1.7 |
| 392 | -8.4 | -1.0 | 5.9 | -0.2 | 0.0 | -3.6 | 0.7 | 3.8 | 4.5 | 0.8 |
| 393 | -3.6 | -0.3 | 2.4 | 0.0 | 0.0 | -1.6 | 0.2 | 1.7 | 1.9 | 0.3 |
| 394 | -16.4 | -1.5 | 10.7 | -0.4 | 0.0 | -7.6 | 0.8 | 7.3 | 8.2 | 0.5 |
| 399 | -26.0 | -2.7 | 18.2 | -0.7 | 0.1 | -11.1 | 1.6 | 11.4 | 13.0 | 1.9 |
| 411 | -85.8 | -8.0 | 66.4 | -2.4 | 0.3 | -29.6 | -10.7 | 39.7 | 28.9 | -0.6 |
| 421 | -59.8 | -5.8 | 47.7 | -1.8 | 0.2 | -19.6 | -8.5 | 27.6 | 19.1 | -0.4 |
| 422 | -48.6 | -4.4 | 37.1 | -1.4 | 0.2 | -17.2 | -5.7 | 21.0 | 15.3 | -1.8 |
| 423 | -202.3 | -24.5 | 156.9 | -5.6 | 0.7 | -74.8 | -39.0 | 113.3 | 74.2 | -0.6 |
| 431 | -68.5 | -6.9 | 43.5 | -1.5 | 0.9 | -32.5 | -3.0 | 33.7 | 30.6 | -1.8 |
| 441 | -47.2 | -5.2 | 37.2 | -1.3 | 0.3 | -16.1 | -7.5 | 24.9 | 17.3 | 1.1 |
| 442 | -30.4 | -3.7 | 21.9 | -0.7 | 0.2 | -12.6 | -3.6 | 16.7 | 13.0 | 0.3 |
| 451 | -30.4 | -3.1 | 19.2 | -0.6 | 0.2 | -14.7 | -0.7 | 14.9 | 14.1 | -0.6 |
| 452 | -30.2 | -3.5 | 23.0 | -0.9 | 0.2 | -11.4 | -3.1 | 15.0 | 11.9 | 0.5 |
| 511 | -168.5 | -8.9 | 107.3 | -3.6 | 1.0 | -72.7 | 0.1 | 58.2 | 58.4 | -14.2 |
| 512 | -98.1 | -6.9 | 67.1 | -2.5 | 0.6 | -39.8 | 0.4 | 37.5 | 38.0 | -1.7 |
| 521 | -36.7 | -1.5 | 20.1 | -0.5 | 0.2 | -18.5 | 0.5 | 12.6 | 13.1 | -5.3 |
| 531 | -286.1 | -5.1 | 146.1 | -3.2 | 1.6 | -146.7 | -2.2 | 86.8 | 84.5 | -62.1 |
| 532 | -14.5 | 0.0 | 7.2 | -0.1 | 0.0 | -7.4 | 0.0 | 3.9 | 3.9 | -3.4 |
| 541 | -56.7 | -1.4 | 28.3 | -0.7 | 0.4 | -30.1 | 0.1 | 17.6 | 17.8 | -12.2 |
| 542 | -66.9 | -1.7 | 35.2 | -0.8 | 0.3 | -33.9 | -3.1 | 22.3 | 19.2 | -14.7 |
| 551 | -145.7 | -4.5 | 80.9 | -2.1 | 0.8 | -70.7 | 3.2 | 46.4 | 49.6 | -21.1 |
| 552 | -160.6 | -10.0 | 92.5 | -3.4 | 3.1 | -78.4 | -3.3 | 56.1 | 52.7 | -25.7 |
| 561 | -30.4 | -1.9 | 16.6 | -0.5 | 0.3 | -15.9 | 0.6 | 11.9 | 12.6 | -3.2 |
| 591 | -151.0 | -6.9 | 83.9 | -2.4 | 1.2 | -75.1 | 9.1 | 51.7 | 60.8 | -14.3 |
| 599 | -88.1 | -5.5 | 55.1 | -1.9 | 0.7 | -39.7 | -1.8 | 32.4 | 30.6 | -9.1 |
| 611 | -67.7 | -4.4 | 43.0 | -1.6 | 0.6 | -30.2 | 2.6 | 24.7 | 27.3 | -2.8 |
| 612 | -152.6 | -11.6 | 101.0 | -4.2 | 2.5 | -64.9 | 4.8 | 55.9 | 60.7 | -4.1 |
| 621 | -146.4 | -11.4 | 91.5 | -3.1 | 2.3 | -67.1 | -7.5 | 61.9 | 54.3 | -12.8 |
| 631 | -25.6 | -1.3 | 15.4 | -0.4 | 0.3 | -11.6 | -1.8 | 9.6 | 7.7 | -3.9 |
| 639 | -9.0 | -0.6 | 5.8 | -0.2 | 0.0 | -3.9 | 0.2 | 3.4 | 3.6 | -0.3 |
| 711 | -24.8 | -3.5 | 17.3 | -0.7 | 0.1 | -11.6 | 3.4 | 13.0 | 16.4 | 4.8 |
| 712 | -131.1 | -16.6 | 80.2 | -3.5 | 0.3 | -70.7 | 36.3 | 62.1 | 98.4 | 27.6 |
| 721 | -83.6 | -12.8 | 61.7 | -2.5 | 0.3 | -37.0 | 8.2 | 48.8 | 57.0 | 19.9 |
| 731 | -67.0 | -7.0 | 40.9 | -1.4 | 0.8 | -33.7 | 4.1 | 32.8 | 37.0 | 3.2 |
| 732 | -50.9 | -3.8 | 29.0 | -0.9 | 0.6 | -26.0 | 0.8 | 21.7 | 22.6 | -3.4 |
| 733 | -86.3 | -13.6 | 62.0 | -2.6 | 1.0 | -39.6 | 8.0 | 50.5 | 58.6 | 19.0 |
| 741 | -87.6 | -8.8 | 56.9 | -2.3 | 1.0 | -40.7 | 6.0 | 38.7 | 44.7 | 3.9 |
| 811 | -33.1 | -6.9 | 25.4 | -1.1 | 0.3 | -15.5 | -1.2 | 23.1 | 21.8 | 6.3 |
| 821 | -66.1 | -12.9 | 47.8 | -1.8 | -0.2 | -33.4 | 7.3 | 48.2 | 55.5 | 22.1 |
| 831 | -13.8 | -2.8 | 10.2 | -0.4 | 0.1 | -6.6 | 0.5 | 9.9 | 10.4 | 3.7 |
| 832 | -14.2 | -2.9 | 9.9 | -0.4 | 0.1 | -7.6 | 2.8 | 9.4 | 12.2 | 4.5 |
| 839 | -18.2 | -2.7 | 11.6 | -0.5 | 0.1 | -9.7 | 3.2 | 10.1 | 13.4 | 3.6 |
| 841 | -23.5 | -3.7 | 17.1 | -0.7 | 0.2 | -10.5 | 0.2 | 13.8 | 14.0 | 3.4 |
| 851 | -35.3 | -4.6 | 24.7 | -0.9 | 0.4 | -15.8 | -2.9 | 19.7 | 16.8 | 1.0 |
| 891 | -11.3 | -1.5 | 7.0 | -0.2 | 0.2 | -5.8 | -0.6 | 6.4 | 5.8 | 0.0 |
| 899 | -53.8 | -8.9 | 36.0 | -1.4 | 0.4 | -27.7 | 1.0 | 33.9 | 34.9 | 7.1 |
| Total | -11178.7 | -933.2 | 7650.6 | -305.3 | 82.0 | -4684.6 | 154.0 | 4530.5 | 4684.6 | 0.0 |