Precision or Automation? The Value–Population Ratio and the Demand for AI across Industries

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Abstract

Industries differ more in how many people they employ than in how much value they create, and the two do not line up. We ask whether this gap is associated with how much, and how, industries use AI. We combine the Anthropic Economic Index (Claude.ai use in April–May 2026; API tasks from one week of February 2026) with US national accounts, the occupational mix of every industry and a firm survey, for 65 private industries covering 146.8 million jobs in 2025. The value–population ratio, an industry's share of value added divided by its share of jobs, spans 40-fold, from 0.27 in social assistance to 11.1 in oil and gas extraction; industries below the average hold 67% of jobs and 40% of value added, and the ranking is nearly the same in the European Union (Spearman 0.93). AI use per worker rises in proportion to the ratio (elasticity 1.16, 95% CI 0.64–1.62) and more steeply with its labour component, pay per worker (1.79), while its capital component shows no detectable association; holding exposure fixed, the pay elasticity falls to 0.67 (standard error 0.30). Industries below the average hold 55% of the work language models could speed up but 29% of observed use. Within that use, compute per task and failure rise with task length, not with pay. A model of the choice between frontier and efficient models prices accuracy in proportion to task value; at current prices it assigns every observed task to the frontier model and places the automation demand of labour-dense industries in short tasks that usage data barely record. The evidence is cross-sectional, from one provider, and describes associations.

1 Introduction

Most measures of AI and work start from occupations. Exposure indices rate the tasks of each occupation by whether a language model could perform or speed them up (Frey & Osborne, 2017; Webb, 2019; Felten et al., 2021; Eloundou et al., 2024), and usage data now show which of those tasks people bring to AI systems (Handa et al., 2025; Tomlinson et al., 2025; Appel et al., 2025). These sources agree that use is concentrated in software development, writing and analysis, and in occupations in the upper part of the wage distribution (Handa et al., 2025; Massenkoff & McCrory, 2026). Adoption decisions, however, are made by firms, which buy AI for the tasks of their own workforce at the value their own output commands (Bonney et al., 2024; McElheran et al., 2024).

Industries differ in two quantities that occupational measures do not separate: how many people they employ and how much value added they create. In the United States in 2025, food services employed 12.46 million people and securities firms 1.18 million, but a securities job produced 2.40 times the private economy's average value added and a food-service job 0.34 times. This gap is a long-standing object of structural economics (Baumol, 1967; McMillan et al., 2014; Gollin et al., 2014); how it relates to AI use has not been measured. The hypothesis that motivated this study is that the ratio of the two orders the demand for AI. It rests on two complementary intuitions. Where each task is valuable and errors are expensive, as in law and finance, the most accurate model is worth its price (Kremer, 1993; Agrawal et al., 2019; Gans & Goldfarb, 2026). Where tasks are many and each is worth little, as in retail, logistics and much of manufacturing, AI pays by running a large volume of work cheaply and reliably, and the most capable model may be the wrong purchase.

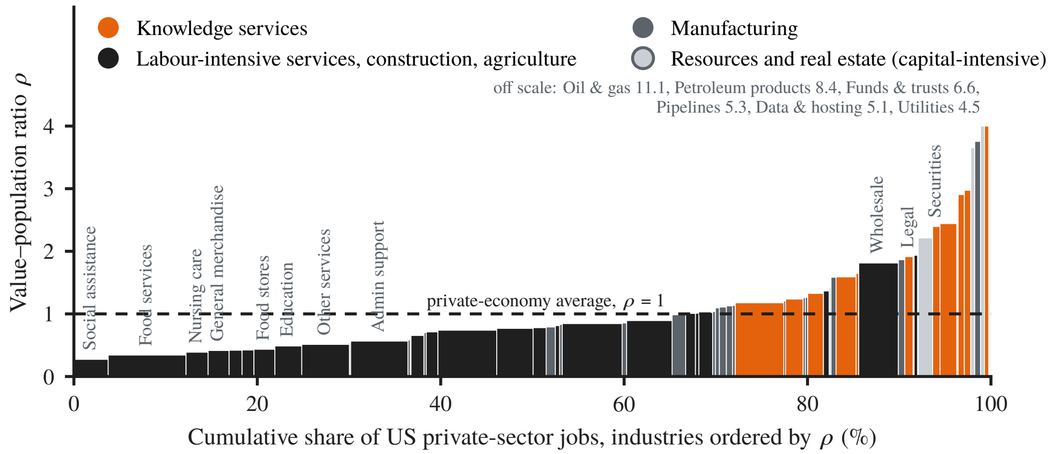

Figure 1: **The US private economy by value–population ratio.** Each bar is one of 65 private industries; its width is the industry's share of private-sector jobs in 2025, its height the ratio ρ of its share of value added to its share of jobs, so its area is its share of value added. Bars are ordered by ρ. Six bars are cut at $\rho = 4$ and their ratios listed at the top; for them the area understates the share of value added. Government (13.8% of all jobs) is excluded because its value added is measured at cost.

We make the contrast measurable. We build a partition of the US private economy into 65 industries with value added from the national accounts, employment and occupational mix from the Bureau of Labor Statistics, and AI use and conversation characteristics from the Anthropic Economic Index, and we compare the result with a firm survey and with European and global data. The central quantity is the **value–population ratio** ρ_i, an industry's share of value added divided by its share of jobs, or relative labour productivity. Figure 1 shows it for every industry. We ask three questions.

- **RQ1 (structure).** How are population and value added distributed across industries, and how stable is the ranking of ρ across economies?
- **RQ2 (use).** Does observed AI use per worker rise with ρ, with which component of it, and how much of the association remains once exposure is held fixed?
- **RQ3 (demand).** Does the value of tasks separate demand for precision from demand for automation, and how large is each pool?

Our contributions are four. First, a data construction that links occupation-level AI measures to industries through each industry's full occupational mix, with self-employment allocated, and an exact decomposition of ρ into pay per worker and value added per dollar of labour cost on one basis. Second, evidence that AI use per worker is proportional to value added per worker across industries, that it goes with pay rather than capital intensity, and that most of the association runs through exposure, with bounds for the allocation of use to industries. Third, task-level evidence that compute and failure rise with task length rather than pay. Fourth, a model of the choice between frontier and efficient models that prices accuracy by task value, locates automation demand in short tasks and motivates hypotheses that we test against a plan fixed before the data were joined (Appendix D).

2 Related work

Measuring AI exposure and use. Exposure indices rate occupations by the susceptibility of their tasks to computerisation, machine learning or language models (Frey & Osborne, 2017; Brynjolfsson et al., 2018; Webb, 2019; Felten et al., 2021; 2023; Eloundou et al., 2024). Usage-based measures map conversations to O*NET tasks (Handa et al., 2025), extended by the Anthropic Economic Index to geography, API traffic and conversation primitives such as task time and autonomy (Appel et al., 2025; 2026; Massenkoff et al., 2026a;b), and by studies of Copilot and ChatGPT (Tomlinson et al., 2025; Chatterji et al., 2025); Massenkoff & McCrory (2026) combine theoretical exposure and use into observed exposure. Surveys and vacancy data track adoption by workers and firms (Bick et al., 2024; Humlum & Vestergaard, 2025b;a; Bonney et al., 2024; McElheran et al., 2024; Acemoglu et al., 2022). We use these measures as inputs; our unit is the industry and our explanatory variable its value added per worker.

Productivity, tasks and the cost of errors. Experiments find large time savings on writing, support, consulting and programming (Noy & Zhang, 2023; Brynjolfsson et al., 2025b; Dell'Acqua et al., 2023; Peng et al., 2023); Patwardhan et al. (2025) evaluate models on economically important tasks, Kwa et al. (2025) show that the length of tasks models complete reliably is rising, and aggregate and labour-market effects so far are modest (Acemoglu, 2025; Brynjolfsson et al., 2025a; Hampole et al., 2025). The task approach models technology as taking over tasks and creating new ones (Autor et al., 2003; Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018; 2019; 2020; Autor, 2015). In the O-ring model the value of reliability rises with the value of output (Kremer, 1993; Gans & Goldfarb, 2026); Agrawal et al. (2019) separate prediction from judgment about the payoff of errors, Athey et al. (2020) analyse when to delegate decisions to AI, Garicano (2000) and Autor & Thompson (2025) relate expertise to the tasks that remain, and cascades that route queries between cheap and expensive models trade accuracy against cost (Chen et al., 2023). Our model states this trade-off in terms of task value.

Structural transformation and factor shares. Sectoral gaps in value added per worker are large and persistent (Gollin et al., 2014; McMillan et al., 2014; Herrendorf et al., 2014; Rodrik, 2016), and sectors with slow productivity growth absorb labour (Baumol, 1967). Splitting value added into labour and capital income requires imputing the labour income of the self-employed (Gollin, 2002), and labour shares vary across industries and over time (Karabarbounis & Neiman, 2014). Gains from general-purpose technologies arrive after complementary investment (Brynjolfsson et al., 2021).

3 Framework

3.1 Population, value and their ratio

Let industry $i \in \{1, \ldots, N\}$ of the private economy employ L_i workers and create value added Y_i, with totals L and Y. Its shares of jobs and of value added are

$$l_i = \frac{L_i}{L}, \qquad y_i = \frac{Y_i}{Y}. \tag{1}$$

The **value–population ratio** is the ratio of the two shares, equivalently value added per worker relative to the private economy (relative labour productivity):

$$\rho_i = \frac{y_i}{l_i} = \frac{Y_i/L_i}{Y/L}. \tag{2}$$

An industry with $\rho_i > 1$ creates more value per worker than the average; with $\rho_i < 1$ it employs more people than its value added would suggest. We call industries with $\rho_i < 0.8$ labour-dense and those with $\rho_i > 1.25$ value-dense. Ordering industries by ρ and cumulating shares gives a Lorenz curve of value over people, with points (X_k, Υ_k), and its Gini coefficient

$$G = 1 - \sum_{k=1}^{N} (X_k - X_{k-1}) (\Upsilon_k + \Upsilon_{k-1}). \tag{3}$$

Value added pays both labour and capital. Let W_i be the labour cost of industry i: compensation per employee times all its jobs, so that the self-employed are assigned the pay of employees in the same industry (Gollin, 2002). Then ρ_i factors exactly into **pay per worker** ω_i and **value added per dollar of labour cost** θ_i:

$$\rho_i = \underbrace{\frac{W_i/L_i}{W/L}}_{\omega_i} \underbrace{\frac{Y_i/W_i}{Y/W}}_{\theta_i}, \qquad \operatorname{Var}\ln\rho = \operatorname{Var}\ln\omega + \operatorname{Var}\ln\theta + 2\operatorname{Cov}(\ln\omega, \ln\theta). \tag{4}$$

The first factor is the price of the human work time that AI would substitute for or complement; the second rises with capital intensity, rents and other non-labour income.

3.2 From occupations to industries

AI measures are published for occupations o. Let M_{io} be the employment of occupation o in industry i and $L_o = \sum_i M_{io}$. For an occupation-level measure x_o (exposure, wage, task time) the industry value is the employment-weighted mean

$$\bar{x}_i = \sum_o \frac{M_{io}}{L_i}\, x_o. \tag{5}$$

For a usage share u_o (the share of AI conversations whose task belongs to o), we allocate each occupation's use to industries in proportion to where its workers are employed:

$$U_i = \sum_o u_o \frac{M_{io}}{L_o}, \qquad \nu_i = \frac{U_i}{l_i}, \qquad \mu_i = \frac{U_i}{y_i} = \frac{\nu_i}{\rho_i}. \tag{6}$$

AI use per worker ν_i is an industry's share of use relative to its share of jobs, and μ_i its use per unit of value added. Equation (6) implies $\nu_i = \sum_o (M_{io}/L_i)\, \nu_o$ with $\nu_o = u_o/(L_o/L)$: industry use per worker is the employment-weighted mean of occupational use per worker. It varies across industries only through their occupational mix, and it attributes to an occupation every conversation about its tasks, whoever asks. Section 5.2 bounds the consequences. The estimating equation is

$$\ln \nu_i = \alpha + \eta \ln \rho_i + \gamma^\top z_i + \varepsilon_i, \tag{7}$$

weighted by employment, with $\ln \omega_i$ and $\ln \theta_i$ in place of $\ln \rho_i$ as Eq. (4) suggests and controls z_i for exposure and occupational composition. An elasticity $\eta = 1$ means that use is proportional to value added, so that μ_i does not vary with ρ_i.

3.3 A model of precision and automation demand

A task has **value** v, the value of the human work it replaces or completes. For occupation o with hourly wage w_o and mean human-only completion time T_o we measure it at labour cost,

$$v_o = w_o T_o. \tag{8}$$

An AI system m completes a task correctly with probability q_m at cost c_m per task. A correct result yields v; an undetected error destroys the task's value and causes a further loss κv, with $\kappa \geq 0$ (rework, liability, a failed downstream step, as in the O-ring model of Kremer (1993)). The expected net value of deploying m is

$$\pi(v; m) = q_m v - (1 - q_m)\, \kappa v - c_m. \tag{9}$$

If $q_m(1+\kappa) \leq \kappa$, then $\pi < 0$ for every v and m is never deployed without verification. Otherwise deployment is viable above a threshold:

$$\pi(v; m) > 0 \iff v > v_m^0 = \frac{c_m}{q_m(1+\kappa) - \kappa}. \tag{10}$$

Consider a frontier model F and an efficient model E with $q_F > q_E$, $c_F > c_E$ and $q_E(1+\kappa) > \kappa$.

Proposition 1 (single crossing)**.** *The frontier model yields the higher net value if and only if*

$$v > v^* = \frac{c_F - c_E}{(1+\kappa)(q_F - q_E)}. \tag{11}$$

If moreover $v_E^0 < v^*$, tasks with $v < v_E^0$ are not served, tasks with $v_E^0 < v < v^*$ are served by the efficient model and tasks with $v > v^*$ by the frontier model.

Proof. $\pi(v; F) - \pi(v; E) = (1 + \kappa)(q_F - q_E)\, v - (c_F - c_E)$ is linear and increasing in v and changes sign at v^*. If $v_E^0 < v^*$, then $\pi(v; E) > 0$ on (v_E^0, v^*) and $\pi(v; F) > \pi(v; E) > 0$ above v^*. □

The price an industry is willing to pay for accuracy follows from the marginal rate of substitution between accuracy and cost:

$$\mathrm{MRS}(v) = \frac{\partial\pi/\partial q}{-\,\partial\pi/\partial c} = (1 + \kappa)\, v. \tag{12}$$

It is proportional to the value of the task: this is the formal sense in which value-dense work demands precision. Verification changes the calculation. If errors are caught with probability d before they cause the further loss, at cost c_d per task, then

$$\pi_d(v; m) = q_m v - (1-q_m)(1-d)\,\kappa v - c_m - c_d, \qquad v_d^* = \frac{c_F - c_E}{(1 + (1-d)\kappa)\,(q_F - q_E)} \geq v^*. \tag{13}$$

Cheap checks, such as tests for code, substitute for model accuracy.

Proposition 2 (comparative statics)**.** *The threshold v^* falls when the frontier premium $c_F - c_E$ falls, when the accuracy gap $q_F - q_E$ widens and when errors are costlier (κ larger); if $\kappa > 0$, it rises with verification (d larger). In terms of task duration, tasks shorter than*

$$t_i^* = \frac{v^*}{w_i} \tag{14}$$

are served more profitably by the efficient model, and tasks shorter than $t_i^0 = v_E^0/w_i$ are not worth automating; this ***automation window*** *is longer where pay per hour w_i is lower, and a uniform fall in prices shortens both bounds in proportion.*

Proof. Differentiate Eq. (11) and Eq. (13); Eq. (14) follows from $v = w\,t$, and v^* and v_E^0 are proportional to prices. □

Whether an industry uses AI at all also depends on fixed costs of adoption, such as integration and training (Brynjolfsson et al., 2021). If adoption costs K per worker, a worker with exposed tasks $j \in E_i$ is equipped only if

$$\sum_{j \in E_i} \Big([q(1+\kappa) - \kappa]\, w_i\, T_j - c \Big) \;\geq\; K, \tag{15}$$

which is more likely where pay per hour and exposed time are higher. The model therefore motivates four hypotheses. **P1:** use per worker rises with pay per worker ω (Eq. 15); because tasks are valued at labour cost (Eq. 8), value added per dollar of labour cost θ should not matter, and finding that it does not supports this valuation over one at output value. **P2:** high-value tasks carry a high premium on accuracy (Eq. 12) and should be reviewed rather than fully delegated, unless verification is cheap (Eq. 13). **P3:** high-value tasks warrant the more capable and more expensive model (Eq. 11). **P4:** where pay is low, the automation window is long, and demand turns on price and reliability rather than on the frontier of capability. P1 and P4 follow from Eqs. (14)–(15); P2 and P3 follow from Eqs. (11)–(13) at the level of a task. Figure 2 illustrates the model with list prices.

4 Data

Industries and value added. We partition the US economy into 67 industries at the level of the Bureau of Economic Analysis (BEA) GDP-by-industry accounts and take value added in current dollars for 2025 (U.S. Bureau of Economic Analysis, 2026). The analysis uses the 65 private industries; the federal civilian government and state and local government are reported in Appendix A but excluded from every statistic, because government value added is measured at cost. We exclude the BEA housing sector (owner- and tenant-occupied dwellings, about $3.0 trillion in 2025), whose value added is mostly the rental value of the housing stock with few workers behind it. The private partition covers

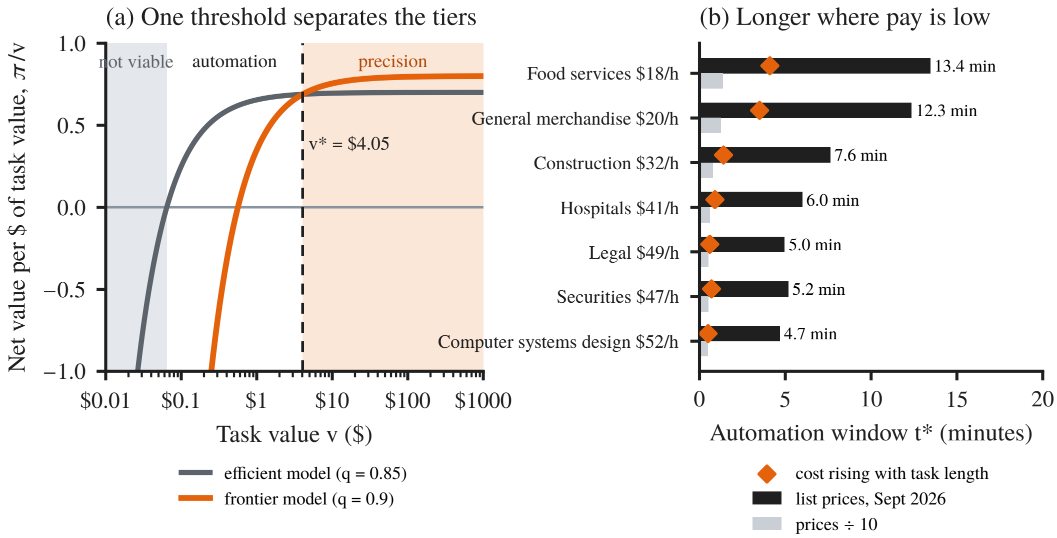

Figure 2: **The choice between frontier and efficient models.** (a) Net value per dollar of task value, π/v, for an efficient model ($q = 0.85$, cost \$0.045 per task) and a frontier model ($q = 0.90$, cost \$0.45), with $\kappa = 1$; per-task costs assume 30,000 input and 3,000 output tokens at September 2026 list prices for Claude Haiku 4.5 and Claude Fable 5.1 (Anthropic, 2026). The frontier model is preferred above $v^* =$ \$4.05. (b) The automation window t^* at each industry's hourly wage (employment-weighted mean of its occupations' median wages): at list prices, at one tenth of them, and with cost rising with task length (Appendix C).

\$24.31 trillion of value added. Labour cost uses 2024 compensation per full- and part-time employee by industry from the national income and product accounts (Tables 6.2D and 6.4D), applied to every job in the industry, including the self-employed.

Employment and occupational mix. The Employment Projections program of the Bureau of Labor Statistics (BLS) publishes the National Employment Matrix: employment in 2025 by detailed occupation in each of 423 industries (U.S. Bureau of Labor Statistics, 2026). We aggregate it to our industries. The matrix records 9.8 million self-employed workers by occupation but not by industry; we allocate them to private industries in proportion to each occupation's private wage-and-salary employment, so that the private partition covers 146.8 million jobs. Median annual wages by occupation for 2025 come from the same release and are converted to hourly wages at 2,080 hours a year.

AI use and conversation characteristics. From the Anthropic Economic Index release of June 2026 we take, for each detailed occupation, its share of Claude.ai conversations in April and May 2026 (weighted by the work share of use) and of first-party API traffic, and conversation characteristics classified by Anthropic: the share in automation mode (directive or feedback-loop) rather than augmentation, human-only task time, AI autonomy and use case (Massenkoff et al., 2026b). At the task level, the March 2026 release covers one week of API traffic (5 to 12 February 2026) and reports for about 2,300 O*NET tasks the relative cost per task, token counts, human-only time and success (Massenkoff et al., 2026a); 1852 tasks in 413 occupations have a wage. Observed exposure comes from Massenkoff & McCrory (2026).

Exposure, adoption and international data. Theoretical exposure β is the share of an occupation's tasks that a language model could complete at least twice as fast, with tasks that need complementary software counted at half weight (Eloundou et al., 2024); we use the GPT-4 rating and, for robustness, the human rating, the index of Felten et al. (2023), the applicability score of Tomlinson et al. (2025) and the computerisation probabilities of Frey & Osborne (2017). Firm adoption is the share of firms that used AI in the previous two weeks, by sector, from the Census Bureau's Business Trends and Outlook Survey (BTOS), averaged over the six waves collected between 29 June and 20 September 2026 (U.S. Census Bureau, 2026); it counts firms, not workers. International data come from Eurostat

Table 1: **Population, value added and AI use by industry, United States.** Jobs and value added (VA) for 2025, as shares of the private economy; ρ, value–population ratio (Eq. 2); ω, pay per worker and θ, value added per dollar of labour cost (Eq. 4); ν and ν_{API}, AI use per worker in Claude.ai work conversations and in API traffic (Eq. 6); observed exposure from Massenkoff & McCrory (2026); υ, employment-weighted task value (Eq. 8). Demand type, a descriptive classification: *precision* if $\beta \geq 0.45$ and $\omega \geq 1.25$; otherwise *automation* if $\rho < 1$; otherwise *asset-intensive* if $\theta \geq 2$; otherwise *mixed*. Rows are ordered by ρ; 23 of 65 private industries shown.

Industry	Jobs (m)	% jobs	% VA	ρ	ω	θ	ν	ν_{API}	Obs. exp. (%)	υ ($)	Demand type
Social assistance	5.49	3.7	1.0	0.27	0.46	0.60	0.28	0.38	8.2	88	Automation
Food services and drinking places	12.46	8.5	2.9	0.34	0.41	0.83	0.07	0.09	2.0	46	Automation
General merchandise stores	3.36	2.3	1.0	0.42	0.44	0.95	0.13	0.13	15.6	50	Automation
Educational services (private)	4.30	2.9	1.4	0.49	0.74	0.65	1.82	1.55	18.4	183	Automation
Textile mills and products	0.18	0.1	0.1	0.54	0.77	0.71	0.46	0.85	6.9	187	Automation
Administrative and support services	9.19	6.3	3.5	0.57	0.75	0.76	0.89	0.88	12.5	167	Automation
Ambulatory health care	9.41	6.4	4.7	0.74	1.02	0.72	0.34	0.53	12.3	137	Automation
Hospitals (private)	5.82	4.0	3.0	0.77	1.12	0.69	0.42	0.52	8.8	157	Automation
Fabricated metal products	1.47	1.0	0.8	0.79	0.98	0.81	0.57	0.74	7.0	201	Automation
Construction	9.58	6.5	5.5	0.85	1.06	0.80	0.24	0.28	6.5	194	Automation
Food, beverage and tobacco products	2.17	1.5	1.5	0.99	0.84	1.17	0.47	0.45	5.1	139	Automation
Machinery	1.12	0.8	0.8	1.11	1.20	0.93	1.11	1.19	10.2	221	Mixed
Other professional, scientific and technical	7.78	5.3	6.2	1.18	1.49	0.79	3.08	3.03	21.4	273	Precision
Computer systems design	2.52	1.7	2.3	1.33	2.02	0.66	5.70	5.31	30.8	284	Precision
Insurance carriers and related	3.20	2.2	3.5	1.59	1.44	1.11	2.21	1.57	28.3	244	Precision
Wholesale trade	6.35	4.3	7.8	1.81	1.32	1.38	1.08	1.04	20.9	179	Mixed
Legal services	1.33	0.9	1.7	1.91	1.72	1.11	1.67	0.99	21.2	291	Precision
Real estate (excluding owner-occupied housing)	2.32	1.6	3.5	2.21	1.00	2.21	0.55	0.52	19.1	168	Asset-intensive
Securities and investments	1.18	0.8	1.9	2.40	3.69	0.65	1.63	1.76	35.5	299	Precision
Banking and credit intermediation	2.70	1.8	4.5	2.44	1.51	1.62	1.51	1.59	27.5	234	Precision
Publishing, including software	1.00	0.7	2.0	2.91	2.45	1.19	9.78	8.03	29.6	287	Precision
Data processing, hosting and other information	0.70	0.5	2.4	5.10	3.05	1.67	5.57	5.51	30.9	277	Precision
Oil and gas extraction	0.13	0.1	1.0	11.07	2.88	3.84	0.87	1.06	10.8	297	Asset-intensive
All 65 private industries	146.8	100.0	100.0	1.00	1.00	1.00	1.00	1.00	12.8	158	

(31 European economies, 2023), the World Development Indicators (174 economies) and the ILO (Eurostat, 2026; World Bank, 2026; International Labour Organization, 2026).

Estimation. Regressions across industries are weighted by employment. We report heteroskedasticity-robust (HC1) standard errors and, for the main elasticities, bootstrap 95% intervals over industries (2,000 draws); both treat the 65 industries as draws from a population of industries and do not capture measurement error in the usage shares. Task-level regressions cluster standard errors by occupation. Hypotheses with metrics and rejection rules were written before the data were joined (Appendix D, Holm-adjusted); the ω–θ decomposition, the exposure controls and the demand typology came later and are exploratory.

5 Results

5.1 RQ1: population and value added are decoupled

The ratio spans a factor of 40 across industries, from 0.27 in social assistance to 11.1 in oil and gas extraction; weighted by jobs, the 90th percentile is 5.4 times the 10th. Job shares vary more than value-added shares (standard deviation of their logarithms 1.36 against 1.15). The 26 industries with $\rho < 1$ hold 67% of jobs and 40% of value added, and the Gini coefficient of value added over jobs (Eq. 3) is 0.37 (Figure 1, Table 1). The knowledge-intensive industries, legal services, computer systems design, publishing including software, data processing and finance, hold 8.6% of jobs and 18.5% of value added ($\rho = 2.14$). The labour-intensive services, construction and farming hold 62.8% of jobs and 37.3% of value added ($\rho = 0.59$).

Manufacturing does not fit the simple picture. Taken as a whole, its ratio is 1.34, above the average, ranging from 0.54 in textile mills to 8.4 in petroleum products; the 8 subsectors below the average (textile mills and products, furniture, apparel and leather, printing, fabricated metal products, wood products, plastics and rubber products, food, beverage and tobacco products) employ 45% of manufacturing workers. Its ratio is also near one in China (1.18, with 155 million workers), India (1.23) and Germany (1.08) (Figure 3c; these figures use GDP and all employment, which gives 1.12 for the United States). Manufacturing is labour-intensive in its headcount, not in value added per worker.

Table 2: **AI use per worker and its correlates.** Least-squares estimates of Eq. (7) across 65 private industries; the dependent variable is $\ln \nu$ (Claude.ai work use). HC1 standard errors in parentheses. β is theoretical exposure; the computer-occupation share is the share of the industry's jobs in computer and mathematical occupations. Column 7 rebuilds ν without computer and mathematical occupations.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln \rho$	1.16		0.22				
	(0.26)		(0.17)				
$\ln \omega$		1.80		0.67	0.59	1.39	1.50
		(0.29)		(0.30)	(0.30)	(0.22)	(0.29)
$\ln \theta$		-0.07		-0.18	-0.11	-0.20	0.04
		(0.29)		(0.28)	(0.29)	(0.22)	(0.27)
$\ln \beta$ (exposure)			2.49	2.08	1.87		
			(0.36)	(0.42)	(0.50)		
Computer-occupation share					2.10		
					(1.35)		
R^2	0.42	0.59	0.72	0.75	0.76	0.43	0.52
Weights	jobs	jobs	jobs	jobs	jobs	none	jobs
Outcome	ν	ν	ν	ν	ν	ν	ν excl. comp.

The ranking is not specific to the United States. Across 29 industry groups, the ratio in the United States (2025) and in the 21 EU member states that report every group (2023) has a Spearman correlation of 0.93 (0.93 without real estate, whose EU value added keeps actual rents), and the median correlation between the United States and each of 22 European economies is 0.86, lowest in Romania (0.43) and Croatia (0.46) (Figure 3a). Agriculture's ratio is below one in 90% of 174 economies; worldwide it employs 26% of workers and creates 4.4% of value added (Figure 3b).

The decomposition of Eq. (4) separates two sources of a high ratio. Weighted by jobs, the variance of $\ln \omega$ is 59% of the variance of $\ln \rho$, that of $\ln \theta$ 27% and twice their covariance 14%; splitting the covariance equally, pay per worker accounts for 66% and value added per dollar of labour cost for 34% (53% and 47% unweighted; Appendix Figure 8). Securities ($\omega = 3.69$), data processing and software have high ratios because their workers are highly paid; oil and gas ($\theta = 3.84$), petroleum refining, utilities, rental and real estate because they are capital-intensive. Once the self-employed are assigned employees' pay, farms have $\theta = 1.18$.

5.2 RQ2: AI use follows pay per worker, largely through exposure

AI use per worker ranges 149-fold across private industries, from 9.8 in publishing including software to 0.07 in food services. It rises with the value–population ratio: the elasticity in Eq. (7) is 1.16 (95% CI 0.64–1.62; $R^2 = 0.42$; Figure 4a). Proportionality ($\eta = 1$) is not rejected ($t = 0.6$): use grows with value added, and use per unit of value added μ shows no trend with ρ. The relationship is steeper and tighter for pay per worker, with an elasticity of 1.79 (1.13–2.23; $R^2 = 0.59$; Figure 4b). Entered together, pay per worker keeps its elasticity and value added per dollar of labour cost shows no detectable association (-0.07, 95% CI -0.63 to 0.49; Table 2, column 2), as P1 predicts: oil and gas ($\rho = 11.1$) uses AI less than its value added per worker suggests ($\nu = 0.87$). API traffic, which reflects deployments by firms, shows the same pattern (elasticities 1.01 and 1.62).

Much of the pay gradient runs through exposure (Table 2). Better-paid industries employ occupations whose tasks language models can do (Spearman of ω with β 0.60); holding $\ln \beta$ fixed lowers the elasticity on ρ to 0.22 (standard error 0.17) and that on ω to 0.67 (0.30), while R^2 rises to 0.75; with the computer-occupation share as well, ω is 0.59 (0.30). Unweighted, the pay elasticity is 1.39 (0.22); without computer and mathematical occupations, which account for 31% of Claude.ai work use but 3.4% of jobs, it is 1.50 (0.29); without the three software and data industries, 1.68. The industry pay measure adds little to the wage of the industry's occupational mix, which alone gives an elasticity of 3.03 (0.52) with the same fit; entered together, neither is significant.

Because ν is built from occupations (Eq. 6), the null result for θ is partly mechanical, and the pay gradient partly re-aggregates the occupational wage gradient of Handa et al. (2025). Two biases work in opposite directions: adoption within an occupation plausibly rises with firm pay, which Eq. (6) averages away, while questions about legal, financial or software tasks also come from people outside those occupations, which inflates use in value-dense industries. If a share s of each occupation's use came from askers spread across industries in proportion to jobs, the pay elasticity would be 1.09 at $s = 0.25$ and 0.70 at $s = 0.5$: the sign survives, the magnitude is not identified.

The one outcome that varies by industry independently of occupational mix is firm adoption. Across 19 BTOS sectors, the share of firms using AI, from 45% in information to 8% in mining, is correlated with our use per worker (Spearman 0.75, 95% CI 0.42 to 0.90) and with pay per worker (0.44, -0.04 to 0.76), but hardly with ρ (0.18, -0.32 to 0.61); the difference between the last two is positive (bootstrap interval 0.01 to 0.52). Regressing adoption on $\ln \omega$ and $\ln \theta$ gives 13.9 (4.6) and -8.0 (6.9) percentage points per log unit: pay, not capital intensity, goes with adoption (Appendix Figure 10).

In cumulative terms (Appendix Figure 5), industries with $\rho < 1$ account for 67% of jobs and 55% of the work that language models could speed up (jobs weighted by β), but 29% of Claude.ai work use and 33% of API use; their share of use relative to their share of exposed work is 0.53, against 1.58 for the other industries (see also Appendix Figure 9).

5.3 RQ3: two kinds of demand

Task value. The value of the tasks that an industry's occupations bring to AI (Eq. 8) rises with its ratio (Spearman 0.71) and more closely with pay per worker (0.85, partly by construction, since both contain wages). It ranges from \$46 per task in food services to \$291 in legal services and \$309 in funds and trusts, against \$158 for the private economy. It covers 72% of jobs (as little as 20% in transit); imputing missing task times from occupational groups leaves its correlation with ρ at 0.71.

How AI is used (P2). Across 412 occupations outside computer and mathematical work, the share of conversations in automation mode falls with task value (Spearman -0.27; Figure 6a), but the association comes from occupations with little use: among the 201 above the median usage share it is -0.01 ($p = 0.9$). Weighted by use, the slope is -3.2 percentage points per log unit of task value (standard error 1.5), splitting into -2.0 (3.2) for the wage and -4.0 (2.8) for task time; after Holm adjustment the pre-specified test is not significant. AI autonomy, the most direct measure of delegation, rises with task value (0.44). Computer and mathematical occupations combine high task value with 64% automation, against 45% elsewhere; programs can be tested, as Eq. (13) allows. Across industries, the automation share rises with pay per worker (Spearman 0.27), a pattern explained by the share of software work (coefficient -1.4, standard error 2.1, with that share held fixed). P2 is not supported at the level of industries.

How much intelligence is bought (P3). Across 1852 O*NET tasks in API traffic, the cost per task rises with task value (elasticity 0.35, standard error 0.02 clustered by occupation), but entirely through task length: the elasticity is 0.48 (0.02) with respect to human time and 0.00 (0.04) with respect to the wage (Figure 6b). Success, observed for 1381 tasks, falls with length (-5.2 percentage points per log unit, standard error 0.9) and rises with the wage (4.0, 1.7; Figure 6c). The value gradient in compute is a length gradient, consistent with the decline of model reliability on longer tasks (Kwa et al., 2025); the data do not show better-paid work buying more compute per task.

Demand pools (P4). Grouping industries by the ratio (Figure 7), the labour-dense industries ($\rho < 0.8$) hold 53% of jobs, 28% of value added and 44% of the work that language models could speed up, but account for 25% of Claude.ai use and 28% of API use; the value-dense industries ($\rho > 1.25$) hold 20% of jobs and 47% of use. In the typology of Table 1, the 12 precision industries employ 17% of workers and account for 56% of use, and the 26 automation industries employ 67% and account for 29%. The typology is descriptive and partly restates RQ2; against indicators not used to define it, the automation share of conversations hardly differs between the two types (52% and 50%), API use relative to Claude.ai use is higher in automation industries (1.13 against 0.91), and at most 2 of 65 industries change type when a threshold moves.

The model locates the automation pool. At September 2026 list prices, the threshold of Proposition 1 is \$4.05 per task (\$1.35 with Claude Opus 5.5 as the frontier model and \$0.45 with Claude Sonnet 5.5; Appendix C). Every private industry's task value lies above it, the lowest being \$46, where a point of accuracy is worth \$0.92 (Eq. 12) against a frontier premium of \$0.081 per point: the model assigns the frontier model to all observed use, and its split concerns shorter tasks. The efficient model is the better purchase for tasks shorter than t^* = 806 seconds in food services, 457 in construction and 297 in legal services (Figure 2b); a tenfold fall in prices shortens the window tenfold (81 seconds in food services) and extends automation to tasks a tenth as long. If cost rises with task length as observed, the windows shrink to 4.1, 1.4 and 0.6 minutes. Current AI use barely contains such tasks: the shortest mean human-only time of any occupation in Claude.ai conversations is 25 minutes, and 1.3% of API task instances take a person less than 15 minutes (median 50 minutes). The automation demand of labour-dense industries is therefore a hypothesis about short tasks that current usage data do not record.

Robustness. The ordering holds with value added per full-time equivalent, with all Claude.ai use and with API use (Appendix Table 5). Across 120 countries, the automation share of Claude.ai use falls with output per worker (Spearman -0.77; Appendix Figure 11), replicating Massenkoff et al. (2026b).

6 Discussion

Two kinds of demand. The evidence supports the first half of the motivating hypothesis in a qualified form and leaves the second half as a hypothesis. Value-dense industries use more AI per worker, in proportion to their value added, through pay rather than capital intensity and largely through the exposure of well-paid occupations; finance and law use 1.5 to 2.2 times the average per worker, and only software and data several times more. Within observed use, compute and failure follow task length, not pay: value-dense work brings longer tasks rather than buying more intelligence per task. Labour-dense industries hold half of all jobs and more of the exposed work than of the use. The model explains why their demand should differ, since a point of accuracy is worth little on a cheap task, but at current prices its threshold lies below every observed task, and the automation it predicts lies in short, frequent steps of physical and administrative workflows. The two pools call for different products: frontier accuracy with human review for long, valuable tasks, and inexpensive, verifiable automation embedded in operations for short ones, whose reach extends as prices fall (Proposition 2).

Old and new automation frontiers. Computerisation probabilities are highest in low-pay industries, language-model exposure and use in high-pay industries (-0.41 against 0.60; Appendix Table 5), as Webb (2019) found for AI patents. Manufacturing sits between: near-average value added per worker, much physical work and low language-model exposure.

Limitations. The usage data come from one provider whose traffic over-represents software work, and the API data cover one week. Tasks are mapped to occupations by what people ask, not by who asks, and our allocation assumes that an occupation's use per worker is the same in every industry (Section 5.2). Task value is measured at labour cost for the tasks brought to AI, with human-only times estimated by a model. The model is static and its accuracy parameters are assumed; at the median observed success rate (64%), deployment without verification is viable only if $\kappa < 1.8$. The analysis is cross-sectional, with 65 industries and about forty tests of which eight were pre-specified, and establishes associations, not causal effects. Measuring use by the industry of the user, and observing short tasks, would test the demand pools directly.

7 Conclusion

Industries that create more value per worker use more AI per worker, roughly in proportion to their value added, and the association runs through pay rather than capital intensity, largely because well-paid industries employ exposed occupations. Within observed use, what consumes compute and fails is task length, not pay. A simple model prices accuracy in proportion to task value and places the automation demand of labour-dense industries in short tasks that current use barely reaches. The value–population ratio, split into pay and capital, is a measurable starting point for studying which kind of AI an industry demands; measuring short tasks is the next step.

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Statements

Data availability. All inputs are public: the Anthropic Economic Index (CC-BY), BEA GDP-by-industry and NIPA tables, BLS Employment Projections, the Census Business Trends and Outlook Survey, Eurostat, the World Development Indicators, ILOSTAT, and the exposure datasets of the cited works. The industry and occupation tables and the scripts that produce every number, table and figure accompany the online version of this article.

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A Full industry table

Table 3: **All 67 industries.** Columns as in Table 1, ordered by ρ; shares and ratios are relative to the private economy. The two government rows are shown for reference and are not comparable.

Industry	Jobs (m)	% jobs	% VA	ρ	ω	θ	ν	ν_{API}	Obs. exp. (%)	υ ($)	Demand type
Social assistance	5.49	3.7	1.0	0.27	0.46	0.60	0.28	0.38	8.2	88	Automation
Food services and drinking places	12.46	8.5	2.9	0.34	0.41	0.83	0.07	0.09	2.0	46	Automation
Nursing and residential care	3.54	2.4	0.9	0.39	0.62	0.62	0.18	0.27	5.2	86	Automation
General merchandise stores	3.36	2.3	1.0	0.42	0.44	0.95	0.13	0.13	15.6	50	Automation
Amusement, gambling and recreation	2.08	1.4	0.6	0.42	0.48	0.88	0.40	0.89	7.7	101	Automation
Warehousing and storage	1.90	1.3	0.5	0.42	0.71	0.59	0.29	0.39	3.9	94	Automation
Food and beverage stores	3.35	2.3	1.0	0.44	0.48	0.91	0.25	0.18	9.9	54	Automation
Educational services (private)	4.30	2.9	1.4	0.49	0.74	0.65	1.82	1.55	18.4	183	Automation
Other services	7.64	5.2	2.7	0.51	0.67	0.77	0.75	0.84	10.0	136	Automation
Textile mills and products	0.18	0.1	0.1	0.54	0.77	0.71	0.46	0.85	6.9	187	Automation
Administrative and support services	9.19	6.3	3.5	0.57	0.75	0.76	0.89	0.88	12.5	167	Automation
Furniture	0.36	0.2	0.1	0.58	0.80	0.73	0.47	0.62	7.3	152	Automation
Apparel and leather	0.12	0.1	0.1	0.63	0.79	0.80	0.55	0.58	8.6	199	Automation
Other transportation and support	2.08	1.4	0.9	0.66	0.84	0.78	0.26	0.35	5.6	167	Automation
Printing	0.36	0.2	0.2	0.70	0.83	0.84	1.41	0.96	13.7	177	Automation
Farms	1.87	1.3	0.9	0.71	0.61	1.18	0.29	0.31	2.9	129	Automation
Ambulatory health care	9.41	6.4	4.7	0.74	1.02	0.72	0.34	0.53	12.3	137	Automation
Hospitals (private)	5.82	4.0	3.0	0.77	1.12	0.69	0.42	0.52	8.8	157	Automation
Accommodation	2.09	1.4	1.1	0.78	0.62	1.26	0.30	0.53	5.9	96	Automation
Fabricated metal products	1.47	1.0	0.8	0.79	0.98	0.81	0.57	0.74	7.0	201	Automation
Transit and ground passenger transportation	0.68	0.5	0.4	0.81	0.87	0.94	0.17	0.17	3.7	150	Automation
Wood products	0.43	0.3	0.2	0.83	0.87	0.96	0.37	0.47	5.8	171	Automation
Construction	9.58	6.5	5.5	0.85	1.06	0.80	0.24	0.28	6.5	194	Automation
Plastics and rubber products	0.72	0.5	0.4	0.85	0.95	0.90	0.55	0.74	6.2	197	Automation
Other retail	7.28	5.0	4.4	0.89	0.61	1.45	0.28	0.29	21.8	98	Automation
Food, beverage and tobacco products	2.17	1.5	1.5	0.99	0.84	1.17	0.47	0.45	5.1	139	Automation
Truck transportation	1.57	1.1	1.1	1.01	0.97	1.04	0.15	0.20	4.8	183	Mixed
Waste management and remediation	0.55	0.4	0.4	1.01	1.07	0.94	0.41	0.76	6.6	197	Mixed
Motor vehicle and parts dealers	2.20	1.5	1.5	1.02	0.93	1.10	0.40	0.38	13.6	101	Mixed
Nonmetallic mineral products	0.44	0.3	0.3	1.04	1.03	1.00	0.42	0.56	6.4	181	Mixed
Miscellaneous manufacturing	0.64	0.4	0.5	1.10	1.25	0.88	1.32	1.46	13.3	223	Mixed
Machinery	1.12	0.8	0.8	1.11	1.20	0.93	1.11	1.19	10.2	221	Mixed
Motor vehicles and parts	0.98	0.7	0.8	1.13	1.08	1.05	0.62	0.80	6.2	204	Mixed
Electrical equipment and appliances	0.44	0.3	0.3	1.14	1.24	0.92	0.93	1.10	11.5	190	Mixed
Other professional, scientific and technical	7.78	5.3	6.2	1.18	1.49	0.79	3.08	3.03	21.4	273	Precision
Forestry, fishing and related	0.26	0.2	0.2	1.21	0.65	1.85	0.59	0.72	4.5	159	Mixed
Management of companies	2.82	1.9	2.4	1.24	2.10	0.59	2.47	2.27	25.3	289	Precision
Paper products	0.36	0.2	0.3	1.26	1.13	1.11	0.61	0.76	6.2	195	Mixed
Primary metals	0.37	0.3	0.3	1.27	1.23	1.03	0.54	0.71	5.0	198	Mixed
Computer systems design	2.52	1.7	2.3	1.33	2.02	0.66	5.70	5.31	30.8	284	Precision
Performing arts, sports and museums	0.93	0.6	0.9	1.37	1.28	1.07	2.65	2.37	12.5	183	Mixed
Support activities for mining	0.28	0.2	0.3	1.42	1.49	0.95	0.33	0.47	5.0	224	Mixed
Other transportation equipment	0.80	0.5	0.9	1.59	1.53	1.04	1.57	2.12	9.1	268	Mixed
Insurance carriers and related	3.20	2.2	3.5	1.59	1.44	1.11	2.21	1.57	28.3	244	Precision
Motion picture and sound recording	0.44	0.3	0.5	1.65	1.23	1.34	3.49	3.68	12.8	240	Mixed
Wholesale trade	6.35	4.3	7.8	1.81	1.32	1.38	1.08	1.04	20.9	179	Mixed
Computer and electronic products	1.03	0.7	1.3	1.87	2.03	0.92	2.77	2.58	16.0	252	Precision
Legal services	1.33	0.9	1.7	1.91	1.72	1.11	1.67	0.99	21.2	291	Precision
Rail transportation	0.16	0.1	0.2	1.93	1.81	1.07	0.31	0.27	4.0	221	Mixed
Air transportation	0.58	0.4	0.8	1.94	1.69	1.14	0.26	0.27	10.9	73	Mixed
Water transportation	0.07	0.1	0.1	1.96	1.58	1.24	0.46	0.47	12.6	195	Mixed
Real estate (excluding owner-occupied housing)	2.32	1.6	3.5	2.21	1.00	2.21	0.55	0.52	19.1	168	Asset-intensive
Securities and investments	1.18	0.8	1.9	2.40	3.69	0.65	1.63	1.76	35.5	299	Precision
Banking and credit intermediation	2.70	1.8	4.5	2.44	1.51	1.62	1.51	1.59	27.5	234	Precision
Mining, except oil and gas	0.20	0.1	0.4	2.65	1.37	1.94	0.31	0.57	4.1	178	Mixed
Publishing, including software	1.00	0.7	2.0	2.91	2.45	1.19	9.78	8.03	29.6	287	Precision
Broadcasting and telecommunications	1.03	0.7	2.1	2.97	1.69	1.76	5.19	4.63	21.1	214	Precision
Rental and leasing	0.64	0.4	1.6	3.65	0.95	3.84	1.05	0.71	13.9	157	Asset-intensive
Chemical products	0.93	0.6	2.4	3.76	1.69	2.22	1.35	2.05	9.9	242	Asset-intensive
Utilities	0.63	0.4	1.9	4.52	1.94	2.33	1.41	1.60	12.2	243	Asset-intensive
Data processing, hosting and other information	0.70	0.5	2.4	5.10	3.05	1.67	5.57	5.51	30.9	277	Precision
Pipeline transportation	0.06	0.0	0.2	5.32	2.15	2.47	0.74	0.89	7.6	257	Asset-intensive
Funds, trusts and other vehicles	0.04	0.0	0.2	6.57	2.41	2.73	1.07	1.19	30.0	309	Precision
Petroleum and coal products	0.12	0.1	0.7	8.45	2.28	3.71	0.85	1.38	7.6	234	Asset-intensive
Oil and gas extraction	0.13	0.1	1.0	11.07	2.88	3.84	0.87	1.06	10.8	297	Asset-intensive
Government (value added measured at cost; not comparable)											
State and local government	20.61	14.0	9.6	0.69	1.03	0.67	1.23	1.36	13.6	156	–
Federal government (civilian)	2.90	2.0	3.6	1.84	1.64	1.12	2.73	3.79	10.5	260	–

B Data construction

Industry partition. The 67 industries follow the BEA GDP-by-industry detail. Retail trade is split into motor-vehicle dealers, food and beverage stores, general merchandise and other retail; transportation into eight modes; finance into credit intermediation, securities, insurance and funds; professional services into legal services, computer systems design and other professional services. Value added of real estate excludes the housing sector; government is split into the federal civilian government, from whose value added we subtract military compensation ($213 billion in 2024, scaled to 2025 with federal value added), and state and local government, which in the BLS matrix includes public schools and hospitals.

Occupation codes. The Anthropic data use O*NET-SOC codes; we aggregate them to 6-digit SOC and map 22 codes that the BLS matrix publishes under a broader code (for example, the three buyer and purchasing-agent occupations to 13-1020). Shares are pooled over the two months and renormalised to sum to one within each month, because privacy thresholds withhold a few percent of conversations. Occupations with no reported use receive zero use; occupations with use cover 603 of 831 occupations and 89% of employment. In the API data, 47 task statements are shared by several occupations and take the mean of their wages.

Self-employment and labour cost. The BLS matrix lists self-employed workers by occupation. We allocate each occupation's self-employed workers to private industries in proportion to that occupation's private wage-and-salary employment; the allocation leaves fewer than 1,000 workers unassigned. Labour cost assigns each job its industry's 2024 compensation per full- and part-time employee, which imputes employees' pay to the self-employed.

Task value. Task value is available for occupations with Claude.ai use and a human-only time estimate, covering 72% of private-sector jobs; industry task value is the employment-weighted mean over those occupations. For robustness we impute the missing times with the use-weighted mean of the occupation's major group.

C Model calibration

Per-task costs assume 30,000 input and 3,000 output tokens, a large agentic task. At list prices of $10 and $50 per million input and output tokens for Claude Fable 5.1 and $1 and $5 for Claude Haiku 4.5 (Anthropic, 2026), a task costs $0.45 and $0.045 ($0.18 for Claude Opus 5.5 and $0.09 for Claude Sonnet 5.5). With $q_F = 0.90$, $q_E = 0.85$ and $\kappa = 1$, the efficient model is viable above $v_E^0 =$ $0.064, the frontier model above $0.56, and $v^* =$ $4.05, so $v_E^0 < v^*$ as Proposition 1 requires. With an accuracy gap of 0.02, 0.05 or 0.10 and κ of 0, 1 or 4, v^* ranges from $0.81 to $20.2. At the success rates observed in API traffic (median 64%, lower quartile 53%), Eq. (10) holds for $\kappa = 1$ (the efficient model is viable above $0.16 at the median) but fails for $\kappa = 4$.

The automation windows in Figure 2b divide v^* by the hourly wage of each industry. With cost rising with task length, $c_m(T) = c_m(T/\tilde{T})^\gamma$, where $\gamma = 0.48$ is the elasticity of API cost with respect to human time and $\tilde{T} = 50$ minutes the median API task, the frontier model is preferred for tasks longer than

$$T_i^* = \left[\frac{c_F - c_E}{(1+\kappa)(q_F - q_E)\, w_i\, \tilde{T}^\gamma}\right]^{1/(1-\gamma)}.$$

D Hypotheses and robustness

Table 4: **Pre-specified hypotheses.** Hypotheses, metrics and rejection rules were written before the data were joined; p-values are Holm-adjusted across the 7 tests with a p-value. H3b is the use-weighted slope across occupations outside computer and mathematical work; H3c is clustered by occupation.

	Hypothesis	Estimate	p	Holm p	Verdict
H1	ρ spans more than 10× across industries	range 40×	–	–	supported
H1b	the ordering of ρ is stable across economies	Spearman US–EU 0.93	<0.001	<0.001	supported
H2	use per worker ν rises with ρ	η = 1.16 (SE 0.26)	<0.001	<0.001	supported
H2b	observed exposure rises with ρ	Spearman 0.39	0.001	0.003	supported
H2b	firm adoption (BTOS) rises with ρ	Spearman 0.18 (n = 19)	0.46	0.46	not supported
H3a	task value rises with ρ	Spearman 0.71	<0.001	<0.001	supported
H3b	automation share falls with task value (non-computer occupations)	slope -3.2 pp per log point (SE 1.5)	0.037	0.075	not supported
H3c	compute per task rises with task value	elasticity 0.35 (SE 0.02)	<0.001	<0.001	supported
H4	industries with $\rho < 1$ hold most jobs and exposed work but a minority of use	67% of jobs, 55% of exposed work, 29% of use	–	–	supported

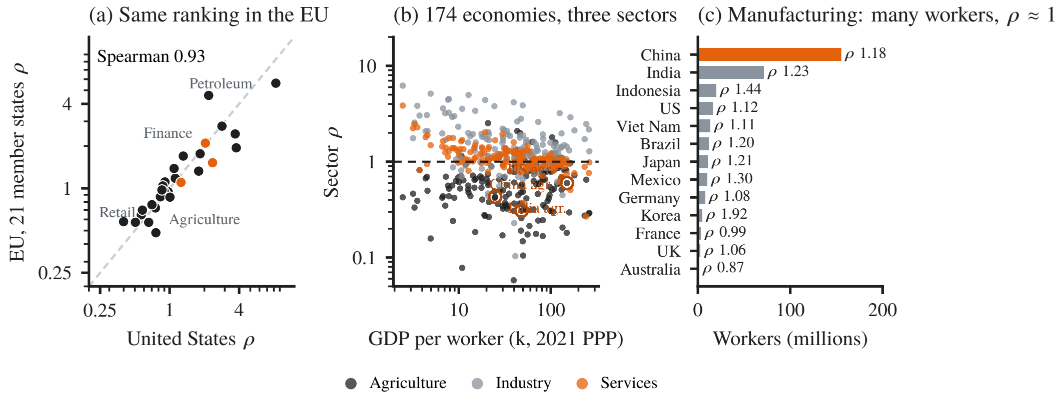

Figure 3: **The ranking of industries is shared across economies.** (a) Value–population ratio for 29 industry groups in the United States (2025) and 21 EU member states (2023). (b) Ratio of agriculture, industry and services in 174 economies against output per worker. (c) Manufacturing employment and its ratio in 13 economies, from World Bank and ILO data.

Table 5: **Robustness of the main associations.** Spearman correlations across the 65 private industries.

Test	Spearman	p	n
ρ (jobs, 2025) vs ν Claude work	0.55	<0.001	65
ρ (FTE, BEA 2024) vs ν Claude work	0.51	<0.001	65
ρ vs ν Claude, all use	0.47	<0.001	65
ρ vs ν API	0.53	<0.001	65
ω vs ν Claude work	0.62	<0.001	65
ω vs ν API	0.63	<0.001	65
θ vs ν Claude work	0.18	0.16	65
ω vs observed exposure	0.45	<0.001	65
ω vs β (GPT-4 rating)	0.60	<0.001	65
ω vs β (human rating)	0.46	<0.001	65
ω vs AI applicability (Copilot)	0.36	0.003	65
ω vs LM-AIOE	0.39	0.001	65
ω vs computerisation probability	-0.41	<0.001	65
ω vs task value	0.85	<0.001	65

E Additional figures

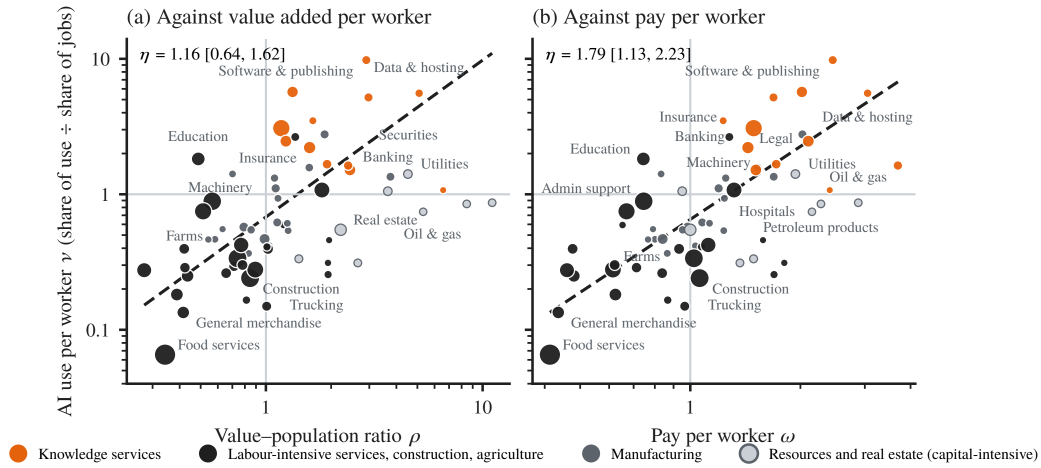

Figure 4: **AI use per worker rises with value added per worker, and more steeply with pay per worker.** Each point is one of 65 private industries, sized by employment; AI use per worker ν is the industry's share of Claude.ai work conversations divided by its share of jobs. Dashed lines are employment-weighted fits; η is the elasticity with a bootstrap 95% interval.

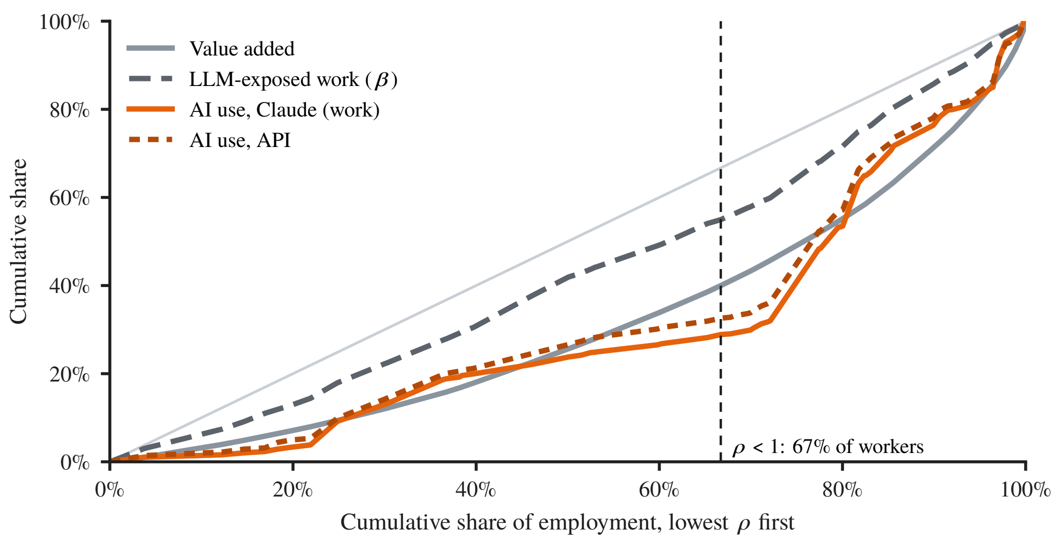

Figure 5: **AI use is concentrated in value-dense industries, more than exposure is.** Cumulative shares of value added, of work that language models could speed up (β-weighted jobs), and of AI use in Claude.ai and API traffic, against the cumulative share of private-sector jobs, with industries ordered from lowest to highest ρ. The diagonal is an equal share per job.

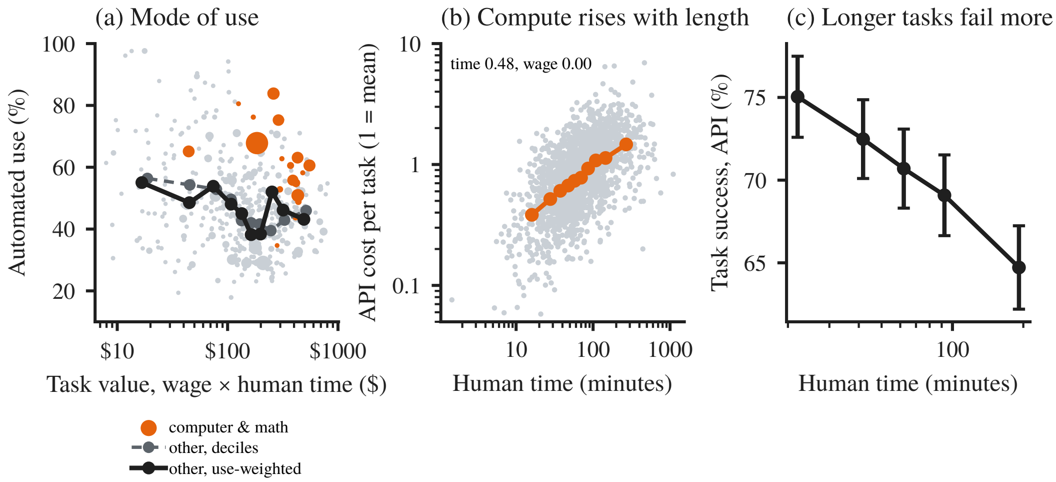

Figure 6: **How AI is used, and what drives compute and failure.** (a) Share of Claude.ai conversations in automation mode against task value for 433 occupations, sized by use; lines show deciles of the 412 occupations outside computer and mathematical work, unweighted and weighted by use. (b) API cost per task (1 = mean task) against human time for 1852 O*NET tasks, with means by tenths. (c) API task success by fifths of human time, with 95% intervals.

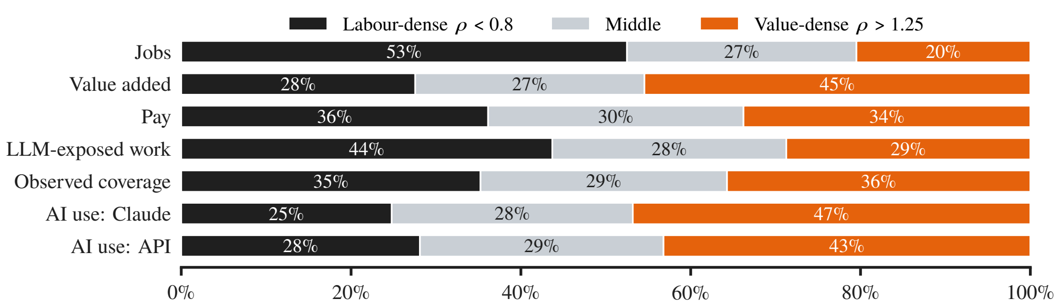

Figure 7: **Labour-dense industries hold most of the jobs and of the exposed work, and less of the use.** Shares of jobs, value added, labour cost, work that language models could speed up, observed exposure, and AI use in Claude.ai and API traffic, for private industries grouped by value–population ratio.

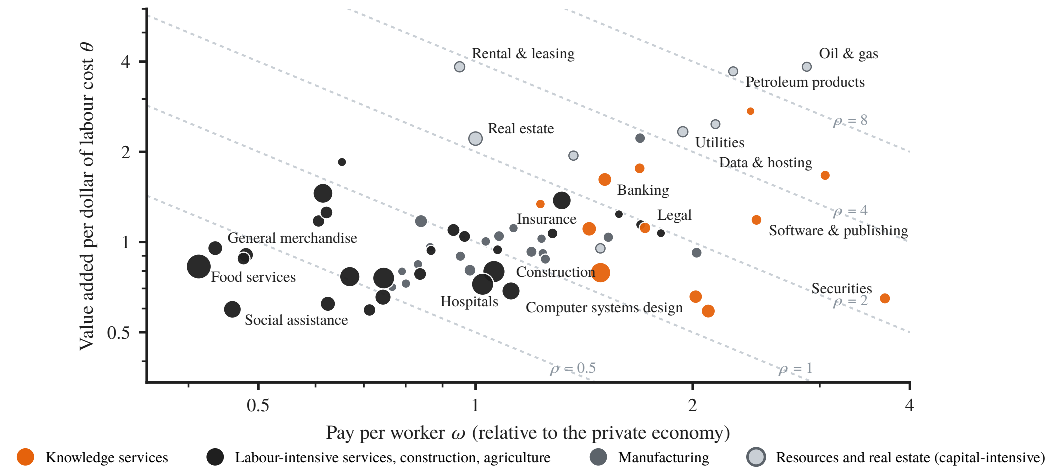

Figure 8: **Two sources of a high value–population ratio.** Pay per worker ω against value added per dollar of labour cost θ for 65 private industries, sized by employment. Dotted lines are constant $\rho = \omega\theta$.

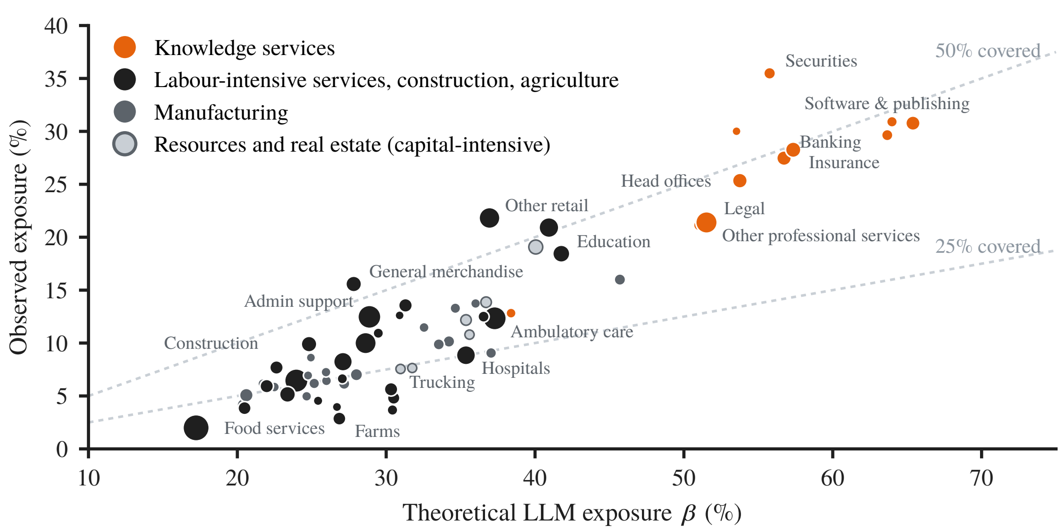

Figure 9: **Observed exposure against theoretical exposure.** Employment-weighted industry means of theoretical exposure β and of observed exposure; dotted lines mark 25% and 50% coverage.

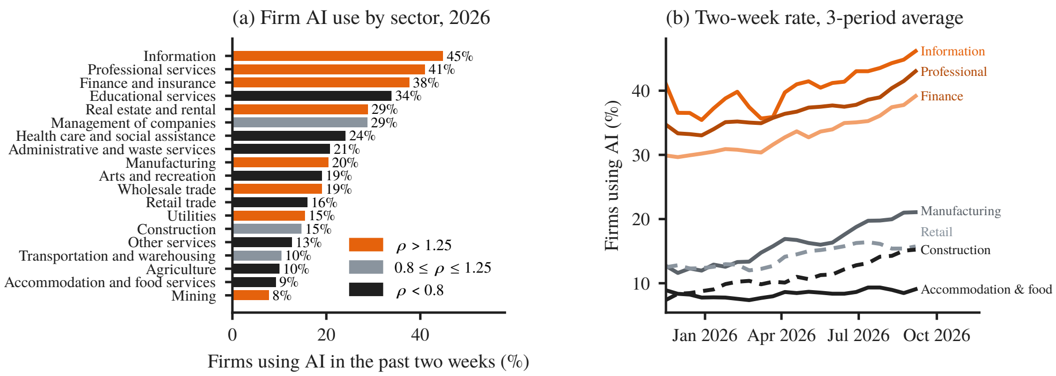

Figure 10: **Firm adoption by sector.** (a) Share of firms that used AI in the previous two weeks, average of the six waves collected between 29 June and 20 September 2026, coloured by the sector's value–population ratio. (b) Biweekly series since the question was introduced in November 2025, three-wave moving average.

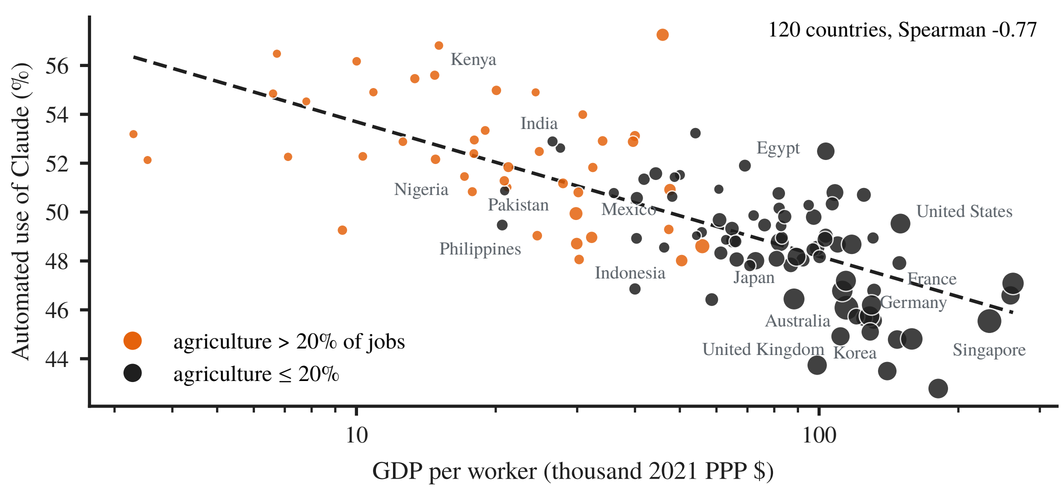

Figure 11: **Countries with lower output per worker use AI in more automated ways.** Share of Claude.ai conversations in automation mode (April–May 2026) against GDP per person employed for 120 countries, sized by the usage index. The dashed line is an unweighted fit, with a slope of -2.4 percentage points per log unit (standard error 0.2), or -1.9 (0.3) with the shares of coursework, work and computer tasks held fixed.