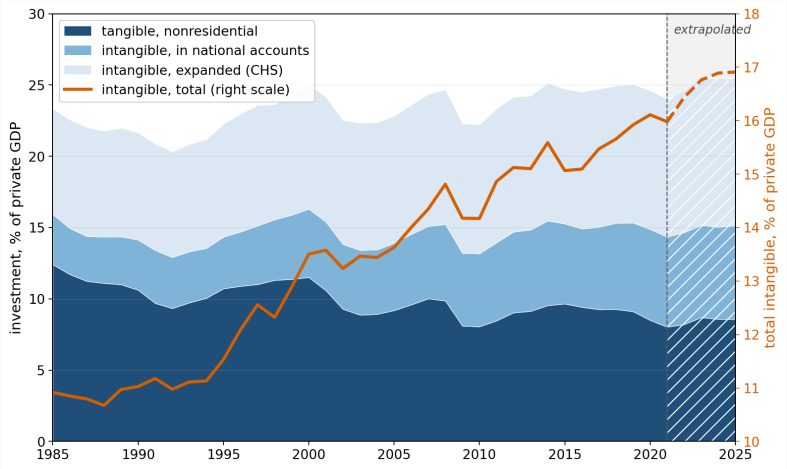
The Great Codification: GenAI and Intangible Capital

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UCLA Anderson School of Management

Motivation

Motivation: increasing importance of intangible capital



Sources. EU KLEMS & INTANProd ends in 2021; the shaded years are our own extension: expanded intangibles grown off their 2021 levels by CHS sum-of-costs, purchased components by BEA gross output of the supplying industry and own-account components by BLS OEWS occupational wage bills (May 2021–May 2025); tangibles, national-accounts intangibles, and private GDP from BEA NIPA 5.3.5 and 1.3.5.

Motivation: changes in organizations & rents

Meta Is Making Workers Train Their AI Replacements

April 21, 2026 at 12:02 PM PDT



By Mark Gongloff
Mark Gongloff is a Bloomberg Opinion editor and columnist covering climate change. He previously worked for Fortune.com, the Huffington Post and the Wall Street Journal.

The Telegraph

The humans training their AI replacements

Chris Stokel-Walker
Sun, July 5, 2026 at 7:00 AM PDT

Changes in rents due to "Codification"?

CIO JOURNAL

AI Is Turning Traditional Corporate Org Charts Upside Down

Teams are getting leaner and flatter, while leaders at the top are overseeing more than ever before. Everyone, everywhere is restructuring. Welcome to the AI age.

AI agents are flattening corporate hierarchies. Here's how companies—and managers—can develop a new playbook

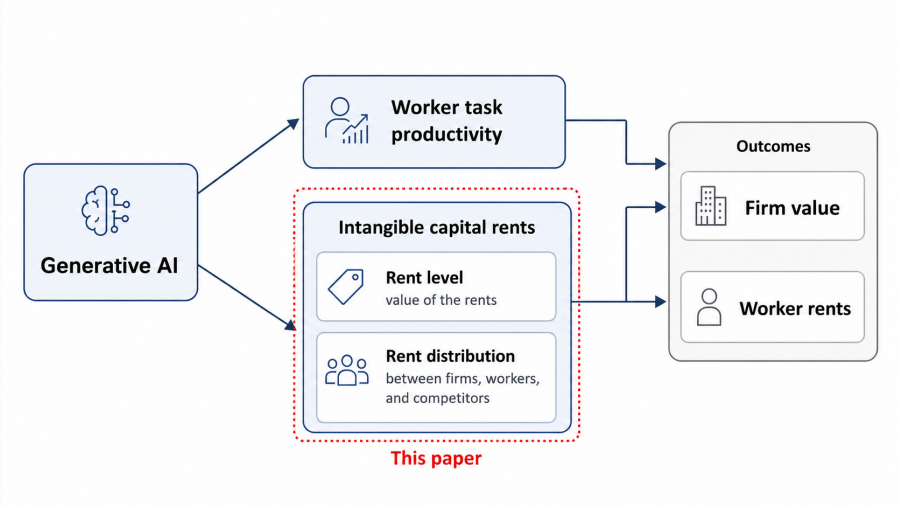


By **Sharon Goldman**
AI Reporter

June 9, 2026, 9:45 AM ET

Changes in the value of Organizational Capital?

This paper


Generative AI
Worker task productivity
Intangible capital rents
Rent level
value of the rents
Rent distribution
between firms, workers, and competitors
This paper
Outcomes
Firm value
Worker rents

Outline

1. Conceptual framework for how GenAI impacts intangible capital
2. A new measure of the composition of intangible capital embedded in labor at different firms
3. GenAI effects on the *value* of intangible capital
4. GenAI effects on *investments* in intangible capital
5. NOT TODAY: Changes in worker rents due to changes in codifiability

"GenAI" includes different capability changes relevant for intangibles

Chatbot AI

ChatGPT release, Nov. 2022

- Converses, drafts, answers, edits
- Augments a worker on an isolated task
- Human stays in the loop: supplies context, checks, and executes delivery, interacts with tools

⇒ **Productivity shock**: raises the value of worker-embodied knowledge & judgment

Agentic AI

Claude Code & other "agents"

- Plans and runs multi-step workflows end-to-end with tools and system access
- Human input moves to instruction, planning, supervision, and verification

⇒ **Reorganization of knowledge work**: automates codifiable work, substitutes for general professional capabilities that are not (too) context-dependent

"AI exposure" means something different in 2025/26 than it did in 2023

Agentic AI capability event in financial markets: “SaaSpocalypse”

Agentic AI event: "SaaSpocalypse" market crash was triggered by an Anthropic product update on January 30, 2026, releasing 11 specialized workflow plugins for Claude Cowork



Forbes

$300 Billion Evaporated. The SaaS -Pocalypse Has Begun.

By Don Muir, Contributor. I write about AI in finance and banking.

Follow Author

Published Feb 04, 2026, 03:19pm EST, Updated Feb 05, 2026, 03:26pm EST

Anthropic’s ‘Claude Cowork’ Release Triggers $285 Billion ‘SaaSpocalypse’: A Brutal Wake-Up Call for Legacy Tech and Finance

By: MarketMinute

February 06, 2026 at 11:41 AM EST

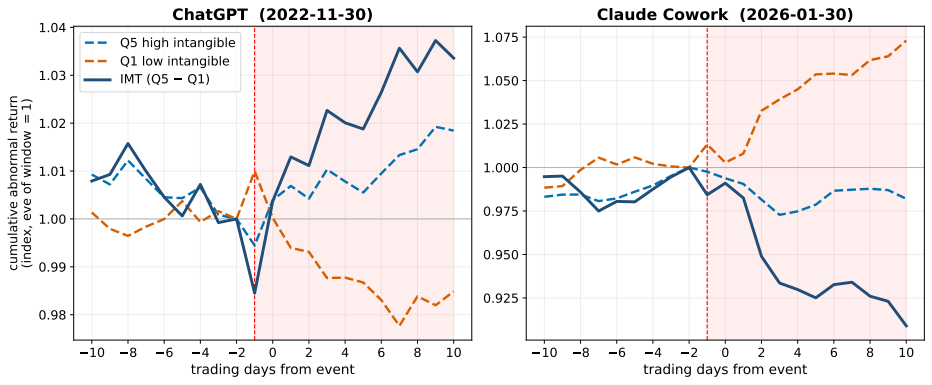
Anthropic’s new AI tools, built for its Claude “Cowork” AI agent, are designed to handle complex professional workflows that many software and data providers sell as core products.

The tools and other similar AI agents target functions ranging from legal and technology research, customer relationship management and analytics. That has raised concerns that AI could undercut traditional software business models.

The S&P 500 Software & Services Index, which has 140 constituents, fell over 4% on Thursday, extending its losing streak to eight sessions. The index is down about 20% so far this year.

Chatbots increase intangible value, Agentic AI decreases it

- **Chatbot AI event:** ChatGPT release Nov. 30, 2022
- **Agentic AI event:** "SaaSpocalypse" market crash



Note: Total intangible wage share. Abnormal returns: $ar_t = (r_t - r_{f,t}) - \hat{\beta}\,\mathrm{mktrf}_t$, each portfolio's own $\hat{\beta}$ estimated on $[t_0 - 136,\ t_0 - 11]$.

NYSE breakpoints, value-weighted, ex-financials.

Conceptual Framework: GenAI and Intangibles

Crouzet, Eberly, Eisfeldt, Papanikolaou (2022) model of intangible capital

1 Produce the stock N

Entrepreneur, manager, or key talent exerts costly effort to create an intangible stock. Future value depends on the private claim to its rents.

2 Choose storage and retention

A share θ remains closely held; $1-\theta$ is externally stored. The storage frontier $x = f(\theta;\delta)$ trades insider retention against firm span.

3 Deploy across streams

The firm uses N across products, customers, locations, or decisions. Non-rivalry ρ makes N and span x complements: $V = ANx^{\rho}$

Here: additional market rents margin that depends on technology "democratization"

How does GenAI impact intangible capital?

Intangible capital has two storage technologies (Crouzet, Eberly, Eisfeldt, Papanikolaou, 2022):

- *Artifacts* the firm owns (code, data, documents, brands)
- *People* the firm rents (routines, client knowledge, know-how)

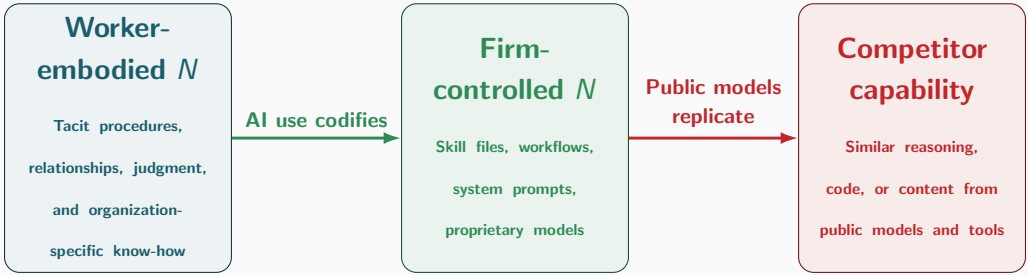
GenAI is a **productivity shock** to workers producing or deploying intangible capital.

GenAI is a **depreciation shock** to intangible capital:

1. Diffusion of professional capabilities to other firms
2. Intangible value depreciates faster (its services are replicable)

GenAI **shifts the storage margin**: worker-embodied knowledge becomes **codifiable** into firm-owned or portable artifacts, changing **division of rent**.

Codification: GenAI changes intangible capital storage



- Internal capitalization and external commoditization can occur simultaneously
- Net effect on shareholder value depends on which boundary moves more
- Net effect may be heterogeneous across types of intangible capital

$\Rightarrow$ **Need to measure intangible type composition of a firm's intangible-related work**

Intangible capital rent impact of GenAI

How GenAI changes split of quasi-rents between shareholders, workers, and competitors depends on...

1. Task codifiability: only some tasks can be written down, stored in skill files, prompts
   - Judgment & decision-making harder to codify
2. Portability: how context-specific the intangibles are
   - Portable general professional knowledge can dissipate rents across the market
   - Firm-specific knowledge limits value to outsides
   - Regulation & property rights can mitigate diffusion threats
3. AI capability:
   - Chatbot exposure: *can a model talk about this task? Can a chatbot do parts of this isolated task?* $\Rightarrow$ augments worker-embodied knowledge and professional tasks
   - Agentic AI exposure: *can a computer-based agent execute the task end-to-end?* $\Rightarrow$ automates codifiable worker-embodied processes

How chatbot and agents move intangible capital values

	Chatbot phase	**Agentic phase**
New AI capability	Task augmentation	End-to-end workflow execution
Intangibles impact	Productivity of workers related to intangibles	Automation of codifiable intangible-related tasks Commoditization of intangible value created by *portable professional* tasks
Intangible value effects		
Chatbot AI exposure	+	
Agentic AI exposure		+
Intangible share	+	?
...portable tasks	+	−
...firm-specific tasks	+	+ (≈ 0)

Mapping to empirical measures

Intangible capital composition: Association of individual tasks with producing or deploying specific types of intangible capital.

Job characteristics that characterize the *mechanism* for GenAI impact:

1. Chatbot AI exposure: task-level measure of productivity increase from chatbot use from Eisfeldt et al. (2023)
2. Agentic AI exposure: task-level measure of whether a computer-based agentic system with tool and system access can execute the task end-to-end
3. Portability: task-level measure of whether knowledge for the task is portable or firm-specific
4. Codifiability: task-level measure of ability to capture processes in writing

Market events related to AI capability advances:

1. ChatGPT Release (Nov. 30, 2022): first chatbot with general capabilities
2. Claude Cowork Plugins (Jan. 30, 2026): "SaaSpocalypse" after release of agentic workflow tools

Measuring Intangible Capital Composition

Existing measures of intangible capital

Measure	Input	What you get
Capitalize spending (perpetual inventory, firm-level)		
Eisfeldt & Papanikolaou (2013)	SG&A, $\delta = 15\%$	Organization capital: one stock
Peters & Taylor (2017)	R&D + 30% of SG&A	Knowledge + organization: two stocks
National accounts		
Corrado, Hulten & Sichel (2005)	Spending surveys	Nine asset types, three groups; US aggregate
Ratios and text		
Crouzet & Eberly (2019, 2023)	Capitalized stocks	Intensity: $K^{int}/(K^{int} + K^{tan})$
Eisfeldt, Hartman-Glaser, Kim & Lee (2026)	10-K MD&A text	Intensity index; know/cust/org shares

This paper: new measure of composition of intangible investments; focusing on worker-embedded intangible capital.

Task-level assignment of intangible capital type and activity

Data: Every statement in the O*NET 27.2 task universe (**19,265 tasks**, 923 occupations)

Measurement: each task is labeled by Claude Sonnet 5, given the task and its occupation as context: ▸ LLM prompt

Which capital type? The single most relevant of **nine** intangible types produced/deployed by the task (or none):

- **Knowledge:** Software, Databases / data, Scientific R&D, Financial product development, Design, Entertainment originals
- **Organizational:** Organizational Capital
- **Brand:** Brand equity, Customer capital

▸ Task examples ▸ Occ. examples

Examples: intangible-related tasks by occupation

Type	Occupation	O*NET task statement
Customer cap.	Sales Representatives	Identify prospective customers by using business directories...
Software	Computer Systems Engineers	Develop application-specific software.
Financial prod.	Securities Sales Agents	Devise trading, option, or hedge strategies.
Data mgmt.	Clinical Data Managers	Design and validate clinical databases

Task-level labeling of task characteristics

Data: the O*NET 27.2 task universe (**19,265 tasks**, 923 occupations).

Measurement: Claude Sonnet 5 (task and occupation as context, anchored scales with exemplars):

▸ LLM prompt

- **physical_task** (0/1): requires physical manipulation or presence
- **codification_feasibility** (0–3): can the *method* be captured well enough to train a replacement?
- **knowledge_locus**: general / professional / firm-specific / relationship-specific
- **agent_executability** (0–3): could a computer-based agent execute the task end-to-end?
- **complementary_assets**: proprietary data / system access / physical presence / license or relationship / none

Aggregation: occupation scores are importance-weighted task means (0–3 scales rescaled to 0–1); further aggregation based on occupation Revelio wage bill.

Mapping intangible capital types to firms

The panel. Revelio Labs workforce data (via WRDS):

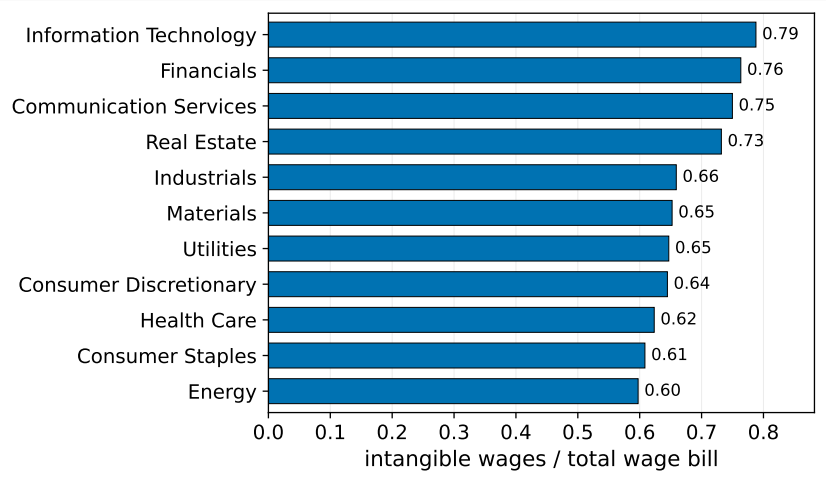
- position spells from worker profiles, **2013Q1–2025Q4**
- **3.69B** position-spell rows → **1.15B** cells, at employer × 8-digit O*NET-SOC × quarter.
- Headcount is fractional FTE presence, not an official count
- Predicted position salary from Revelio used as proxy for wage bill

From panel to firm.

- Data contains *employer* ID — sometimes a subsidiary. Consolidate to ultimate parent
  - e.g., Alphabet's ≈196 employer IDs → **165k** employees, not the **0.6k** only at the holding company
- Parent → `gvkey`: **489,091** firm-quarters, **9,879** public firms
- labeled task shares cover **95%** of employment

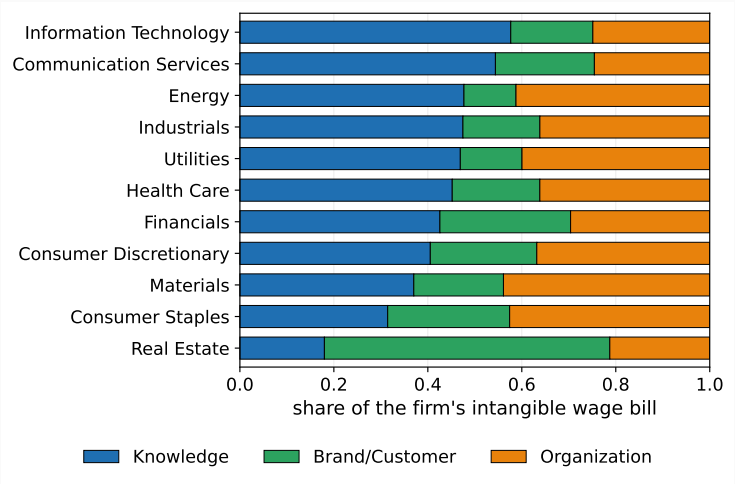
▸ Economy shares ▸ Task shares ▸ Firm size association ▸ Firm growth association

Intangible share of the wage bill by industry



Note: 3,605 firms, 2022Q3, payroll-weighted. GICS sectors.

Intangible composition by industry



Note: 3,605 firms, 2022Q3, payroll-weighted. Shares of each sector's intangible wage bill.

▸ Detailed types

Internal validation of measurement

Blind hand-label validation (200 stratified tasks, coded by the author)

- **Human vs. Sonnet 5, type only: 89.0%**
- Type + direction: 87.5% agreement
- Direction, given same type: 97.7%

Cross-model reliability (full 19,265-task universe)

- **Haiku vs. Sonnet 5, type only: 83.0%**
- Type + direction: 79.9%
- Direction, given same type: 88.2%

External validation: SG&A spending, R&D spending, Advertising spending

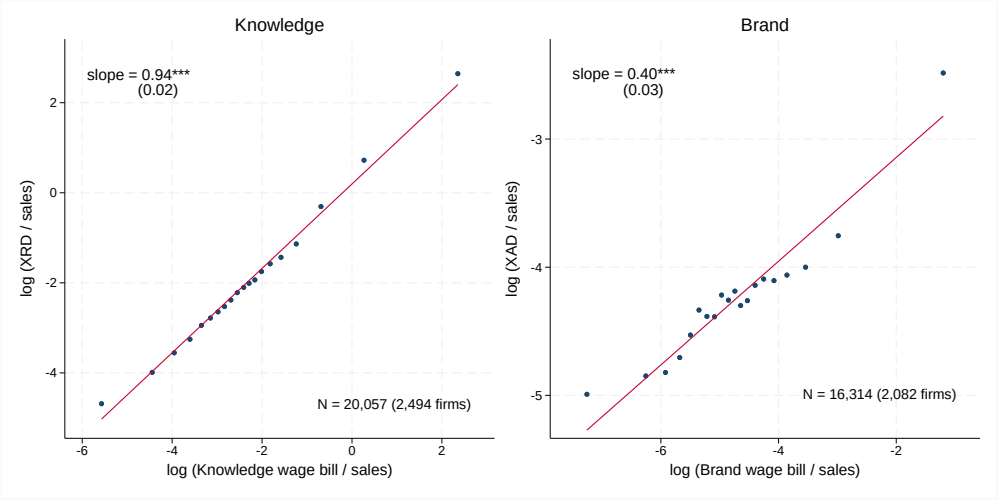
- **Eisfeldt & Papanikolaou (2013)** — capitalize SG&A into intangible capital using perpetual inventory method.

$$K_{i,t} = (1 - \delta) K_{i,t-1} + \text{SG\&A}_{i,t}, \qquad K_{i,0} = \frac{\text{SG\&A}_{i,1}}{g + \delta}$$

  where $K_{i,t}$ is the intangible capital of firm i at time t, $\text{SG\&A}_{i,t}$ is the SG&A of firm i at time t, δ is the depreciation rate, and g is the growth rate of intangible capital. $K_{i,0}$ is the initial intangible capital of firm i.

- **R&D and advertising spending** reported on income statements
- **Caveats:**
  - Unknown intangible share out of SG&A
  - Low, uneven R&D and advertising reporting rates in Compustat ▸ reporting rates

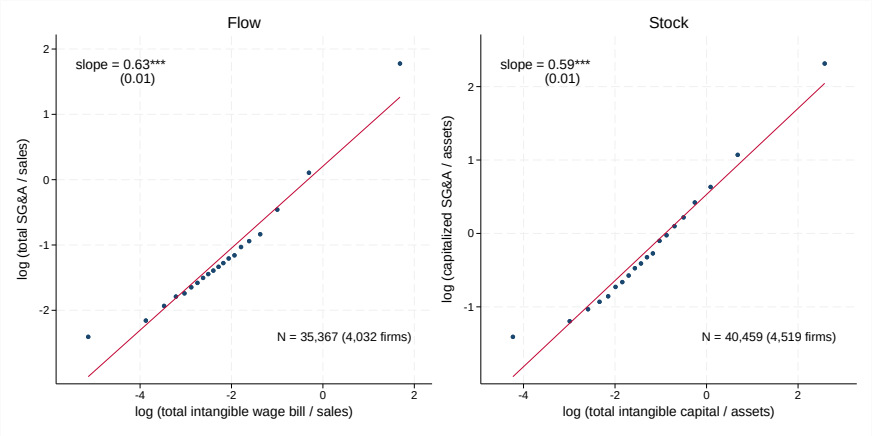
Benchmark: our measured intangible wage bill vs. booked R&D and advertising



Both axes scaled by sales; firms reporting the line; within NAICS3 × year FE; s.e. clustered by firm.

▸ Stock comparison

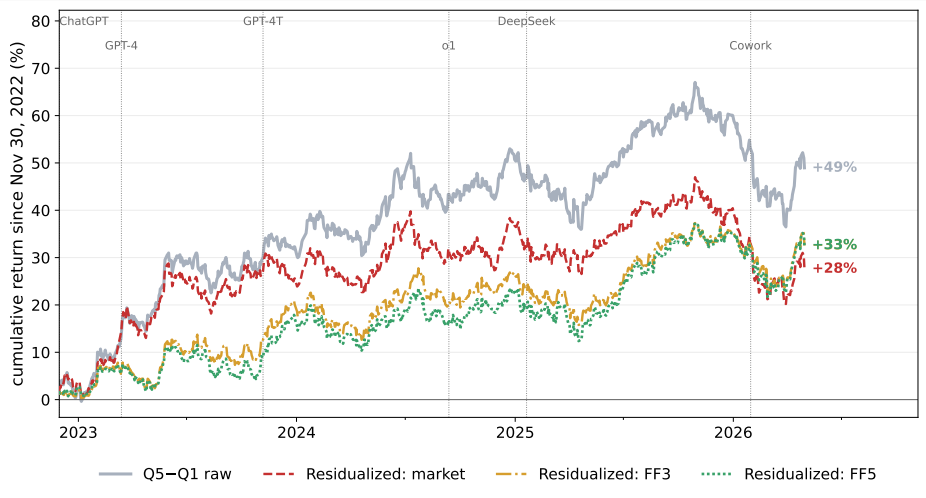
Benchmark: our intangible measure vs. capitalized SG&A (flow and stock)



Flow scaled by sales, stock by assets; within NAICS3 $\times$ year FE. SG&A capitalized at $\delta = 20\%$.

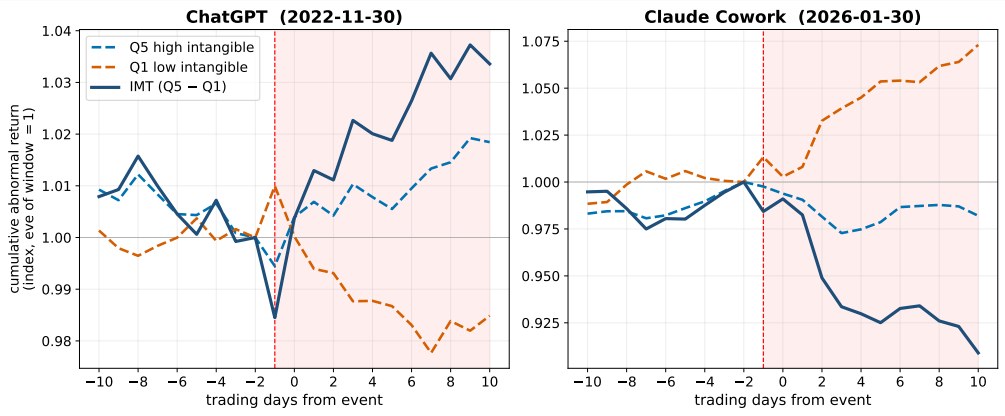
Changes in Intangible Capital Valuation in the GenAI Era

Long-short total intangible wage share portfolio returns



"IMT" portfolio: Q5-Q1 on total intangible wage share, sorted once on 2022Q3 and held, cumulated from ChatGPT release.

AI capability events and intangible wage share portfolio returns



Note: "IMT" portfolio: Q5-Q1 on total intangible wage share. $ar_t = (r_t - r_{f,t}) - \hat{\beta}\,\mathrm{mktrf}_t$, each portfolio's own $\hat{\beta}$ estimated on $[t_0 - 136,\ t_0 - 11]$. NYSE breakpoints, value-weighted, ex-financials.

CAR specification for AI capability events

Cross-section, one observation per firm:

$$\mathrm{CAR}_i[-1,+10] = a + b\, z\big(\mathrm{IWS}_i^{\mathrm{tot}}\big) + \boldsymbol{\gamma}'\mathbf{x}_i + \varepsilon_i, \qquad \mathrm{CAR}_i = \sum_{t=t_0-1}^{t_0+10} \big(r_{it} - r_{f,t} - \hat{\beta}_i\, \mathrm{MKT}_t\big).$$

$\mathrm{IWS}^{\mathrm{tot}}$: intangible wage bill share $\hat{\beta}_i$ on $[t_0 - 136,\ t_0 - 11]$.

t_0: ChatGPT 2022-11-30; Cowork 2026-01-30.

Estimator. WLS (weight = market equity at t_0), ex-financials.

Controls $\mathbf{x}_i$ (pre-event, standardized): log size, Tobin's Q, ROA, labor intensity, mkt. leverage.

Intangible wage share impact turns negative during "SaaSpocalypse"

Dep. var.: CAR[−1, +10], %

	ChatGPT			Claude Cowork		
	(1)	(2)	(3)	(4)	(5)	(6)
Intangible wage share	+1.07**	+1.16**	+1.58	−4.18***	−3.44***	−4.23**
	(0.48)	(0.54)	(0.96)	(0.94)	(1.04)	(1.66)
Log Size		−0.42	+0.17		−2.39	−1.24
		(0.54)	(0.42)		(2.08)	(0.98)
Tobin's Q		+0.02	−0.00		+0.06	−0.47
		(0.81)	(0.72)		(0.61)	(0.32)
ROA		−1.84	−1.50		+12.04	+8.10**
		(1.70)	(1.80)		(7.79)	(4.08)
Labor Intensity		+0.41	+1.82***		−0.23	−0.85
		(0.43)	(0.63)		(1.19)	(1.03)
Mkt. Leverage		−0.05	−0.70		+5.21***	+5.75***
		(0.64)	(0.66)		(1.31)	(1.37)
Controls	No	Yes	Yes	No	Yes	Yes
NAICS-2 FE	No	No	Yes	No	No	Yes
R^2	0.026	0.046	0.158	0.119	0.197	0.440
N	3,019	2,738	2,737	2,467	2,310	2,309

Mechanisms

What explains the market reaction to chatbots vs. agentic AI?

1. Does generic AI chatbot exposure mediate the intangible wage share effect on returns?
2. Does portability vs. firm-specificity matter for intangible capital revaluation?
3. Does codifiability predict greater agentic AI exposure?
4. Does agentic AI capability exposure explain returns during the agentic AI event?

GenAI chatbot exposure mediates intangible effects during ChatGPT release, but not for Claude Cowork effect

Horserace with Eisfeldt, Schubert, Taska, Zhang (2026) firm-level GenAI exposure:

Dep. var.: CAR$[-1, +10]$, %						
	ChatGPT			Claude Cowork		
	(1)	(2)	(3)	(4)	(5)	(6)
Intangible wage share	-0.21	-0.12	$+0.61$	-3.97^{***}	-1.86^{**}	-3.40^{**}
	(0.55)	(0.47)	(0.70)	(1.26)	(0.84)	(1.72)
GenAI exposure	$+1.88^{***}$	$+1.88^{***}$	$+1.99^{**}$	-0.63	-2.15	-2.06^{*}
	(0.69)	(0.72)	(0.97)	(1.74)	(1.34)	(1.10)
Controls	No	Yes	Yes	No	Yes	Yes
NAICS-2 FE	No	No	Yes	No	No	Yes
R^2	0.091	0.115	0.228	0.140	0.264	0.485
N	1,559	1,463	1,462	1,371	1,312	1,311

Mechanism example: Agentic AI erodes software moats through fast replication

Bain & Company now "vibecodes" working replicas of takeover targets' software during private-equity due diligence:

> *The replicas are built "to show what a software company can and can't do, to understand where it fits in the value chain and to understand whether it is the actual code that is the defensible part of the business or something else."*
>
> *— Rebecca Burack, head of Bain's global private-equity practice, Financial Times, June 22, 2026*

⇒ **Value shifts away from portable capabilities to the complementary firm-specific assets that cannot be copied.**

Source: FT, "Bain tests software takeover targets by vibecoding AI replicas" (ft.com/content/e5bac4d1-b1f8-43a4-bd54-b182d5357af0).

Measuring locus of knowledge of tasks

Definition. Where does the *rent-bearing knowledge* live — **what makes an experienced incumbent hard to replace at this task?**

- Portable knowledge (professional / general) can walk out the door *and be re-hired on the market.*
- Firm-specific and relationship-specific knowledge is worker-embedded, but less valuable in different context

Locus	Knowledge is. . .	Anchor task
general	what most literate adults have	"Sort and distribute incoming mail"
professional (portable)	portable expertise from public corpora, training, experience	"Prepare financial statements per GAAP"
firm-specific	this employer's own products, systems, procedures, data	"Troubleshoot the company's proprietary billing platform"
relationship-specific	durable personal trust with particular clients	"Manage and grow key client accounts"

Examples: which tasks are portable vs. firm-specific

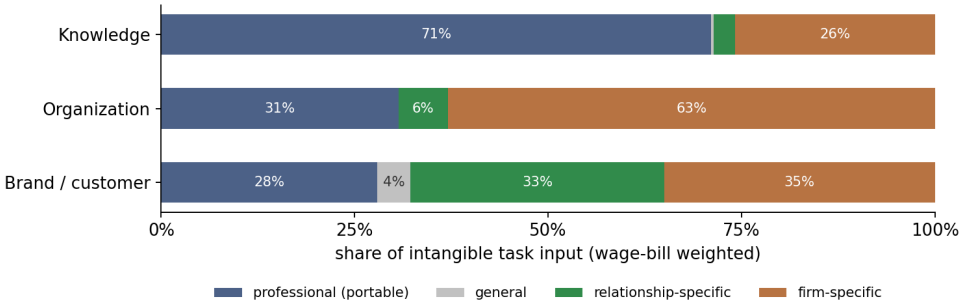
Portable (professional / general)

- **Web Developers**: "Establish appropriate server directory trees"
- **Data Scientists**: "Clean and manipulate raw data using statistical software"
- **Public Relations Specialists**: "Write press releases or other media communications to promote clients"
- **Securities Sales Agents**: "Explain stock market terms or trading practices to clients"

Firm- / relationship-specific

- **Receptionists & Information Clerks**: "Provide information about establishment, such as location of departments or offices, or employees within the organization" (firm)
- **Loss Prevention Managers**: "Visit stores to ensure compliance with company policies and procedures" (firm)
- **Insurance Underwriters**: "Quote rates, or explain company underwriting policies" (firm)
- **Real Estate Sales Agents**: "Arrange meetings between buyers and sellers when transaction details need negotiation" (relationship)

Knowledge-related intangible worker tasks are more portable across firms



▸ Detailed intangible types

AI event CAR Estimates: Brand, Knowledge, Organization Intangibles

Dep. var.: CAR$[-1, +10]$, %; intangible wage share

	ChatGPT			Claude Cowork		
	(1)	(2)	(3)	(4)	(5)	(6)
Knowledge	$+1.02^{**}$	$+1.15^{**}$	$+1.79^{*}$	-2.30^{***}	-2.43^{**}	-4.72^{**}
	(0.50)	(0.51)	(0.98)	(0.83)	(1.04)	(1.86)
Brand/Customer	$+1.30^{**}$	$+0.83$	$+0.77$	-2.88^{***}	-2.53^{**}	-1.63
	(0.63)	(0.72)	(0.93)	(0.85)	(1.13)	(1.24)
Organization	$+0.32$	$+0.03$	$+0.36$	$+3.83^{***}$	$+3.48^{***}$	-0.75
	(0.57)	(0.60)	(0.56)	(1.19)	(0.98)	(1.51)
Controls	No	Yes	Yes	No	Yes	Yes
NAICS-2 FE	No	No	Yes	No	No	Yes
R^2	0.030	0.051	0.164	0.220	0.274	0.454
N	3,019	2,738	2,737	2,467	2,310	2,309

Note: The three group wage bill shares enter *jointly*. Shares are z-scored.

Decline in firm value associated with the most portable intangible category drives negative SaaSpocalypse returns

Measuring agent executability of tasks

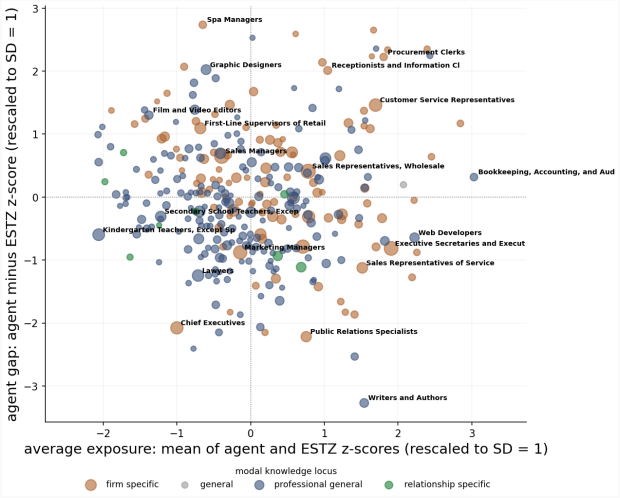
Definition. Could an agentic AI system with appropriate tool and system access **execute the task end-to-end** — multi-step, with a defined completion state and a machine- or cheaply-verifiable outcome?

- An LLM scores each task **0–3** (Claude Sonnet 5).
- The agent is computer-based (tools, APIs, files) — **no physical action or presence**; physical tasks capped at 1.
- **Occupation score:** importance-weighted task mean, rescaled to 0–1

▸ Occ. examples ▸ High agent gap occs ▸ Intangible types

	Delegation is...	Anchor task
3	fully delegable: machine-checkable outcome, standard tools	"Monitor system logs and open incident tickets"
2	end-to-end with human checkpoints; defined completion	"Reconcile monthly accounts and flag discrepancies"
1	isolated sub-steps only	"Supervise and coordinate nursing staff"
0	none: physical action, open-ended authority, no completion state	"Set strategic direction for the division"

Agentic vs. chatbot AI exposure



Note: large ($\geq$200k Revelio positions), non-physical occupations ($n = 312$); bubble area $\propto$ employment; $r(z_{agent}, z_{ESTZ}) = +0.63$; Axes: horizontal = average of the agent and ESTZ z-scores (common exposure); vertical = agent minus ESTZ z-score (agent tilt); each rescaled to unit variance.

Measuring codifiability

Definition. Could a task's *method* be captured — from documents, system logs, demonstrations, or interviews — well enough to **configure a system or train a replacement without the incumbent?**

- An LLM scores each task **0–3**.
- Codifiable know-how is worker-embodied procedure a firm can **convert into an artifact**.
- It shifts *who* gets the rent: key worker → firm (the **division** of rents, not the level)
- Converted into **occupation score:** % of tasks that have *codifiability* ≥ 2.

▸ Firm-level roll-up

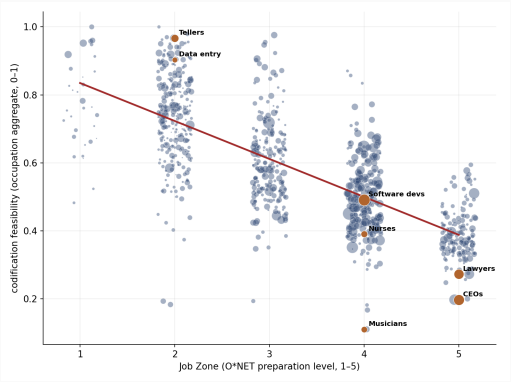
Rubric

	Method is...	Anchor task
3	fully proceduralizable from artifacts / logs	"Enter invoice data into the accounting system"
2	mostly codifiable with effort; edge cases remain	"Review loan applications against underwriting criteria"
1	articulable in steps, but needs tacit adaptation	"Counsel patients on treatment options"
0	resists articulation; rests on judgment / trust	"Negotiate acquisition terms with founders"

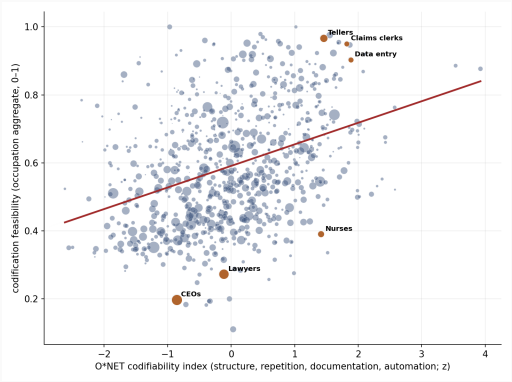
Higher = more codifiable

Codifiability intuitively aligns with O*NET proxies for job complexity

(a) O*NET preparation vs. task codifiability



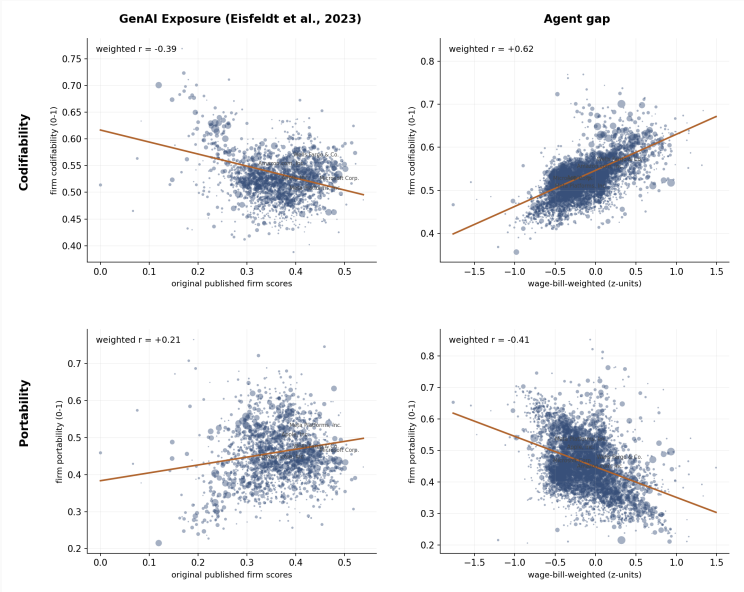
(a) O*NET codifiability vs. task codifiability



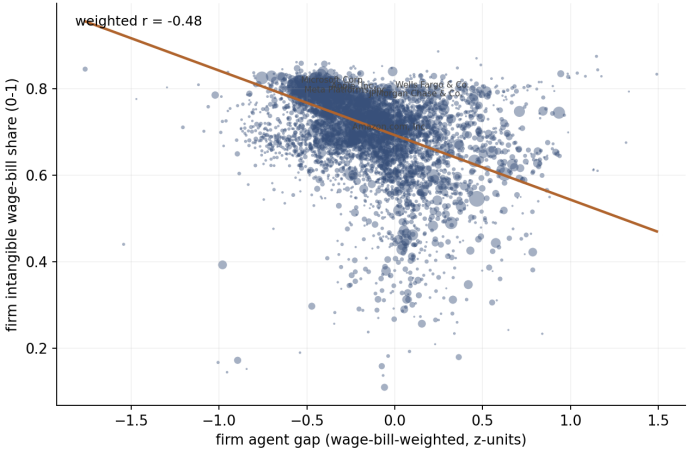
- O*NET Job Zone: level of preparation (incl. experience, degrees, training) required
- O*NET codifiability index is z-score of structure, repetition, documentation, automation intensity

▸ Mentoring correlation

Codifiability predicts firms' Agentic AI exposure



Intangible-intensive firms have less agentic AI exposure



Sample: 4,380 public firms, Revelio 2022Q3 composition. Firm measures = occupation-level agent_gap_estz / intangible_share (share of task weight typed intangible capital type) aggregated over the firm x occupation panel, weights = occupation wage bill within firm. Filters: headcount >= 50, coverage >= 5 Bubble = firm wage bill; weighted r and fit use the same weights.

Agentic AI event returns are explained by agentic AI exposure

- Agent gap: agentic AI exposure minus chatbot AI exposure (z-score)

Dep. var.: CAR[−1, +10], %; +controls, NAICS-2 FE

	ChatGPT		Claude Cowork	
	(1)	(2)	(3)	(4)
AgentGap		−1.53***		+2.92**
		(0.53)		(1.39)
GenAI Exposure	+2.23**	+1.91*	−3.25***	−2.67**
	(1.04)	(1.07)	(1.26)	(1.22)
Controls	Yes	Yes	Yes	Yes
NAICS-2 FE	Yes	Yes	Yes	Yes
R^2	0.226	0.243	0.470	0.487
N	1,462	1,462	1,311	1,311

⇒ **Intangible-intensive firms have fewer of the tasks that drive agentic AI event value increases**

Changes in Intangible Capital Investments

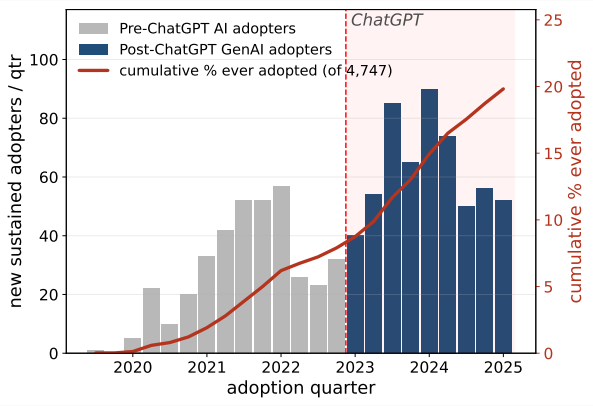
Defining AI Adoption Events using Job Postings

Data. Revelio job postings, 2017–2025.

AI Adoption event

The first of two consecutive quarters with $\geq$2 GenAI-keyword postings each: 88 terms (LLM, GPT, RAG, ...) matched on the job *description text*.

- Post-ChatGPT only: onset $\geq$2023Q1
- Parent firm: earliest adopting subsidiary



Event-study specification

Dynamic two-way fixed effects:

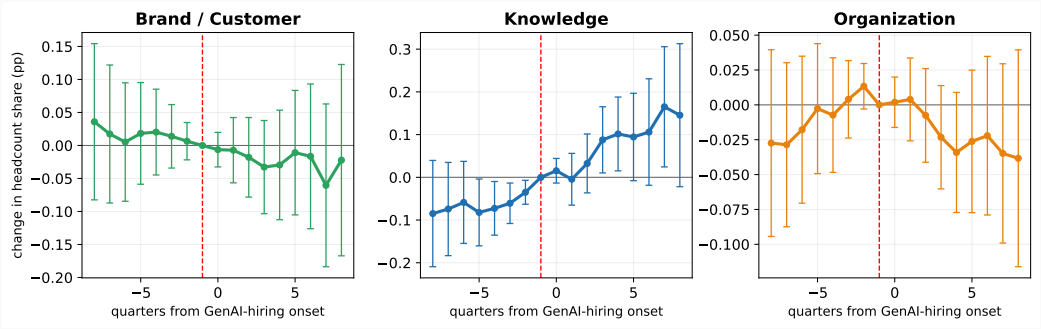
$$y_{it}^{c} = \mu_i + \lambda_t + \sum_{k=-8,\ k\neq -1}^{8} \theta_k \, \mathbf{1}\{t - G_i = k\} + \varepsilon_{it}, \qquad \theta_{-1} \equiv 0.$$

y_{it}^{c}: share of firm i's headcount in intangible category c (nine types), quarter t. Adoption quarter G_i; event time $k = t - G_i$.

Estimator:

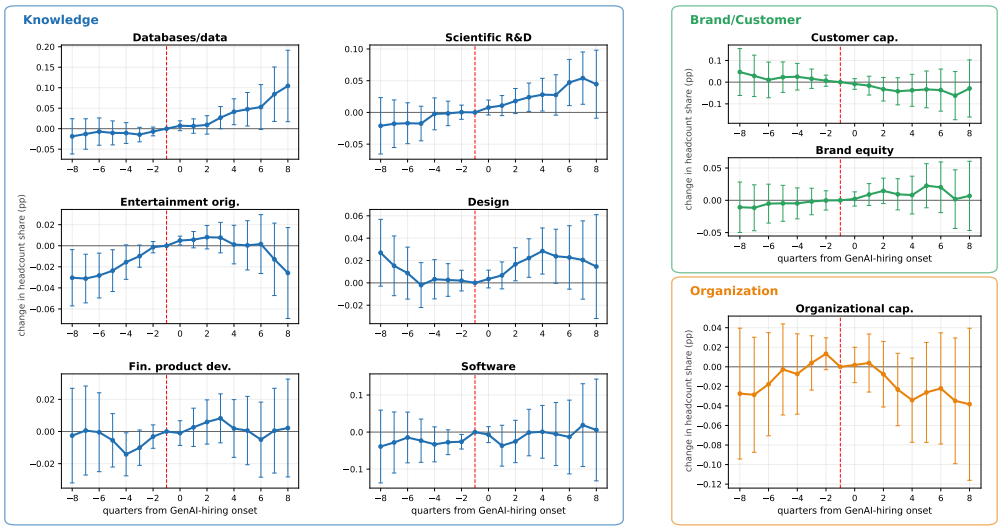
- Estimate group-time ATT off not-yet-treated firms (Callaway–Sant'Anna, 2021)
- Aggregated with cohort-size weights $\theta(k) = \sum_g \omega_g \, ATT(g, k)$
- Reference period is 2022Q4
- Event window in quarters is $[-8, +8]$ over period 2021Q1–2025Q4.

Intangible employment after AI adoption: Brand / Knowledge / Org

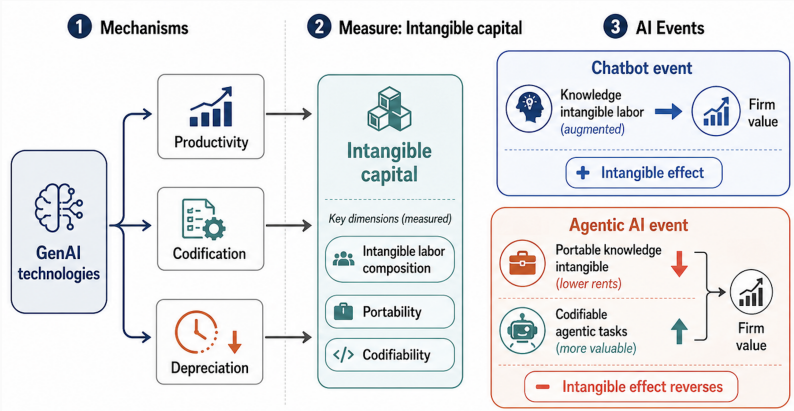


- Treated group: post-ChatGPT GenAI hiring surge (onset $\geq$2023Q1), no pre-ChatGPT AI postings
- Control group: never-treated + not-yet-treated
- Controls: industry$\times$qtr FE + pre-event size$\times$qtr FE

Intangible employment after AI adoption: detailed intangible types



GenAI changes which intangible capital is valuable and who owns it



Additional implications:

- Firms should prevent outside access to firm-specific assets? ("training on our data")
- Workers should resist codification / invest in non-codifiable skills
- Legal conflicts arise over ownership of codified intangibles

Impact on worker rents

Exploring the impact of AI and codification on worker rents

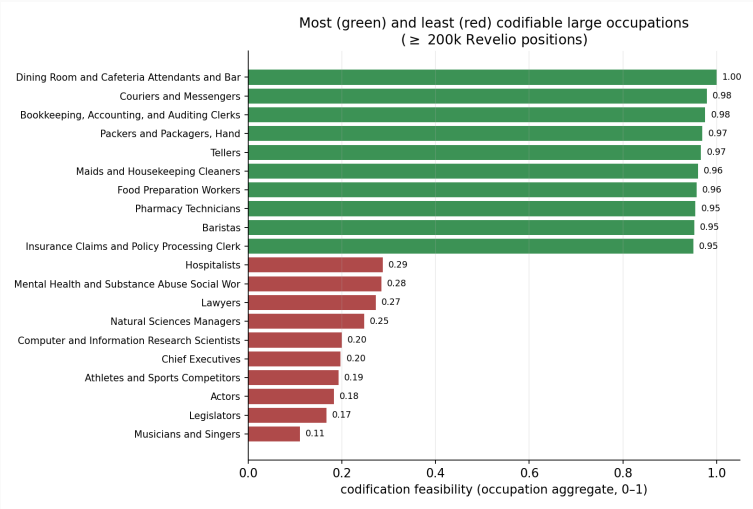
How does GenAI changing intangible capital values impact worker rents?

- **Productivity effects:** Exposure to chatbot augmentation likely negative for employment of affected occupations (but may shift to other occupations!)
- **Codification effects:**
  - Within-firm codification allows firm to appropriate worker-embedded intangible capital $\Rightarrow$ shifts bargaining power to firm
  - Agentic AI increases span of control for key talent - lower labor demand for codifiable jobs?
  - Across-firm commoditization of codifiable skills lowers demand for codifiable labor

Data: Occupational Employment Statistics (BLS) panel of employment and wages by occupation 2015-2025

- Mostly precedes agentic AI diffusion

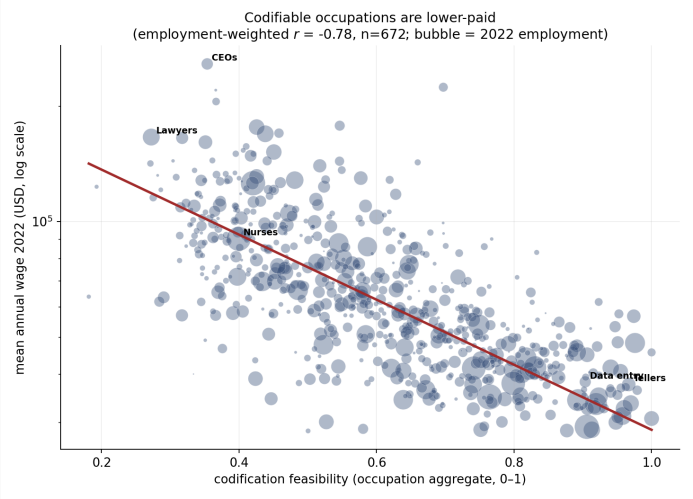
Highest and lowest codifiability occupations



Note: not AI exposure: proceduralized work (including physical work) scores highest.

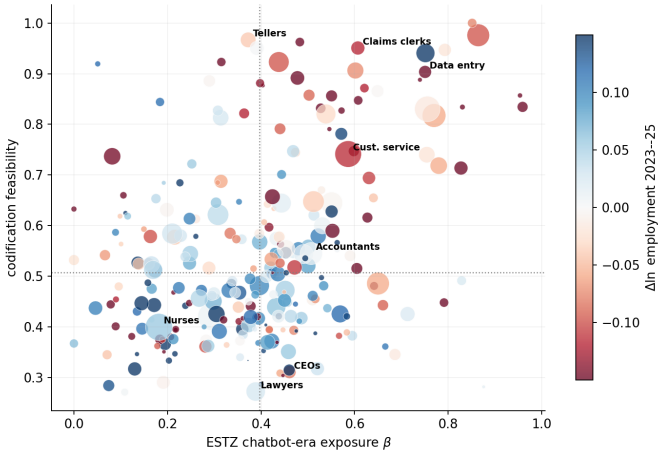
▸ Industry codifiability

Codifiability correlates negatively with occupational wages.



Note: Eisfeldt et al. (2026) AI exposure correlates positively with wages.

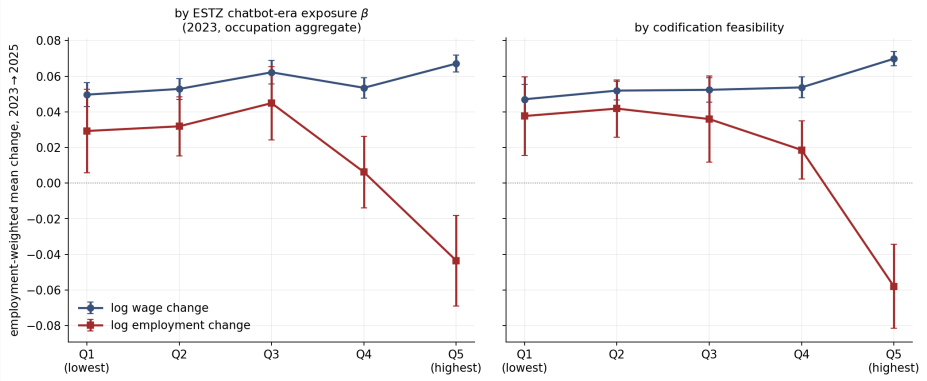
Codifiability × Chatbot AI exposure map



Sample: 266 non-physical occupations (physical task share < 0.6) with 2015–19 OES data, matched to O*NET on 6-digit SOC. Bubble area ∝ 2022 OES employment. Colo
Sources: BLS OES national panel; ESTZ (2023) task exposure; codifiability from our task instrument (O*NET 27.2, Sonnet-5 labels).

Codifiability and chatbot AI exposure predict employment declines 2023-2025

2023–25 employment change, non-physical occupations:



Note: occupation-level quintile bins; left panel bins by ESTZ chatbot-era exposure β alone, right panel by codification feasibility; employment-weighted means with 95% CIs; non-physical = importance-weighted physical-task share < 0.6 (310 of 672 matched OES occupations).

Employment regressions: codifiability and GenAI exposure capture different impacts on employment

	Δ ln employment 2023–25		
	(1)	(2)	(3)
ESTZ exposure β (z)	-0.027***		-0.018***
	(0.008)		(0.007)
Codifiability (z)		-0.033***	-0.034***
		(0.010)	(0.009)
ESTZ × Codifiability			0.015*
			(0.008)
Pre-trend control (2015–19)	Yes	Yes	Yes
R^2	0.23	0.28	0.32
N	266	266	266

Dep. var.: Δ ln employment 2023–25 (OES). Pre-trend control = the occupation's annualized 2015–19 employment growth (z); pre-trend-available sample. WLS, weights = 2023 employment; HC1 SEs in parentheses. Non-physical occupations (physical share < 0.6). $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Thank you!

From occupation scores to a firm codifiability measure

1. **Task → occupation.** Average the 0–3 task scores to 8-digit O*NET, then unweighted to SOC-6
2. **Consolidate to the listed parent.** Map subsidiaries to ultimate parent (Revelio) before scoring — same firm definition as A_{tot}.
3. **Firm employment mix.** Revelio firm × occupation headcounts, frozen at the pre-event snapshot (2022Q3, pre-ChatGPT).
4. **Link to Compustat.** Parent `rcid` → `gvkey`.
5. **Firm score.** cod_firm = headcount-weighted mean of occupation scores; in $[0, 1]$, higher = more codifiable.

◂ Back

How each term is built

Step 1, task → occupation. Every term below is an O*NET importance-weighted mean over the tasks of the SOC-6 (tasks pooled across 8-digit variants, missing weights imputed to the occupation mean), 798 occupations. The three LLM fields come from one Claude Sonnet 5 run over the same 19,264 tasks — which is why differencing two of them cancels common labeling error, and differencing against ESTZ does not.

Term	Built from	Role
Cod_o	LLM `codification_feasibility`, 0–3 rescaled to [0, 1]	in both compounds
ChatExposure_o	LLM `chatbot_substitution`, 0–3 rescaled to [0, 1]	Augment, chat basis
AgentMean_o	LLM `agent_executability`, 0–3 rescaled to [0, 1]	inside the gap
ESTZ_o	ESTZ β, map {E0:0, E1:1, E2:0.5, E3:0}, joined on O*NET Task ID (19,264 of 19,264 matched; E3 counts as unexposed, as in ESTZ)	Augment, ESTZ basis
Portable_o	share of tasks with professional-portable knowledge locus	splits Replace
FirmSpecific_o	share of tasks with firm-specific knowledge locus	splits Internalize

Step 2, the gap. Standardize the *two* measures separately across the 798 occupations, subtract, and rescale so the result has SD 1. High where an agent can execute more of the job than a chatbot can write. (It is a difference between two variables, not a centering of one: `agent_mean`'s "mean" is the task average in Step 1.)

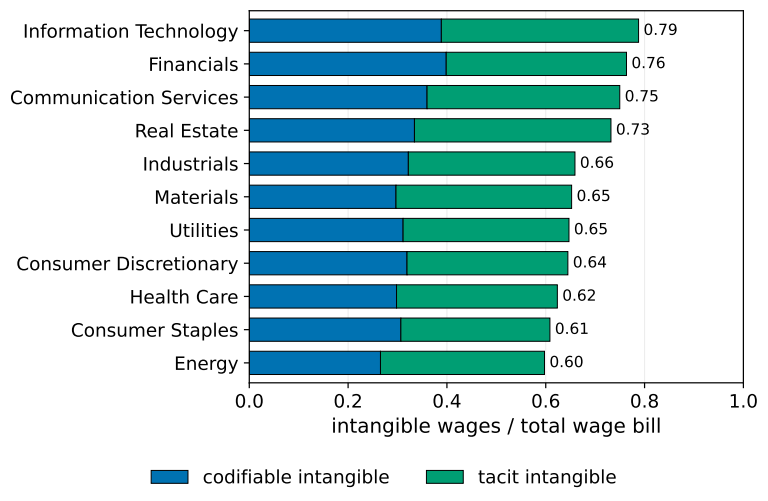
$$\text{AgentGap}_o = (z_{\text{agent}} - z_{\text{chat}})/0.4232, \qquad 0.4232 = \sqrt{2(1-r)},\ r = 0.910$$
$$\text{AgentGap}_o^{\text{ESTZ}} = (z_{\text{agent}} - z_{\text{ESTZ}})/0.5501, \qquad 0.5501 = \sqrt{2(1-r)},\ r = 0.849$$

The CAR table uses the second row, and races it against z_{ESTZ} itself — ESTZ's task β on these same wage-bill weights, not their published firm score — so the gap and the control are one measure. The first row is the appendix backup.

The gap is the only term that can be negative — Cod and both shares are non-negative — so every negative Replace or Internalize comes from it.

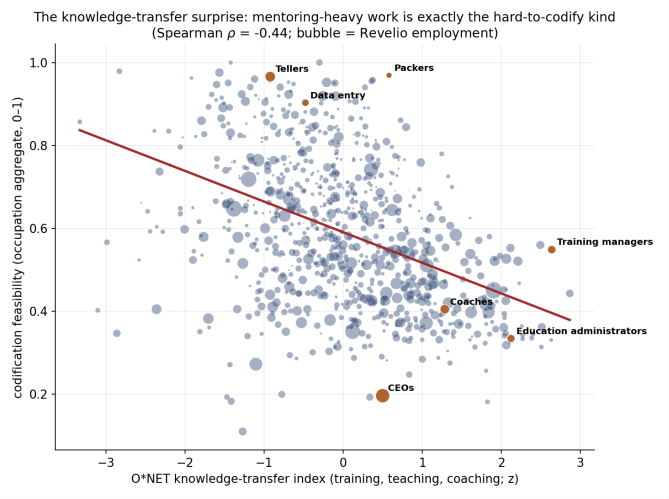
Step 3, firm roll-up. $X_i = \sum_o w_{io} X_o$, w_{io} the frozen 2022Q3 Revelio wage-bill share (child `rcid` consolidated to ultimate parent, `rcid`→`gvkey` at 2022Q3); headcount twin in backup. Products are formed at the occupation level, then rolled up: $\text{Replace}_i = \sum_o w_{io}(\text{Cod}_o \times \text{AgentGap}_o \times \text{Portable}_o)$, *not* the product of the firm-level roll-ups. Portable and FirmSpecific do not sum to one; the other loci are general and relationship-specific.

Codifiable versus tacit intangibles by industry



3,604 firms, 2022Q3, payroll-weighted. Codifiable = tasks with codification feasibility ≥ 2. Back

Tacit knowledge transferred through mentoring is hard to codify



Back

The task-labeling prompt (1/3: task & key terms)

You are labeling O*NET task statements for a research project on intangible capital. Each item gives an OCCUPATION and one TASK. Decide which intangible capital TYPE from the menu the task is most relevant to, and whether it PRODUCES that capital or DEPLOYS it; if none applies, answer NONE.

KEY TERMS

- STOCK: a durable, firm-owned asset that persists beyond the current transaction (codebases, databases, patents, processes, brand, customer relationships, designs, content). A worker's own skill is NOT a stock.
- PRODUCE (build the stock): output accumulates in the chosen stock --- after the task the firm owns more or better capital of that type (create, extend, improve, codify, maintain to offset depreciation).
- DEPLOY (harvest the stock): the task generates current output or revenue and the stock is an essential input, without materially adding to it.
- NONE: no menu stock is built or essential --- tasks using only the worker's own expertise or generic effort, physical/in-person delivery, or capital off the menu.

▸ Decision & output ◂ Back

The task-labeling prompt (2/3: decision procedure & output)

DECISION PROCEDURE

1. TYPE: which ONE menu type's stock does the task build or use as an essential input? Pick where most of the task's economic contribution sits; no loose connections. If none qualifies, answer NONE.
2. DIRECTION: adding to or renewing the stock → PRODUCE; extracting current value from the existing stock → DEPLOY. Do not use NONE to break a tie.
3. CONFIDENCE: 1 = coin flip, 3 = defensible, 5 = unambiguous, covering the combined type + direction choice.

OUTPUT: JSON only. ("label" is null iff "type" is NONE.) {"type": SOFTWARE | DATA | SCIENTIFIC_RD | FINANCIAL_PRODUCTS | ORGANIZATIONAL | BRAND | CUSTOMER | DESIGN | ENTERTAINMENT | NONE,
"label": PRODUCE | DEPLOY | null, "confidence": 1--5, "rationale": "≤20 words"}

▸ Worked examples ◂ Key terms ◂ Back

The task-labeling prompt (3/3: worked examples)

EXAMPLES (occupation | task → label)

- Software Developers | ‘‘Modify existing software to correct errors, adapt it to new hardware, or improve performance.’’
  → {"type":"SOFTWARE", "label":"PRODUCE", "confidence":5, "rationale":"Maintains and improves the software stock itself."}
- Computer User Support Specialists | ‘‘Answer user inquiries regarding software or hardware operation to resolve problems.’’
  → {"type":"SOFTWARE", "label":"DEPLOY", "confidence":4, "rationale":"Delivers services from existing systems without extending them."}
- Sales Representatives | ‘‘Identify prospective customers using directories, leads, and trade shows.’’
  → {"type":"CUSTOMER", "label":"PRODUCE", "confidence":5, "rationale":"Acquires new customer relationships, adding to the stock."}
- Customer Service Representatives | ‘‘Process orders for merchandise or services.’’
  → {"type":"CUSTOMER", "label":"DEPLOY", "confidence":5, "rationale":"Transacts with existing customers; extracts services from the stock."}

The task-characteristics prompt (1/3: capturability & locus)

codification_feasibility (0--3). Could the METHOD be captured --- from documents, system logs, demonstrations, or interviews --- well enough to configure a system or train a replacement without the incumbent?

- 0 Method resists articulation; rests on unarticulated judgment or trust. ‘‘Negotiate acquisition terms with target-company founders.’’
- 1 Key steps articulable, but success depends on tacit adaptation. ‘‘Counsel patients on treatment options.’’
- 2 Mostly codifiable with structured effort; edge cases remain. ‘‘Review loan applications against underwriting criteria.’’
- 3 Fully proceduralizable from existing artifacts and logs. ‘‘Enter invoice data into the accounting system.’’

knowledge_locus. Where does the rent-bearing knowledge live --- what makes an experienced incumbent hard to replace at this task? general | professional_general | firm_specific | relationship_specific

The task-characteristics prompt (2/3: AI substitution fields)

chatbot_substitution (0--3). Can a prompted frontier chatbot (human supplies context and executes delivery) produce the core work product? 0 = no text/analysis component (‘‘Install drywall’’) ... 3 = essentially complete (‘‘Summarize meeting transcripts’’).

agent_executability (0--3). Could an agentic AI system with tool and system access execute the task end-to-end --- multi-step, defined completion state, cheaply-verifiable outcome? COMPUTER-BASED: it cannot act physically.

0 No meaningful end-to-end delegation: physical action, open-ended authority, or no defined completion state. ‘‘Set strategic direction.’’

1 Isolated sub-steps automatable only.

2 End-to-end with human checkpoints; defined completion. ‘‘Reconcile monthly accounts.’’

3 Fully delegable: clear completion state, machine-checkable outcome. ‘‘Monitor logs and open incident tickets.’’

verification_cost (0--3). How costly for a non-expert or automated check to verify the output is correct?

The task-characteristics prompt (3/3: assets, rules & output)

complementary_assets (list). If AI systems performed the substitutable portion, which scarce inputs would still be required? Select ALL that apply: proprietary_data / system_access / physical_presence / license_or_relationship / none. Hardest-to-obtain first.

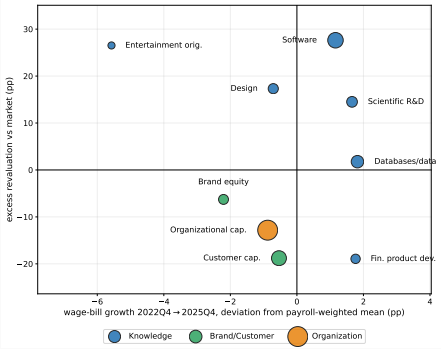
RULES (selected)

- knowledge_locus: do not code firm_specific merely because the statement mentions ‘‘the company’’; ask whether employer-specific knowledge is the scarce input.
- If physical_task = 1, cap chatbot_substitution and agent_executability at 1 unless the digital sub-component dominates.

OUTPUT: JSON only. {"physical_task": 0/1, "codification_feasibility": 0--3, "knowledge_locus": general | professional_general | firm_specific | relationship_specific, "chatbot_substitution": 0--3, "agent_executability": 0--3, "verification_cost": 0--3, "frontier_capability_requirement": 0--3, "complementary_assets": [...], "confidence": low/medium/high, "rationale": "$\leq$25 words"}

◂ AI fields ◂ Back

Appendix: reallocation vs. revaluation, 2022Q4 start



The headline window, repeated for comparison with the 2023Q4 start. Software (+27.6pp) and R&D grew *and* re-rated; Organizational (32% of the intangible payroll) and Customer capital shrank *and* were marked down.

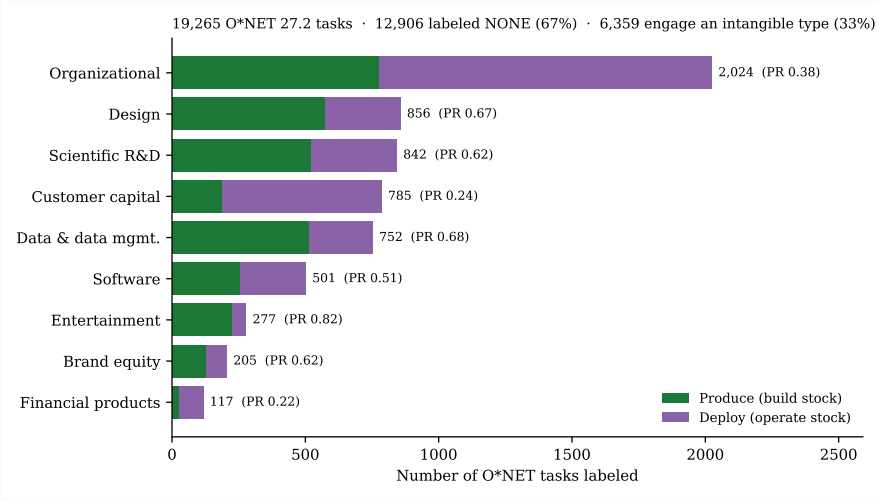
2022Q4→2025Q4, $N = 3{,}595$ firms, market +75.0%; revaluation on 2022-fixed weights, so it cannot reflect post-shock reallocation.

Examples: same occupation can both produce & deploy intangibles

Type	Occupation	O*NET task statement	Label
Customer cap.	Sales Representatives	Identify prospective customers by using business directories, fo...	**Produce**
		Answer customers' questions about products, prices, availability...	**Deploy**
Software	Computer Systems Engineers	Develop application-specific software.	**Produce**
		Monitor system operation to detect potential problems.	**Deploy**
Financial prod.	Securities Sales Agents	Devise trading, option, or hedge strategies.	**Produce**
		Make bids or offers to buy or sell securities.	**Deploy**
Data mgmt.	Clinical Data Managers	Design and validate clinical databases, including designing or t...	**Produce**
		Analyze clinical data using appropriate statistical tools.	**Deploy**

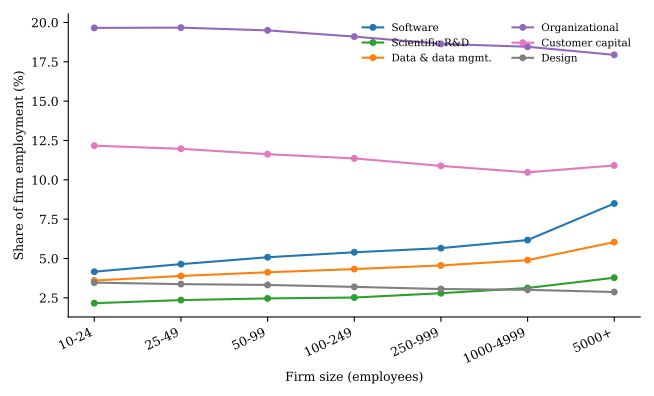
▸ Back to methodology

Intangible tasks by intangible type



▸ Back to economy shares

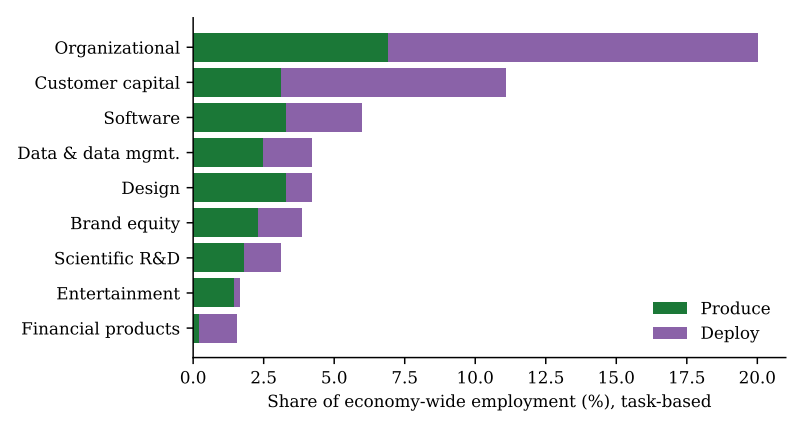
Across the firm-size distribution: the type mix moves a lot



Large firms are more technical, less coordination/sales-intensive per worker.

Back

Intangible engagement tasks as share of the economy



Aggregating task shares × occupation employment: 55.6% of work engages intangible capital

▸ Back ▸ Task shares ▸ Firm size association ▸ Firm growth association

Which occupations build vs. deploy intangible capital

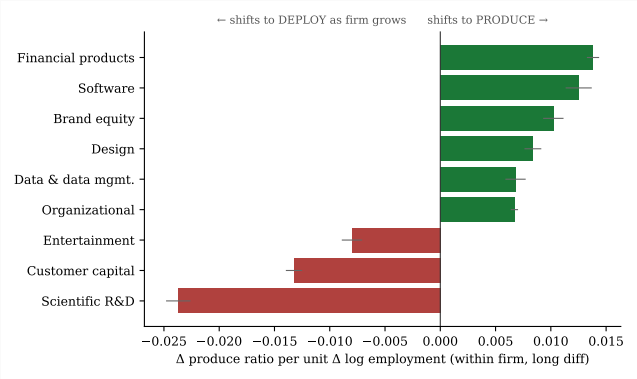
Occupation	HC (M)	Eng. %	PR
Most produce-heavy (build)			
Management Analysts	0.8	90	1.00
Data Entry Keyers	0.5	57	1.00
Writers and Authors	3.7	98	0.98
Fine Artists, Including Pa.	0.7	48	0.94
Medical Scientists, Except.	0.2	78	0.92
Musicians and Singers	0.8	39	0.92
Most deploy-heavy (operate)			
Retail Salespersons	5.4	42	0.00
Motion Picture Projectioni.	0.6	51	0.00
Concierges	0.9	38	0.00
Credit Analysts	0.8	100	0.00
Cashiers	0.4	42	0.00
Counter and Rental Clerks	0.6	83	0.00

188 large occupations (engaged $\geq$0.35, above-median headcount), ranked by produce ratio (PR).

Builders leave behind an asset — writers, artists, scientists, management analysts.

Operators are the transaction/service layer — retail sales, cashiers, counter clerks, credit analysts — drawing current output from a stock others built.

As firms grow, they change which intangibles they produce vs. deploy

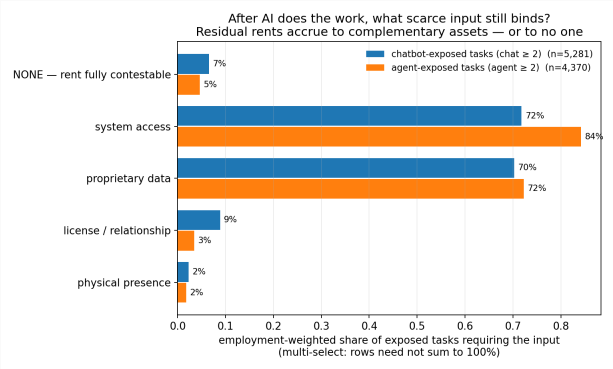


Back

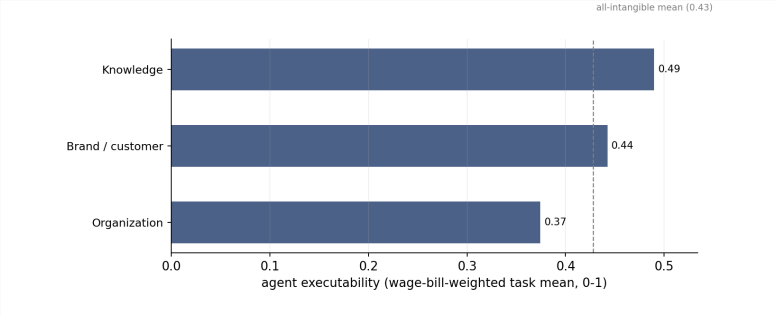
Tracking the *same* firm as it grows (373,170 firms, long differences; firm + quarter FE differences out fixed type):

- Aggregate produce ratio slope ≈ 0 ($+0.003$/log emp) — growth does *not* push firms toward deployment on net.

After AI does the work, the binding complements are the firm's own

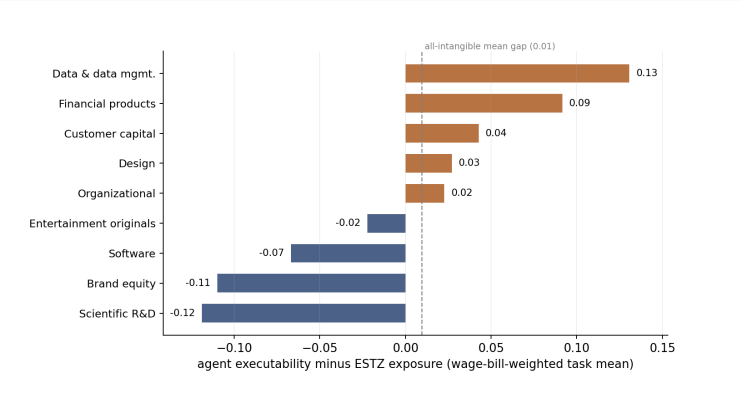


Agentic task exposure: knowledge vs. brand/customer vs. organization



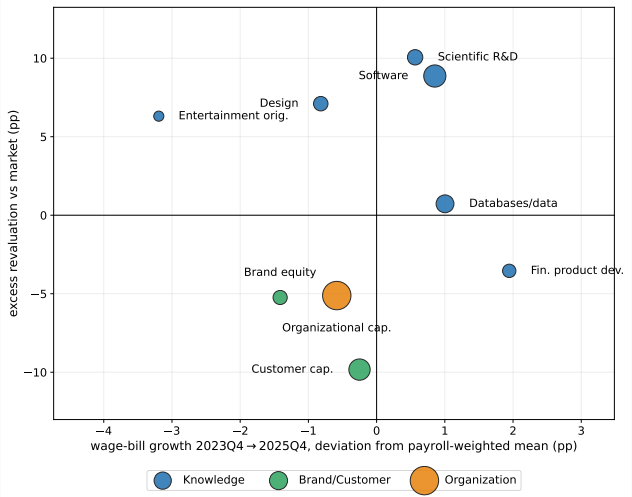
Note: same sample and weights; groups as in the locus chart — Knowledge = software, data, scientific R&D, financial products, design, entertainment originals; Brand/customer = brand equity + customer capital.

The agent gap: agentic minus chatbot (ESTZ) exposure by intangible type



Note: gap = wage-bill-weighted task mean of agent executability (0–1) minus ESTZ β (0–1), by rubric-v3 intangible type; dashed line = all-intangible mean gap (+0.01); orange = more agent-tilted than the average intangible task. Data, financial products, customer and organizational capital gain exposure on the agentic margin; scientific R&D, brand and software were already chatbot-exposed.

Appendix: reallocation vs. revaluation, 2023Q4 start



Which occupations build vs. deploy intangible capital

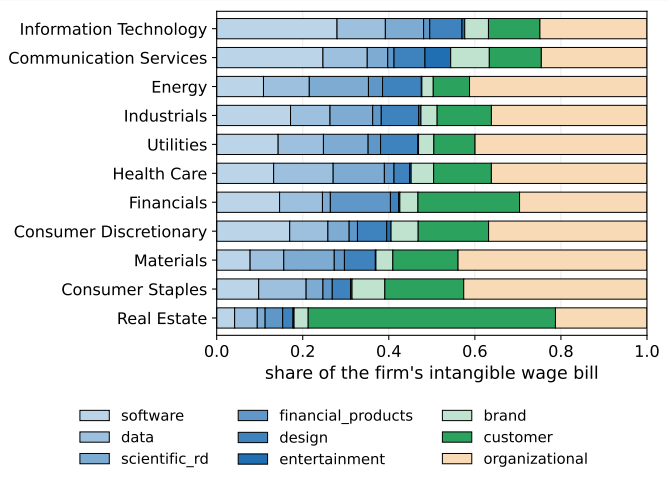
Occupation	HC (M)	Eng. %	PR
Most produce-heavy (build)			
Management Analysts	0.8	90	1.00
Data Entry Keyers	0.5	57	1.00
Writers and Authors	3.7	98	0.98
Fine Artists, Including Pa.	0.7	48	0.94
Medical Scientists, Except.	0.2	78	0.92
Musicians and Singers	0.8	39	0.92
Most deploy-heavy (operate)			
Retail Salespersons	5.4	42	0.00
Motion Picture Projectioni.	0.6	51	0.00
Concierges	0.9	38	0.00
Credit Analysts	0.8	100	0.00
Cashiers	0.4	42	0.00
Counter and Rental Clerks	0.6	83	0.00

188 large occupations (engaged $\geq$0.35, above-median headcount), ranked by produce ratio (PR).

Builders leave behind an asset — writers, artists, scientists, management analysts.

Operators are the transaction/service layer — retail sales, cashiers, counter clerks, credit analysts — drawing current output from a stock others built.

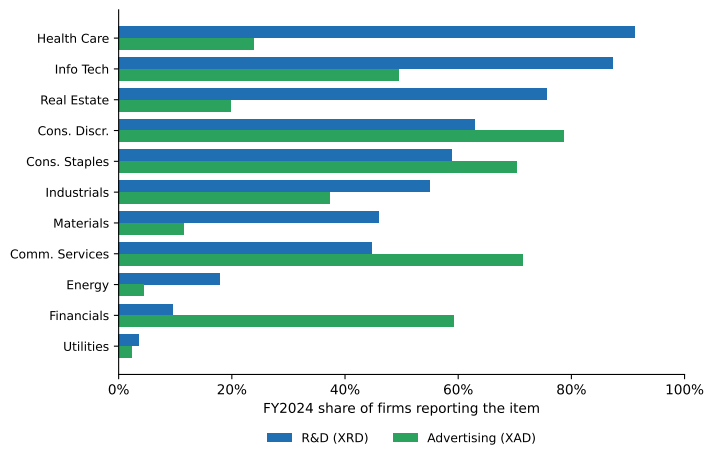
[Jul 25] Intangible composition by industry — nine types



ChatGPT sample, 3,605 firms, 2022Q3, payroll-weighted. Shares of each sector's intangible wage bill; the nine types shade within their Knowledge / Brand-Customer / Organization group.

Back

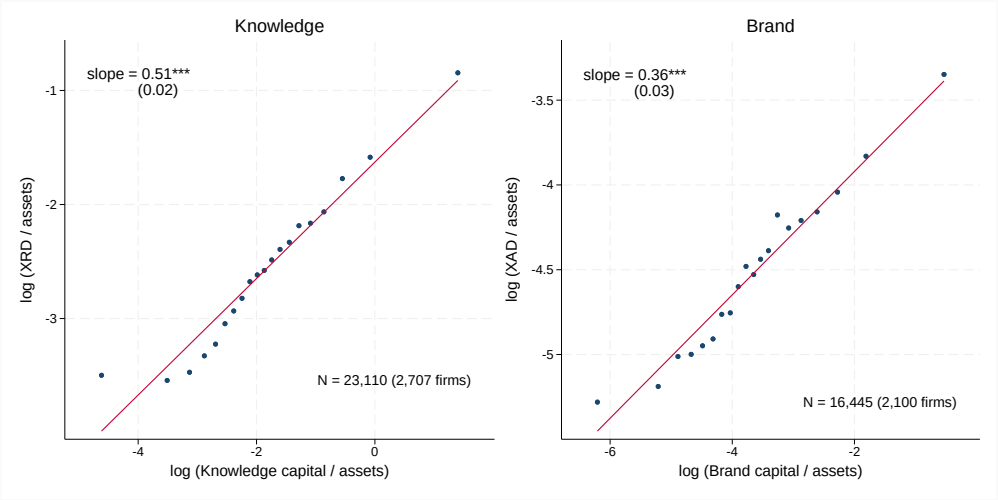
Appendix: R&D and advertising reporting coverage by industry



GICS sectors, FY2024, all Compustat firms (no SG&A-reporting screen), $N = 4{,}063$.

Back

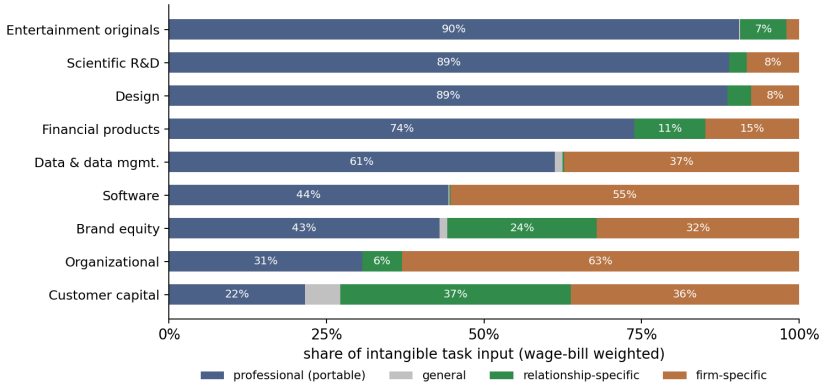
Benchmark: intangible capital stocks vs. booked R&D and advertising



Both axes scaled by assets; firms reporting the line; within NAICS3 × year FE; s.e. clustered by firm.

▸ Back to flow comparison

Locus of knowledge by intangible type



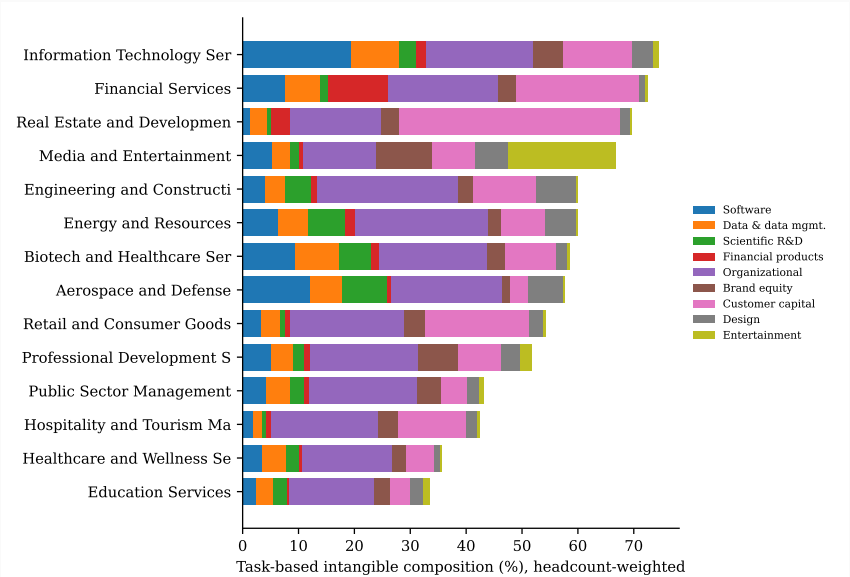
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Appendix: the physicality lesson in one table row

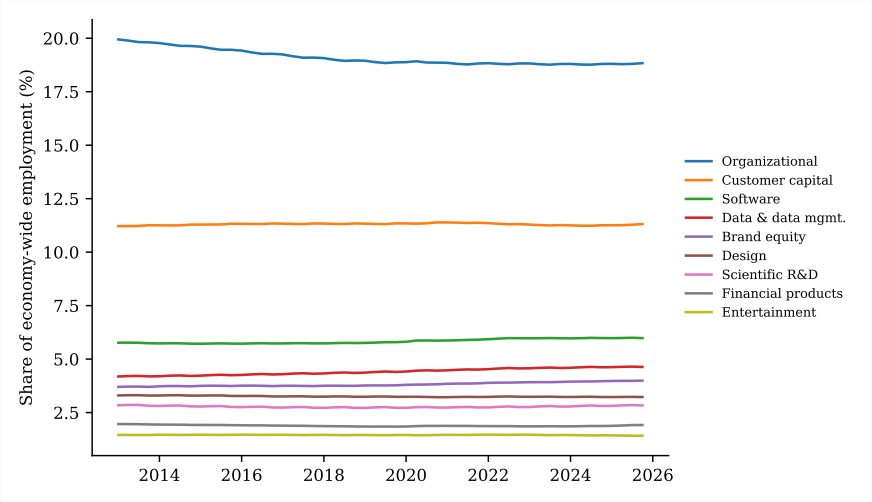
LLM field	O*NET element	All occs	Non-physical
agent executability	Degree of Automation	+0.21	+0.57
agent executability	Repeating Same Tasks	+0.13	+0.53
agent executability	Job Zone	**+0.48**	**−0.61**
chatbot substitution	Interpersonal Relationships	+0.54	−0.06
chatbot substitution	Social Perceptiveness	+0.52	−0.22

Unconditional correlations mix the cognitive–physical divide into everything; within cognitive work, every field behaves as designed. All conditional analyses labeled post-hoc; pre-registered verdicts stand.

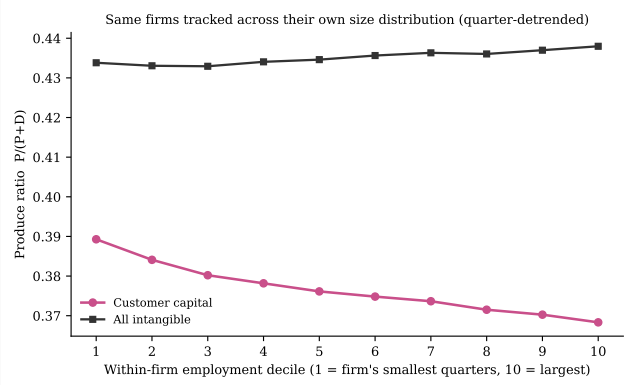
Appendix: industry face validity (2025Q4)



Appendix: economy-wide composition by type, 2013–2025

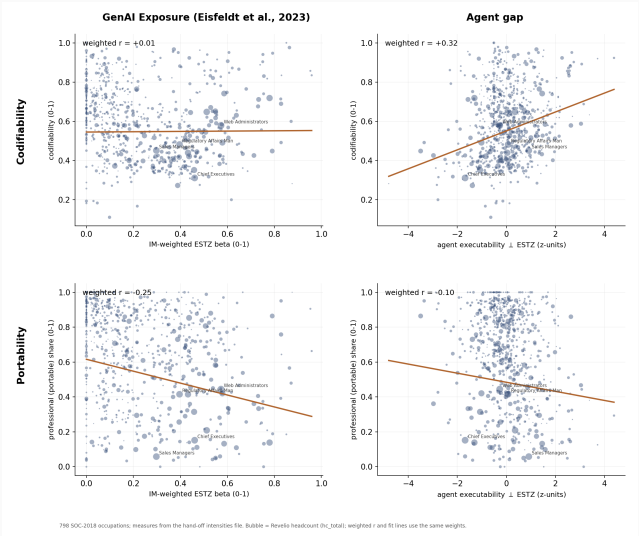


Appendix: customer capital builds-then-exploits within firm



The same firms tracked across their own size distribution (quarter-detrended): the customer-capital produce ratio declines monotonically from a firm's smallest to largest quarters, while the all-intangible ratio is flat.

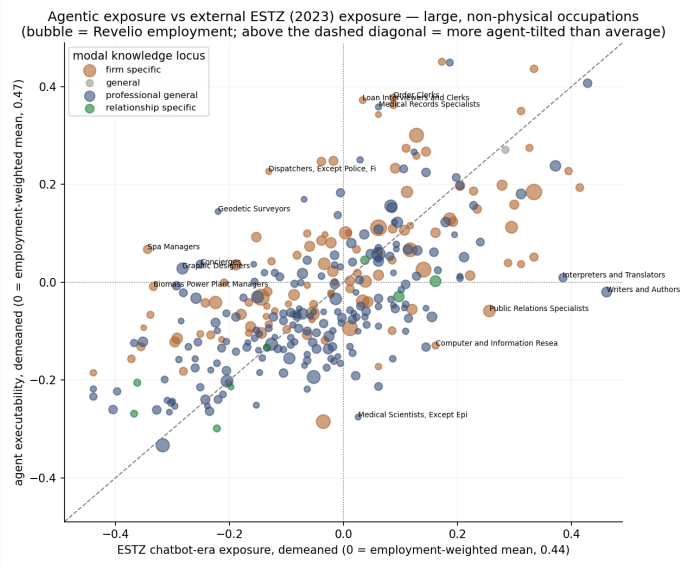
Codifiability predicts occupation Agentic AI exposure



798 SOC-2018 occupations; measures from the hand-off intensities file. Bubble = Revelio headcount (hc_total); weighted r and fit lines use the same weights.

▸ Firm version

The new margin: what agents can do vs. what chatbots can write



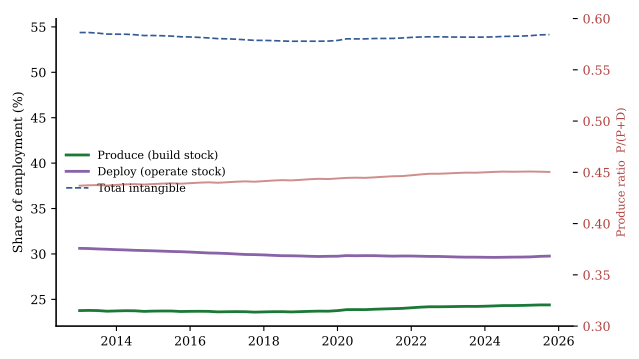
Intangibles versus firm characteristics

	Firm size and life cycle		Performance		Worker characteristics		
	Log Employee	Log Firm Age	Tobin's Q	ROA	Gini Seniority	Middle Mgmt Ratio	Worker Tenure
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel 1: ours — intangible wages / wage bill							
	-0.276***	-0.050***	0.587***	-0.062**	-0.027***	0.032***	-0.134**
	(0.060)	(0.018)	(0.226)	(0.028)	(0.003)	(0.002)	(0.064)
Panel 2: EP — 100% SG&A share of operating expense							
	-1.753***	-0.231***	2.674***	-0.440***	-0.009***	0.031***	-1.128***
	(0.042)	(0.020)	(0.195)	(0.029)	(0.002)	(0.002)	(0.070)
Fixed Effects				Ind × Year			
Obs	32,204	32,058	30,665	32,203	30,613	30,142	30,254

Each cell is a separate regression on one standardized index (Ind × Year FE; controls: log employment, log assets, except col. 1).

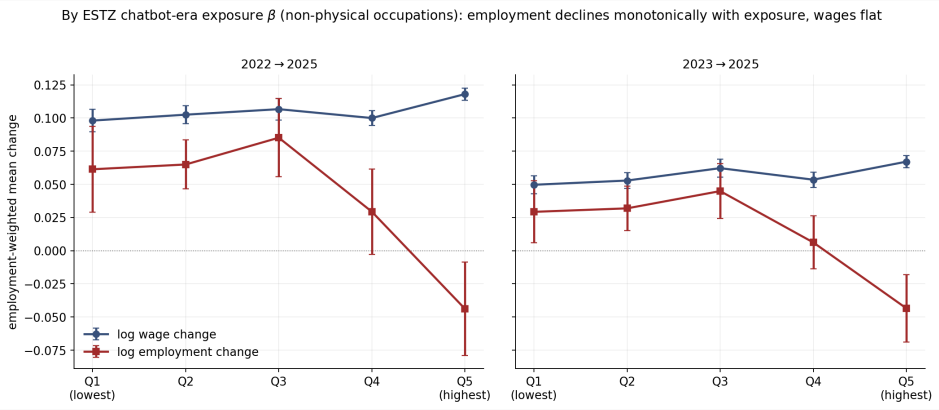
- Gini Seniority = Gini of Revelio's 7-level seniority ladder.
- Middle Mgmt Ratio = headcount share at seniority levels 4–5 (Manager, Director).

Over time: composition drifts, the build/operate balance does not

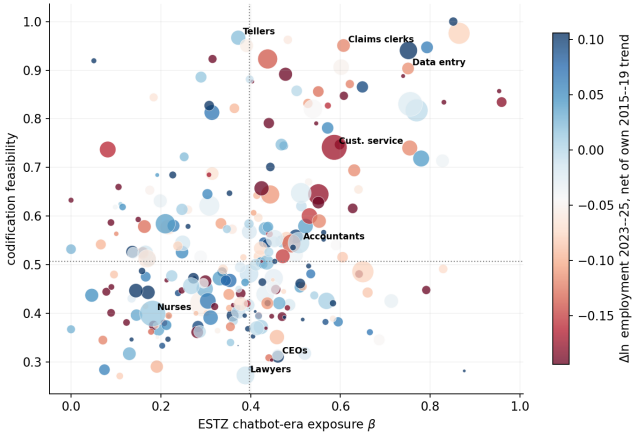


Across 2013–2025 the produce ratio is flat at ≈0.44 (0.437 → 0.450), even as software and data work rise. Because produce/deploy is a fixed within-occupation attribute, the aggregate balance moves only through occupation reallocation — and builders and operators scale together.

Same picture for raw chatbot-era exposure (ESTZ β)



Same map, net of each occupation's own pre-AI trend



Sample: 266 non-physical occupations (physical task share < 0.6) with 2015–19 OES data, matched to O*NET on 6-digit SOC. Bubble area ∝ 2022 OES employment. TREN
Sources: BLS OES national panel; ESTZ (2023) task exposure; codifiability from our task instrument (O*NET 27.2, Sonnet-5 labels).

Mapping the conceptual framework to predicted AI effects

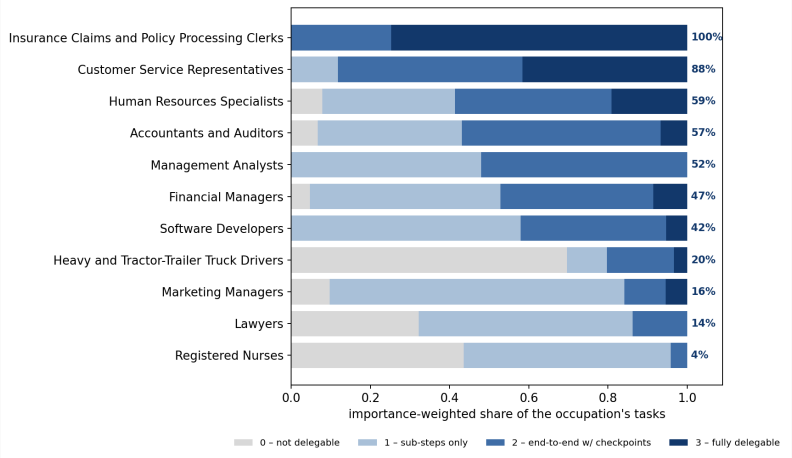
	Firm-specific / proprietary	Professional / portable
High codifiability & agent execution	**Internal capitalization.** Worker-embodied procedure becomes firm-controlled. Worker rents and routine employment fall; firm value positive or less negative.	**Commoditization.** Agents reproduce service or product. Incumbent asset value and exposed employment fall.
Tacit or hard-to-verify	Protected by judgment, relationships, system access, or trust. Smaller employment response.	Chatbot augmentation more likely than replacement until verification improves.

CAR Estimates: Chatbot, Agentic Gap, Codifiability, and interactions

Dep. var.: CAR[−1, +10], %; +controls, NAICS-2 FE

	ChatGPT			Claude Cowork		
	(1)	(2)	(3)	(4)	(5)	(6)
AgentGap	+0.72		+0.28	+1.11		+1.42
	(1.21)		(0.92)	(1.46)		(1.37)
GenAI Exposure		+1.63*	+1.61*		−1.91	−1.48
		(0.97)	(0.92)		(1.20)	(1.05)
Codifiability	−3.76**	−2.53***	−2.76**	+2.51	+2.96**	+1.57
	(1.82)	(0.68)	(1.19)	(1.79)	(1.50)	(1.81)
AgentGap × Cod	+0.59		−0.06	+3.09***		+2.91***
	(0.45)		(0.44)	(1.00)		(0.81)
GenAI Exposure × Cod		−0.84**	−0.88**		−1.20	+0.08
		(0.34)	(0.38)		(0.93)	(0.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
NAICS-2 FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.243	0.278	0.278	0.518	0.505	0.525
N	1,462	1,462	1,462	1,311	1,311	1,311

Agent executability varies intuitively across occupations



Note: illustrative set of 11 occupations spanning the agent executability range. Bars: importance-weighted share of each occupation's tasks at each agent-executability level (0–3); bold number = share of task weight at level 2+ (end-to-end delegable).

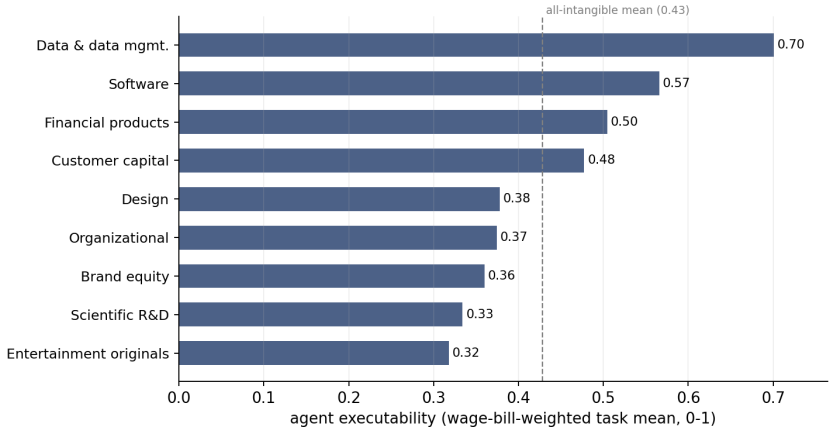
▸ Back to agent measurement

Occupations with high agent vs. chatbot exposure

	Positions (M)	Agentic Exp.	Chatbot Exp.	Gap
Dispatchers (Non-Emergency)	0.3	0.69	0.31	+0.38
Loan Interviewers and Clerks	0.4	0.84	0.47	+0.37
Medical Records Specialists	0.3	0.82	0.50	+0.32
Order Clerks	0.4	0.84	0.53	+0.32
New Accounts Clerks	1.0	0.71	0.40	+0.31
Insurance Claims Processing Clerks	0.5	0.92	0.61	+0.30
vs. Writers and Authors	1.8	0.45	0.90	−0.45
Interpreters and Translators	0.9	0.47	0.82	−0.35
Public Relations Specialists	3.5	0.41	0.69	−0.29

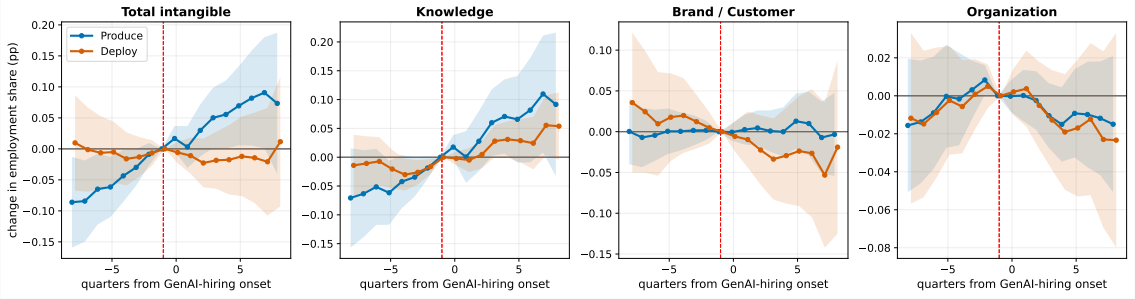
▸ Back to agent measurement

Agentic task exposure by intangible type



▸ Back to agent measurement

Intangible employment after AI adoption: produce vs. deploy employment



- Produce: headcount *building* intangible capital
- Deploy: headcount *operating* the existing stock.