Generative AI and Firm Values

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ChatGPT and Generative AI are rapidly changing the economy

ChatGPT is about to revolutionize the economy. We need to decide what that looks like.

AI to boost world economy by over 15 trillion dollars in seven years

Goldman Sachs: ChatGPT could see the loss of 300 million jobs worldwide

Tinkering With ChatGPT, Workers Wonder: Will This Take My Job?

Artificial intelligence is confronting white-collar professionals more directly than ever. It could make them more productive — or obsolete.

Enchanted by ChatGPT, Bill Gates calls AI 2nd revolutionary tech after GPU

AI "will be able to do everything that a human brain can, but without any practical limits on the size of its memory or the speed at which it operates," says Microsoft co-founder.

Yes, ChatGPT Is Coming for Your Office Job

White-collar workers may soon face the AI disruption everyone's been panicking about. But the news may be better than you think.

The Robots Have Finally Come for My Job

Could ChatGPT lay waste to millions of professional jobs, including journalists?

- McKinsey: *"Generative AI could add the equivalent of \$2.6 trillion to \$4.4 trillion annually...to the global economy"*

What are the consequences for firms and workers?

Potential GenAI benefits for firms

1. **Productivity improvements from incorporating AI (our focus)**
   - "General Purpose Technology" likely to affect *all* workers to *some* degree
   - Affects a **broad range of companies -** which ones?
   - To improve productivity, can either be a substitute for or complementary to labor

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2. Generative AI improvements can also create product demand

- Companies *making* or *supporting* AI advances benefit directly from booming demand
- For example, semiconductor manufacturers, cloud computing providers, big technology companies with AI products (e..g Nvidia, Microsoft) have seen high returns since ChatGPT release on Nov. 30, 2022.
- Affects a **smaller number of companies/industries**

Challenges

1. **Measuring jobs' exposure to technology shocks in real-time is difficult**
   - Speed of ChatGPT adoption allows us to study effect on financial market expectations in real time
   - We rely on ChatGPT and job "task" information to provide a real-time assessment of what the new technology can do
2. **Whether a technology substitutes or complements exposed jobs is unclear**
   - If some of your tasks can be replaced by Generative AI, is that good or bad for you?
   - We devise a new approach relying on whether an occupation's "core tasks" or "supplemental tasks" are replaceable by Generative AI
3. **Assessing GPT's impact on firm requires detailed firm-level occupational data**
   - Using LinkedIn data and O*Net job task data, we construct the first firm-level workforce exposure to Generative AI

Exposure to GenAI: Measurement

tasks $\rightarrow$ occupations $\rightarrow$ firms

Task Exposure to Generative AI Technology

- **Data:** Occupational Information Network (ONET): details 19,265 tasks for 923 occupations
- **Approach:** Score worker *tasks* for exposure to GenAI
- **Scoring:**
  - Submit rubric, two examples, and an occupation-task statement pair to Open AI's GPT 3.5 Turbo API $\Rightarrow$ returns a score and an explanation for the scoring (Eloundou et al., 2023)
    1. $X^T = 0$ No exposure
    2. $X^T = 1$ 50% time saving, equal quality is already feasible
    3. $X^T = 0.5$ 50% time saving equal quality requires overlays

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- **Firm Exposure** to Generative AI technology
  - **Data:** LinkedIn profiles from Revelio Labs $\Rightarrow$ firm employment by occupation
  - **Firm Gen. AI exposure:** computed for 5,907 Compustat firms in March 2022:

$$X^f = \sum_{O \in f} EmpShare_{f,O} * X^O$$

Examples: GPT Scoring of **Task Exposure** to Generative AI

Occupation	Task	Score	Explanation
Telemarketers	Adjust sales scripts to better target the needs and interests of specific individuals.	1	The model can learn from the sales scripts and the needs and interests of specific individuals to adjust the sales scripts.
Web Developers	Write supporting code for Web applications or Web sites.	1	The model can write code based on the specifications provided in the text input.
Paralegals and Legal Assistants	Investigate facts and law of cases and search pertinent sources, such as public records and internet sources, to determine causes of action and to prepare cases.	.5	The model can assist in searching pertinent sources and summarizing information, but it may not be able to retrieve up-to-date facts from the internet. Additional software could be developed on top of the LLM to retrieve up-to-date facts and combine them with the LLM capabilities.
Heating, Air Conditioning, and Refrigeration Mechanics and Installers	Connect heating or air conditioning equipment to fuel, water, or refrigerant source to form complete circuit.	0	The task requires physical interaction with equipment and materials, which cannot be done by the LLM.
Physician Assistants	Perform therapeutic procedures, such as injections, immunizations, suturing and wound care, and infection management.	0	The task requires physical interaction with patients, which cannot be done by the LLM.

Highest **Occupation Exposure** to Generative AI Technology

SOC Code	Occupation Title	Exposure Score
41-9041	Telemarketers	.96
43-9081	Proofreaders and copy markers	.95
43-3031	Bookkeeping, accounting, and auditing clerks	.87
15-2021	Mathematicians	.86
15-1251	Computer programmers	.85
43-9022	Word processors and typists	.85
43-3011	Bill and account collectors	.83
27-3091	Interpreters and translators	.82
43-9111	Statistical assistants	.82
15-1254	Web developers	.81
43-6011	Executive secretaries and executive administrative assistants	.77
43-3051	Payroll and timekeeping clerks	.77
43-6014	Secretaries and administrative assistants, except legal, medical, and executive	.77
43-5061	Production, planning, and expediting clerks	.76
15-1212	Information security analysts	.75
43-6013	Medical secretaries and administrative assistants	.75
27-3043	Writers and authors	.75
43-4021	Correspondence clerks	.74
43-9061	Office clerks, general	.74
41-3091	Sales representatives of services, except advertising, insurance, financial services, and travel	.73

Lowest **Occupation Exposure** to Generative AI Technology

SOC Code	Occupation Title	Exposure Score
39-5093	Shampooers	0
51-6041	Shoe and leather workers and repairers	0
51-6042	Shoe machine operators and tenders	0
51-3023	Slaughterers and meat packers	0
47-2022	Stonemasons	0
47-2221	Structural iron and steel workers	0
51-2041	Structural metal fabricators and fitters	0
29-9093	Surgical assistants	0
51-6052	Tailors, dressmakers, and custom sewers	0
47-2082	Tapers	0
49-9052	Telecommunications line installers and repairers	0
47-2053	Terrazzo workers and finishers	0
51-6064	Textile winding, twisting, and drawing out machine setters, operators, and tenders	0
47-2044	Tile and stone setters	0
51-9197	Tire builders	0
49-3093	Tire repairers and changers	0
51-4194	Tool grinders, filers, and sharpeners	0
39-3031	Ushers, lobby attendants, and ticket takers	0
49-9064	Watch and clock repairers	0
53-7073	Wellhead pumpers	0

17% (132 of 785) BLS occupations have zero exposure - subset shown.

Occupation Exposure to Generative AI Technology and Wages

...also higher exposure in **cognitive** than in **manual** skill jobs.

Firm Exposure to Generative AI technology

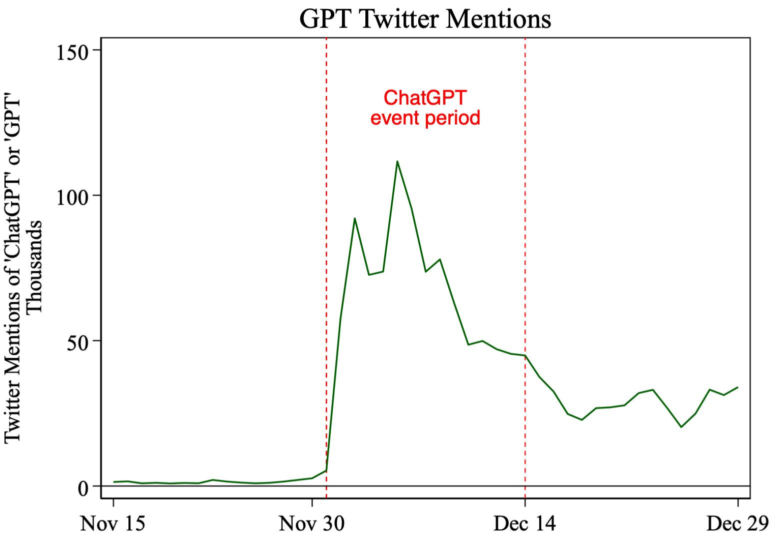
Panel A: Top 15 Large U.S. Companies with Highest Exposure to Generative AI			
Company Name	Gen. AI exposure	MktCap	Subsector
International Business Machines Corp	.488	128	Other Information Svcs
Intuit Inc.	.48	110	Publishing Industries (exc. Internet)
QUALCOMM Inc.	.479	123	Computer & Electronic Prod. Mfg.
Fiserv Inc.	.475	64	Data Processing, Hosting, & Related Svcs
NVIDIA Corporation	.468	360	Computer & Electronic Prod. Mfg.
S&P Global Inc	.452	108	Admin. & Support Svcs
Broadcom Inc	.449	234	Computer & Electronic Prod. Mfg.
Verizon Communications Inc	.444	165	Telecommunications
Microsoft Corp	.442	1790	Publishing Industries (exc. Internet)
3M Co	.442	66	Paper Mfg.
Advanced Micro Devices Inc	.441	104	Computer & Electronic Prod. Mfg.
ServiceNow Inc	.434	79	Publishing Industries (exc. Internet)
Adobe Inc	.427	155	Data Processing, Hosting, & Related Svcs
PayPal Holdings Inc	.418	81	Data Processing, Hosting, & Related Svcs
Thermo Fisher Scientific Inc	.411	215	Computer & Electronic Prod. Mfg.

Firm Exposure to Generative AI technology

Panel B: Bottom 15 Large U.S. Companies with Lowest Exposure to Generative AI			
Company Name	Gen. AI exposure	MktCap	Subsector
Starbucks Corp	.119	114	Food Svcs & Drinking Places
McDonald's Corp	.194	193	Food Svcs & Drinking Places
Target Corp	.235	69	General Merchandise Stores
Walmart Inc	.235	382	General Merchandise Stores
Lowe's Cos Inc	.238	120	Build. Mat., Gard. Equip., Supplies Dealers
TJX Companies Inc (The)	.243	92	Clothing & Clothing Accessories Stores
Costco Wholesale Corp	.252	202	General Merchandise Stores
Union Pacific Corp	.253	127	Rail Transp.
CSX Corp	.256	64	Rail Transp.
United Parcel Service Inc	.256	149	Couriers & Messengers
Home Depot Inc. (The)	.261	321	Build. Mat., Gard. Equip., Supplies Dealers
Norfolk Southern Corp	.272	56	Rail Transp.
Tesla Inc	.283	390	Transp. Equipment Mfg.
Northrop Grumman Corp	.291	84	Computer & Electronic Prod. Mfg.
Mondelez International Inc	.292	91	Food Mfg.

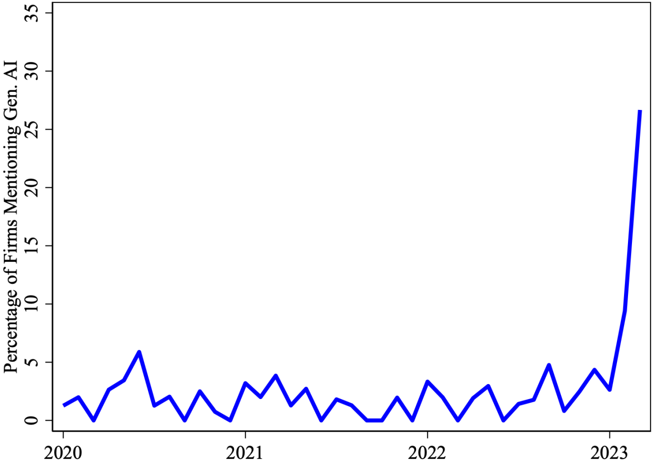
Impact on **Firm Values** from **Firm Exposure** to Generative AI

Public attention to Generative AI spiked after ChatGPT release



Firms communicate with investors about Gen. AI in earnings calls

- Manually collected panel of earnings conference call transcripts for S&P 500 firms
- Count monthly mentions of:: “llm”, “chatgpt”, “gpt”, “generative”, “language model”



Only non-tech | ML mentions | Avg. mentions per call

More exposed firms communicate *more* about Gen. AI

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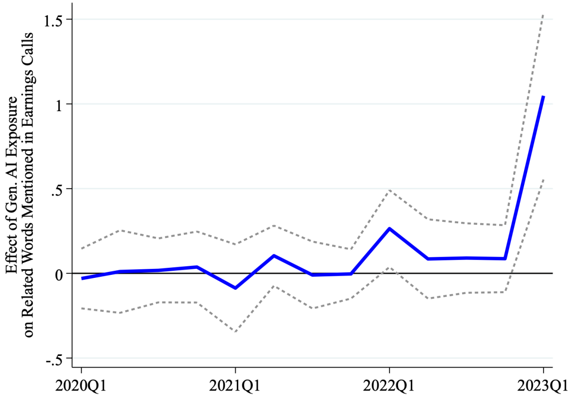
- Count monthly mentions of:: "llm", "chatgpt", "gpt", "generative", "language model"

$$\mathbb{1}[\text{Mentions Gen. AI}]_{it} = \alpha_t + \beta_t \text{Gen AIExposure}_i + \gamma \mathbb{1}[\text{Mentions Gen. AI}]_{i,2019} + \varepsilon_{i,t}$$

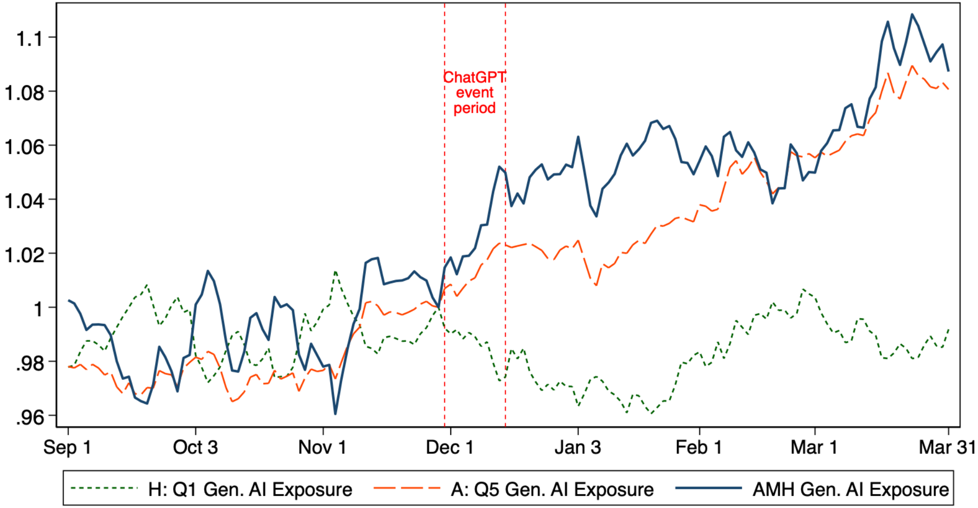


1 SD Δ in firm exposure $\Rightarrow$ 6.7ppt increase in likelihood of mentioning Gen. AI in Q1 2023

Stock Portfolio Returns and Generative AI Exposure

- Sort stocks by Gen. AI exposure quintiles
- Form long-short portfolio that **compares stock returns of high vs. low exposure firms**
- Q5 (Artificial) - Q1 (Human) = AMH
- **AMH returned 0.4% daily during 2 weeks after ChatGPT release**
- Overall market return was *negative* over these 2 weeks
- Differences in returns are insignificant during rest of sample

AMH Portfolio Returns Over Time



Robustness

- Event period portfolio returns are robust to...
  - FF5 exposure: 0.35% daily AMH returns
  - excl. tech sector: 0.38% daily AMH returns
  - sorting *within* industries: 0.30% (NAICS 3D) and 0.23% (FIC) daily AMH returns

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- Control for **product market exposure** by analyzing variation in cumulative abnormal returns across firms

$$\text{CAR}_i = \beta \times \text{GenAI Exp}_i + \gamma \times \text{Product Exposure}_i + \textit{IndFEs} + \varepsilon_i \qquad (1)$$

4 different measures of product market exposure:

1. 10K-based measure of AI product impact: enabling or scaling AI technologies, or direct product functionality
2. 10K mentions of “data”
3. Goldman Sachs list of “near term beneficiaries of AI”
4. AI skill share from Babina, Fedyk, He, Hodson (2024)

Product Market Exposure does not explain release period CARs

1 SD Δ in firm Gen. AI exposure $\Rightarrow$ 1.4-2.2 pp higher cumulative abnormal returns

Dep. var.:	CAR[-1,10]					
	(1)	(2)	(3)	(4)	(5)	(6)
GenAI Exp	**0.288*** **	**0.291*** **	**0.187** **	**0.264*** **	**0.200** **	**0.175** **
	(2.770)	(2.835)	(2.246)	(3.074)	(2.223)	(2.029)
GPT10K Product Exp		0.011				-0.016
		(0.614)				(-0.845)
Count10K Product Exp			0.002***			0.002
			(5.521)			(1.608)
GS Product Exp				0.041**		0.013
				(2.293)		(0.437)
BFHH Product Exp					1.251***	0.081
					(5.012)	(0.164)
R^2	0.36	0.37	0.40	0.38	0.38	0.40
Observations	2,080	1,905	1,905	2,080	1,493	1,374
NAICS3 FE	X	X	X	X	X	X

Is Data a Complement to Generative AI?

Agrawal, Gans & Goldfarb (2019): "***Machine learning****...[represents]...one particular aspect of intelligence: prediction...[which] also* ***requires collection and organization of data****.*"

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Many Generative AI applications require proprietary **data and data management** capabilities:

- **Fine-tuning** and customization of LLMs requires large firm-specific training data sets
- **Process automation** requires data pipeline to/from LLM
- **Task-specific prompting** is improved by data on desired outputs (e.g. past customer interactions)
- LLM **analytical capabilities** enable extraction of new data from existing data, decision support and creative output generation based on input data

Measuring firm data access & capabilities

2 methods of measurement for a firm's "data assets":

1. ***10K Data Assets***: Assesses (using GPT model) if firm's business description suggests **access to data** relevant for Generative AI analytics.
   - First, assess mentions of 6 topics in recent annual report:
     - a General nature of the company's business
     - b Scale and reach of the firm
     - c Data collection mechanisms
     - d Data utilization
     - e Data infrastructure & management
     - f Data regulation and privacy
   - Then, assign **overall score** for data assets: 0 = none, 1 = little, 2 = moderate, 3 = high

2. ***Abis & Veldkamp Data Assets***: share of roles that tend to require high level of **"data management skills"** in a firm's employment structure $\Rightarrow$ data managers as a proxy for valuable data to be managed (Abis & Veldkamp, 2023)

More data access increases firm value impact of Generative AI

$$\text{CAR}_i = \beta \text{GenAI Exp}_i + \gamma \text{GenAI Exp}_i \times \textbf{Data}_i + \psi \textit{Data}_i + \textit{IndFEs} + \varepsilon_i$$

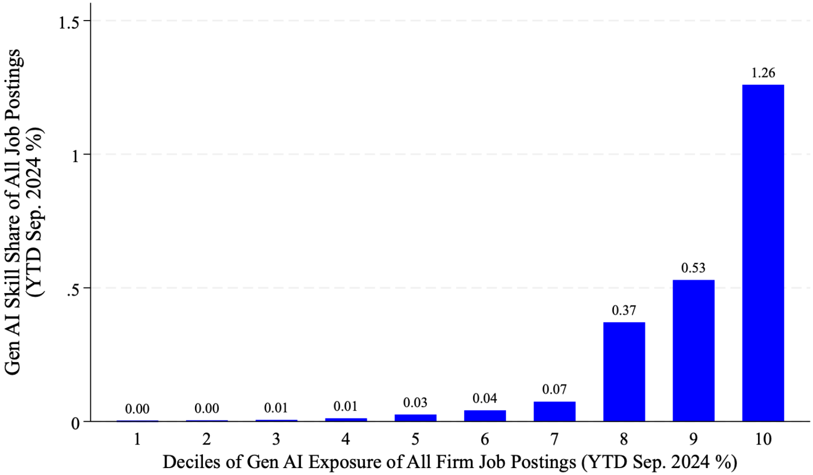
Dep. var.:	CAR[-1,10]	
	(1)	(2)
GenAI Exp	-0.035	-0.085
	(-0.403)	(-0.992)
GenAI Exp $\times$ ***10K Data Assets***	**0.216****	
	(2.144)	
GenAI Exp $\times$ ***AV Data Assets***		**12.122****
		(2.339)
10K Data Assets	-0.073*	
	(-1.816)	
AV Data Assets		-3.815
		(-1.644)
R^2	0.11	0.12
Observations	1,910	2,043
NAICS3 FE	X	X

Mechanism:

labor $\rightarrow$ cashflows $\rightarrow$ value

Gen. AI exposure strongly predicts actual adoption

Schubert (2025): *"Organizational Technology Ladders: Remote Work and Generative AI Adoption"*



Labor Impact: Substitute or complement to workers?

Important to distinguish between Gen. AI **substituting or complementing** workers

- **Substitute:** can use Gen. AI *instead* of worker $\Rightarrow$ **lower** labor demand and wages
- **Complement:** Gen. AI used *by* the worker increases productivity $\Rightarrow$ **higher** labor demand and wages

We **distinguish impact** by which tasks in an occupation Gen.

Task Replacement $\neq$ Job Replacement

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- **Core task exposure:** high potential for replacement by Gen. AI and become obsolete $\Rightarrow$ *substitute?*
- **Supplemental task exposure:** worker becomes more effective in performing key occupational functions $\Rightarrow$ *complement?*

Core vs. supplemental task distinction based on O*NET classification - compute *share of exposure from supplemental tasks*:

$$ShareSupp^{O} = \frac{\sum_{T \in (O|Supplemental)} X^{T}}{\sum_{T \in O} X^{T}}. \tag{2}$$

Core-exposed firms reduce hiring for exposed roles

Test for change in job postings and LinkedIn employment after ChatGPT:

$$Y_{firm,t} = \beta_1 \text{Post-ChatGPT}_t \times \text{GenAI Exp}_{firm} + \beta_2 \text{Post-ChatGPT}_t \times \text{GenAI Exp}_{firm} \times \text{ShareSupp}^f + \text{FEs} + \varepsilon_{firm,t},$$

Dep var.:	High-Exposure Job Postings		High-Exposure Employment	
	(1)	(2)	(3)	(4)
Post × GenAI Exp	-1.378***	-3.038***	-0.083*	-0.414***
	(-3.747)	(-2.991)	(-1.810)	(-3.169)
Post × ShareSupp		-2.302**		-0.665***
		(-2.029)		(-3.074)
Post × GenAI Exp × ShareSupp		8.100**		1.500**
		(2.037)		(2.356)
Observations	36,900	36,880	31,644	31,644
	Addl. controls & fixed effects			
Month FE	X	X	X	X
Firm FE	X	X	X	X

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Exposed firms reduce employment - more so if driven by core task exposure

Cash flow channel for firm value effects

For each firm in each month, we estimate changes before/after ChatGPT release in

- Median monthly analyst forecasts of the firm's EPS in the fiscal year ending in December 2023
- Median monthly analyst forecasts of the firm's long-term annual percentage growth rate in EPS
- Quarterly gross profitability using Compustat quarterly data from Q1 2022 to Q3 2024

Data:	I/B/E/S Analyst Forecasts		Compustat
Measure:	EPS	LTG	Gross Profit
	(1)	(2)	(3)
Post$\times$ GenAI Exp	1.463**	12.770*	1.711**
	(2.113)	(1.675)	(2.213)
Observations	11,671	4,125	22,275
		Addl. controls & fixed effects	
Time FEs	X	X	X
Firm FEs	X	X	X

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Time FEs	X	X	X
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GenAI Exposed firms see increased forecast and realized profits

Cash flow effects stronger for core task Gen. AI exposure

Data:	I/B/E/S Analyst Forecasts		Compustat
Measure:	EPS	LTG	Gross Profit
	(1)	(2)	(3)
Post $\times$ GenAI Exp	2.563**	21.077**	6.087***
	(2.431)	(1.967)	(3.369)
Post $\times$ ShareSupp	1.599**	9.121	6.786**
	(2.487)	(0.754)	(2.434)
Post $\times$ GenAI Exp $\times$ ShareSupp	-4.892*	-87.229**	-24.678***
	(-1.795)	(-2.055)	(-3.193)
Observations	11,664	4,125	22,267
		Addl. controls & fixed effects	
Time FEs	X	X	X
Firm FEs	X	X	X

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Time FEs	X	X	X
Firm FEs	X	X	X

GenAI Exposed firms see increased forecast and realized profits —More so for core-task-exposed firms

ChatGPT release returns higher for core task Gen. AI exposure

$$\text{CAR}_{firm} = \beta_1 \text{GenAI Exp}_{firm} + \beta_2 \text{GenAI Exp}_{firm} \times \text{ShareSupp}^f + \varepsilon_{firm},$$

Dep. var.:	CAR[-1,10]	
	(1)	(2)
GenAI Exp	0.216***	**0.380*** **
	(2.621)	**(2.579)**
ShareSupp		0.272
		(1.447)
GenAI Exp $\times$ ShareSupp		**-1.937*** **
		(-3.226)
Observations	2,085	2,084

Firms with Gen. AI exposure only from **Core tasks have higher release period returns** than firms with **greater share of exposure from supplemental tasks**.

Summary

- Large technological shock with immediate **positive impact on value of exposed firms**
  - Labor channel Gen. AI exposure predicts higher returns
  - Firms with more exposure reduce hiring for exposed jobs, and increase profitability
  - Firm hiring & profitability effects - and value gains - are greater if exposure is driven by employees' core tasks
- Importance of **data assets** for realizing value of Gen. AI leads to heterogeneity - greater firm value gains for data-savvy firms
- Short-run impact on exposed workers is negative on average (fewer jobs, lower wages), but...
  - Depends on *which* tasks are exposed to Generative AI: **core vs. supplemental**
- Important policy implications: **winners *and* losers** from the technology both among firms and workers

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Thank you for listening!

Appendix

Early studies show large potential for productivity improvements through Gen. AI

Large effects of incorporating AI language models into white-collar work:

- *Jia et al. (2023)*: sales agents with upfront AI lead generation and phone screening are more likely to learn to solve unusual problems, and double their conversion rate
- *Noy & Zhang (2023)*: writing press releases, short reports, analysis plans, and delicate emails with ChatGPT decreases time taken by 0.8 SDs and increases output quality by 0.4 SDs
- *Peng et al. (2023)*: AI pair programmer (GitHub Copilot) makes software developers 56% faster
- **General pattern: greater improvement for less-skilled workers**

Methodology note: rubrics constrain the LLM

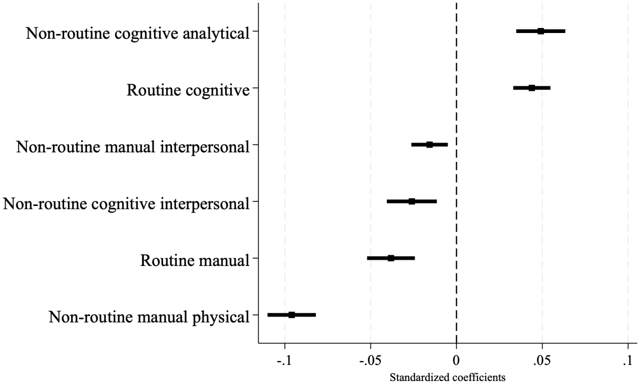
What happens when we ask an LLM to "return a score"?

- Important clarification: this is **not** "asking the LLM about its capabilities". No special LLM wisdom is required!
- We provide detailed **rubrics** and the LLM just maps a statement into the **pre-defined** matrix of capabilities
  - e.g. *E1 - Direct exposure*
    - *Rubric: Label tasks E1 if direct access to the LLM through an interface like ChatGPT or the OpenAI playground alone can reduce the time it takes to complete the task with equivalent quality by at least half. This includes tasks that can be reduced to: - Writing and transforming text and code according to complex instructions, - Providing edits to existing text or code following specifications, - Writing code that can help perform a task that used to be done by hand, - Translating text between languages, - Summarizing medium-length documents, - Providing feedback on documents, - Answering questions about a document, - Generating questions a user might want to ask about a document, - Writing questions for an interview or assessment, - Writing and responding to emails, including ones that involve refuting information or engaging in a negotiation (but only if the negotiation is via written correspondence), - Maintain records of written data, - Prepare training materials based on general knowledge, or - Inform anyone of any information via any written or spoken medium.*
- **Efficiency gain:** counterfactual to LLM-based scoring is using human RAs - LLM affects speed (2 days) and cost ($78), not capabilities

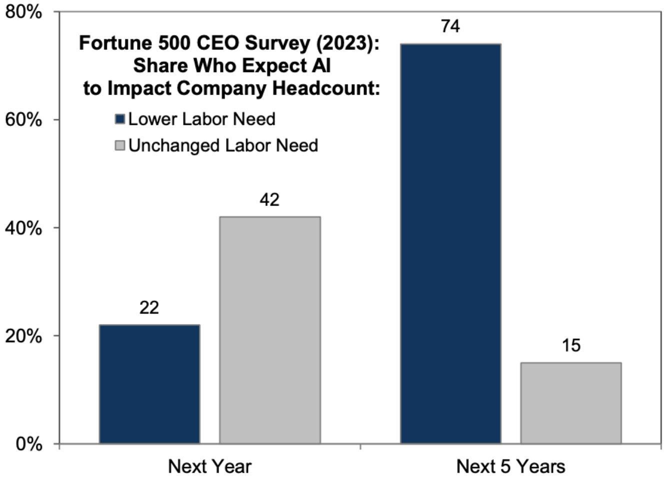
Occupation Exposure to Gen. AI Differs from Previous Automation

Acemoglu & Autor (2011) occupational skill scores and Generative AI exposure:

$$A_o^{\text{GenAI}} = \alpha + \sum_S \beta_S \text{Skill}_o + \varepsilon_o$$



CEOs quickly realized that Generative AI will affect labor needs



Source: Fortune, Goldman Sachs Global Investment Research

Example: Core task exposure in finance occupations