Remote Work and AI:
Exposed, but not complementary?
Evidence from the USA

Guillermo Gallacher*

June 15, 2024

Abstract

In this preliminary paper I find that the potential for remote work and exposure to AI are positively correlated. I also show that, given the exposure to AI, remote jobs tend to be relatively less complementarity to AI. I use detailed occupation data for the USA and compare aggregations across (a) major occupations, (b) industries, (c) states, (d) cities and (e) demographic characteristics. I provide preliminary results and discuss next steps.

*Preliminary draft. Comments welcome. Email: guillermogallacher@gmail.com. Web: https://guillgall.github.io

1 Preliminary introduction

The increasing adoption of Remote Work (RW henceforth) and Artificial Intelligence (AI henceforth) technologies is transforming the modern workplace. Remote work arrangements allow for greater flexibility and access to a broader pool of talent, while AI tools can assist with a variety of tasks. This raises the question: are remote jobs complementary to AI? In other words, do the skills and tasks that make a job suitable for remote work also make it more likely to be enhanced rather than replaced by AI? Answering this question is crucial for understanding the future of work in post COVID-19 economies increasingly shaped by AI.

Using data for the USA, I find that the potential for RW and exposure to AI are positively correlated across (a) occupations, (b) industries, (c) states, (d) cities and (e) demographic characteristics. However, I also show that, conditional on AI exposure, the potential for RW is inversely related to complementarity. This suggests that while many jobs that can be done remotely are also more likely to be impacted by AI, the tasks and skills that make a job suitable for RW do not necessarily overlap with those that make a job complementary to AI systems. This finding has important implications for understanding the future of work in an increasingly digital and AI-driven economy.

On one hand, the strong correlation between RW potential and AI exposure indicates that jobs which can be performed from anywhere are also more susceptible to automation or augmentation by AI. This makes intuitive sense, as jobs that rely heavily on digital tools and interfaces, information processing, and knowledge work are often both location-independent and AI-relevant.

On the other hand, the negative relationship between RW and AI complementarity hints at a more nuanced picture. Just because a job can be done remotely does not mean the core tasks are ones in which humans and AI are mutually enhancing. For example, many customer service roles can be done remotely but may be more likely to be fully automated than symbiotically combined with AI. Conversely, some jobs that are less amenable to RW, such as those requiring physical manipulation or in-person interaction, may nonetheless involve tasks in which human and machine intelligence are strongly complementary. An example might be a surgeon using AI-powered diagnostic and surgical planning tools.

TBC

1.1 Contribution to the literature:

- AI metrics: Felten et al. (2021), Felten et al. (2023), Pizzinelli et al. (2023), Eloundou et al. (2023)
- RW: Dingel and Neiman (2020), Hansen et al. (2023)
- AI and RW: Baldwin and Okubo (2024) is a first attempt to empirically investigate whether AI and RW are complements or substitutes. They provide preliminary evidence that suggests that AI and RW are complements rather than substitutes. In this paper I find the opposite. Note that Baldwin and Okubo (2024) focus on the COVID-19 period, and use automation estimates that rely on routine/non-routine differences, so it is pre Gen-AI. Thus, the studies are not directly comparable.
- AI and productivity: Brynjolfsson et al. (2023), Noy and Zhang (2023), Acemoglu (2024)
- RW and productivity: Bloom et al. (2015)

TBC

2 Data

2.1 Data Sources

The RW metric from Dingel and Neiman (2020) classifies occupations based on whether they can be done entirely from home or not. It uses O*NET data on work context and work activities to determine if an occupation requires on-site work. Occupations are scored as either 0 or 1 based on whether they can be fully done remotely.

The AI Occupation Exposure (AIOE) metric is from Felten et al. (2021, 2023). AIOE measures each occupation's potential exposure to AI technologies. It links AI applications to O*NET abilities and aggregates the AI exposure across all abilities used in an occupation. Occupations are given a continuous score reflecting their relative exposure to AI. The AIOE metric is a measure of exposure to AI but is agnostic as to the complementarity or substitutability of AI.

The complementarity metric from Pizzinelli et al. (2023) arises from the agnosticism of the AIOE: Pizzinelli et al. (2023) extend the AIOE measure to introduce complementary. They have two main, interrelated metrics: θ (which is a measure of complementarity) and C-AIOE (which is inversely related to θ and hence is a measure of substitutability).[1]

I also use data from Bureau of Labor Statistics (BLS), in particular the Occupational Employment and Wage Statistics databases. I use 2023 data for the main analysis, and data of previous years for the dynamic analysis.

2.2 Plots

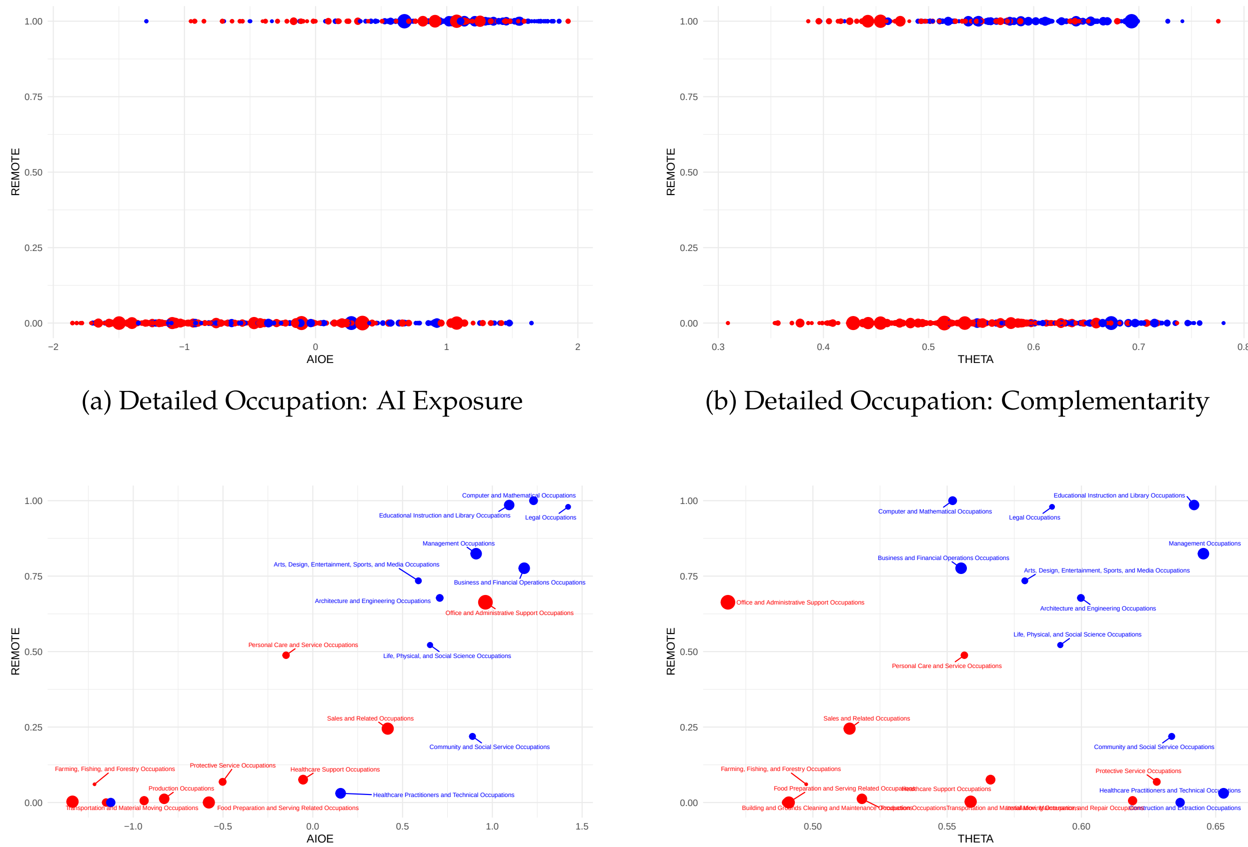
Figure (1a) illustrate the the relationship between RW potential and AI exposure across BLS detailed occupations, while (1c) aggregates this data into major occupations. In all cases there is a positive association between RW potential and AI exposure.

The seemingly lack of relationship between RW and AI complementarity (Figures (1b) and (1b)) hints at a more nuanced picture: RW might not be complementary to AI.

A similar pattern occurs across industries, states and cities (Figures (2) and (3) as well as demographics (Figure (4)).

TBC

[1] I thank Carlo Pizzinelli and co-authors for sharing their estimates with me.



(a) Detailed Occupation: AI Exposure

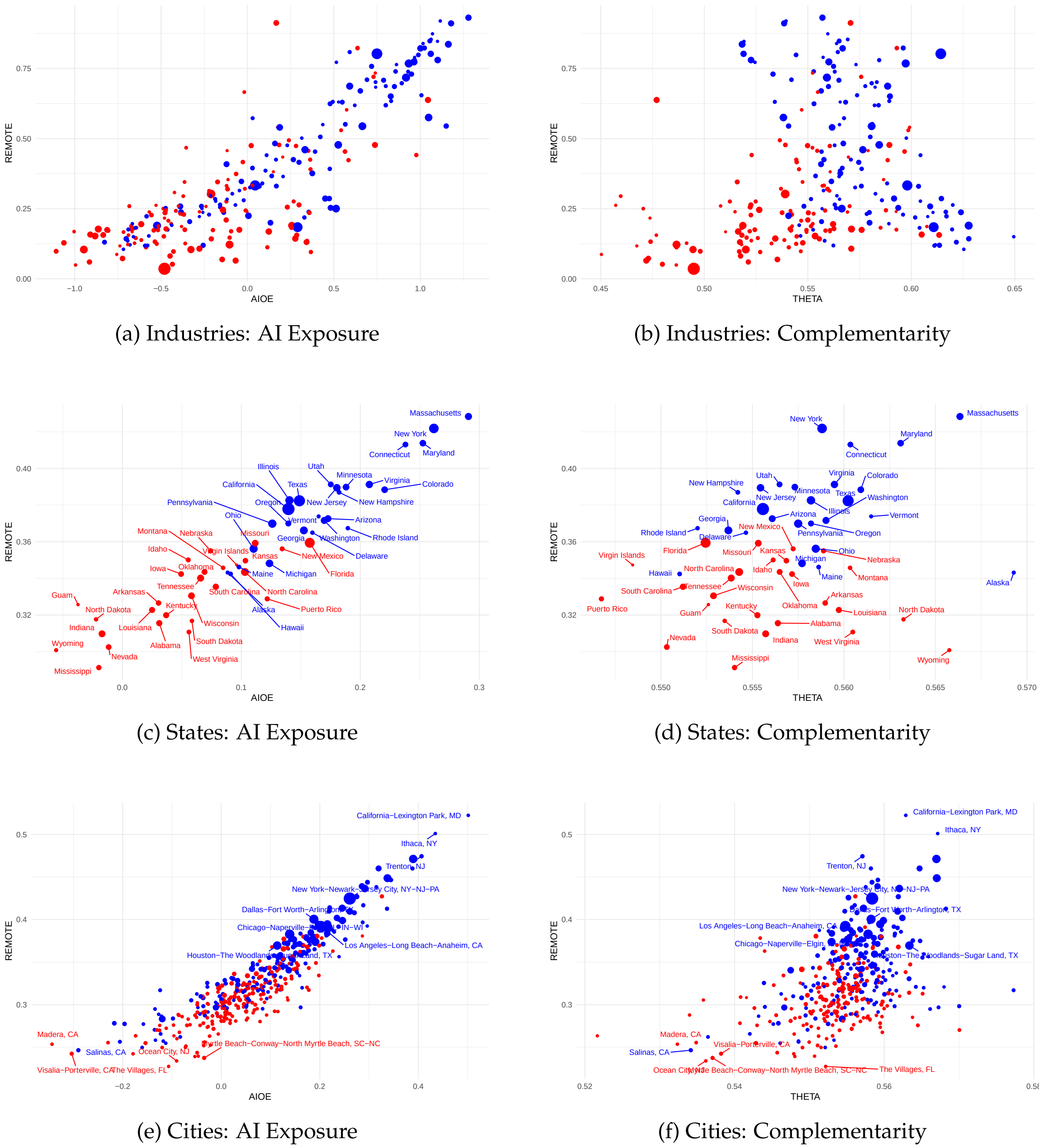
(b) Detailed Occupation: Complementarity

(c) Major Occupation: AI Exposure

(d) Major Occupation: Complementarity

Figure 1: RW and AI Exposure Across Different Dimensions

Note: in red are observation below median income, and in blue those above median income. Size represents employment.
Source: Employment and wage data from BLS. RW estimates from Dingel and Neiman (2020) and AI exposure from Felten et al. (2023) and AI complementarity from Pizzinelli et al. (2023). District of Columbia excluded in the States plot.



(a) Industries: AI Exposure

(b) Industries: Complementarity

(c) States: AI Exposure

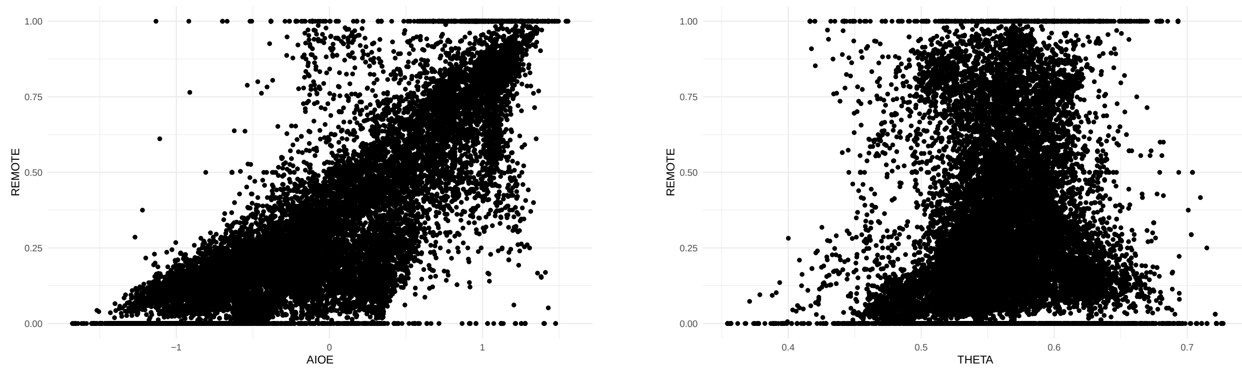
(d) States: Complementarity

(e) Cities: AI Exposure

(f) Cities: Complementarity

Figure 2: RW and AI Exposure Across Different Dimensions

Note: in red are observation below median income, and in blue those above median income. Size represents employment.
Source: Employment and wage data from BLS. RW estimates from Dingel and Neiman (2020) and AI exposure from Felten et al. (2023). District of Columbia excluded in the States plot.



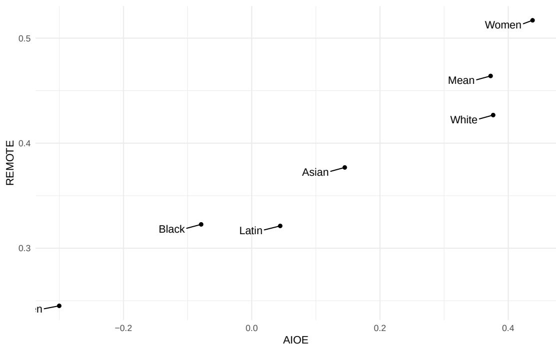
(a) AI Exposure

(b) Complementarity

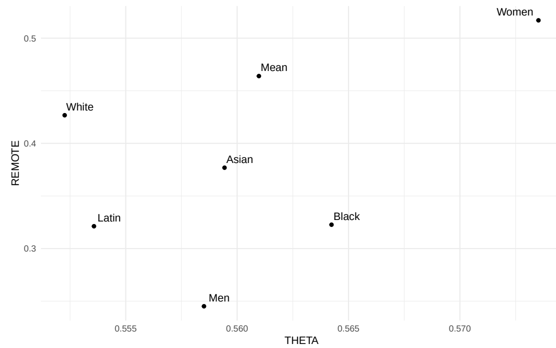
Figure 3: RW and AI: Industries and States ($n = 17606$)

Source: Employment and wage data from BLS. RW estimates from Dingel and Neiman (2020) and AI exposure from Felten et al. (2023) and AI complementarity from Pizzinelli et al. (2023).

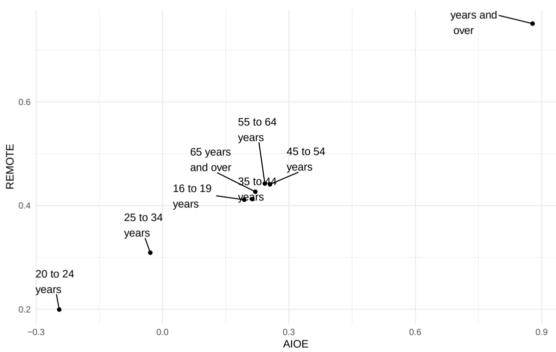
Figure 4: Demographic Characteristics



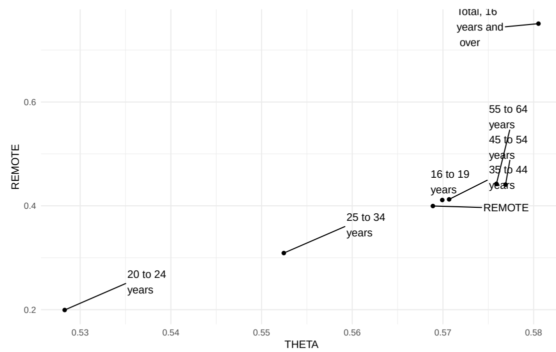
(a) Demographics AI Exposure



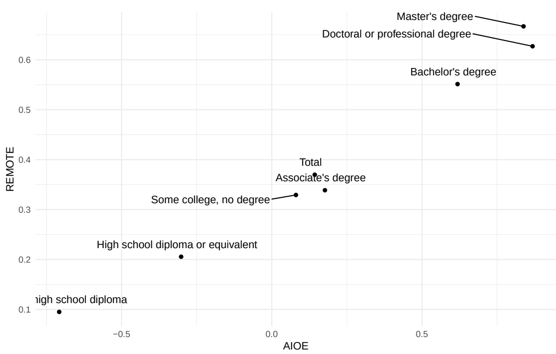
(b) Demographics AI Complementarity



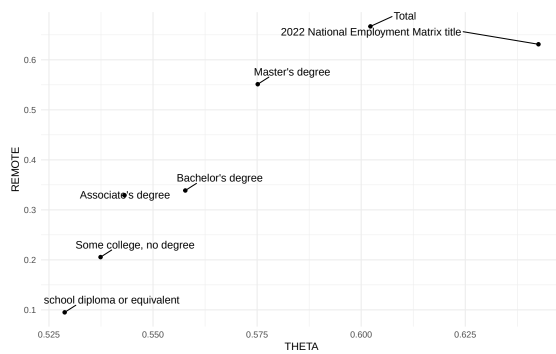
(c) Age AI Exposure



(d) Age AI Complementarity



(e) Education AI Exposure



(f) Education AI Complementarity

Source: Author's calculations

3 Preliminary Regression Analysis

Table 1: Logistic Regression. Remote Work and AI: Across Occupations

	Dependent variable:				
	RW				
	(1)	(2)	(3)	(4)	(5)
AIOE	2.11***		2.16***	2.05***	1.98***
	(0.16)		(0.16)	(0.16)	(0.17)
Theta		0.64	−3.82**	−6.21***	−8.32***
		(1.01)	(1.53)	(1.77)	(1.93)
Annual Income				0.0000***	
				(0.0000)	
Hourly Income					0.02**
					(0.01)
Constant	−1.14***	−0.97*	1.06	1.75*	2.77***
	(0.13)	(0.58)	(0.88)	(0.91)	(0.96)
Observations	646	646	646	643	597
Log Likelihood	−243.43	−419.21	−240.21	−235.50	−216.43
Akaike Inf. Crit.	490.87	842.42	486.42	479.00	440.85
Note:					*p<0.1; **p<0.05; ***p<0.01

Table (1) (Occupations): The logistic regression results show that across detailed occupations, AI exposure (AIOE) has a significant positive association with the potential for remote work, while AI complementarity (Theta) has a significant negative association (when controlling for income). This suggests that occupations more exposed to AI are more likely to be remote-capable, but among those occupations, the ones with higher AI complementarity are less likely to be remote-capable.

Table 2: Remote Work and AI: Across Major Occupations

	Dependent variable:				
	RW				
	(1)	(2)	(3)	(4)	(5)
AIOE	0.36***		0.37***	0.30***	0.32***
	(0.05)		(0.05)	(0.06)	(0.06)
Theta		1.03	−0.32	−1.01	−0.82
		(1.48)	(0.78)	(0.86)	(0.86)
Annual Income				0.0000	
				(0.0000)	
Hourly Income					0.01
					(0.004)
Constant	0.34***	−0.21	0.53	0.69	0.64
	(0.04)	(0.85)	(0.45)	(0.44)	(0.45)
Observations	22	22	22	22	22
R^2	0.75	0.02	0.75	0.79	0.78
Adjusted R^2	0.74	−0.03	0.73	0.75	0.74
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table (2) (Major Occupations): Across major occupations, AI exposure remains positively associated with remote work potential, but the relationship is weaker than for detailed occupations. The association between AI complementarity and remote work is not statistically significant, possibly due to the small sample size (22 observations).

Table 3: Remote Work and AI: Across Industries

	Dependent variable:				
	RW				
	(1)	(2)	(3)	(4)	(5)
AIOE	0.34***		0.34***	0.30***	0.30***
	(0.01)		(0.01)	(0.02)	(0.02)
Theta		1.13***	0.49**	−0.04	0.004
		(0.41)	(0.22)	(0.24)	(0.24)
Annual Income				0.0000***	
				(0.0000)	
Hourly Income					0.004***
					(0.001)
Constant	0.35***	−0.27	0.08	0.24**	0.22*
	(0.01)	(0.23)	(0.12)	(0.12)	(0.12)
Observations	247	247	247	247	247
R^2	0.72	0.03	0.73	0.75	0.75
Adjusted R^2	0.72	0.03	0.73	0.75	0.75
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table (3) (Industries): Across industries, AI exposure is positively associated with RW potential, while AI complementarity shows a positive association that becomes insignificant when controlling for AI exposure and income. This suggests that industries with higher AI exposure tend to have more remote-capable jobs, but the link between AI complementarity and RW is less clear at the industry level.

Table 4: Remote Work and AI: Across Industries and States

	Dependent variable:							
	RW							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AIOE	0.32***		0.32***	0.29***	0.28***	0.32***	0.29***	0.28***
	(0.002)		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Theta		0.75***	0.43***	−0.003	−0.06*	0.42***	−0.04	−0.10***
		(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Annual Income				0.0000***			0.0000***	
				(0.0000)			(0.0000)	
Hourly Income					0.005***			0.01***
					(0.0002)			(0.0002)
Constant	0.34***	−0.07***	0.10***	0.23***	0.23***	0.10***	0.25***	0.25***
	(0.001)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
State FE?	No	No	No	No	No	Yes	Yes	Yes
Observations	17,603	17,603	17,603	14,144	13,138	17,603	14,144	13,138
R^2	0.60	0.02	0.61	0.60	0.60	0.61	0.61	0.61
Adjusted R^2	0.60	0.02	0.61	0.60	0.60	0.61	0.61	0.61
Note:						*p<0.1; **p<0.05; ***p<0.01		

Table (4) (Industries and States): When looking at the interaction of industries and states, the positive association between AI exposure and RW persists, while the association with AI complementarity is mixed, becoming negative when state fixed effects and income controls are included (Column 8). This indicates that within states, industries with higher AI exposure tend to have more remote-capable jobs, but those with higher AI complementarity may have fewer, all else equal.

Table 5: Remote Work and AI: Across Cities

	Dependent variable:				
	RW				
	(1)	(2)	(3)	(4)	(5)
AIOE	0.36***		0.34***	0.31***	0.31***
	(0.01)		(0.01)	(0.01)	(0.01)
Theta		3.52***	0.78***	0.06	0.07
		(0.35)	(0.18)	(0.16)	(0.17)
Annual Income				0.0000***	
				(0.0000)	
Hourly Income					0.003***
					(0.0002)
Constant	0.30***	−1.63***	−0.13	0.19**	0.19**
	(0.001)	(0.19)	(0.10)	(0.09)	(0.09)
Observations	396	396	396	396	396
R^2	0.81	0.21	0.82	0.87	0.87
Adjusted R^2	0.81	0.21	0.82	0.87	0.87
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table (5) (Cities): Across cities, AI exposure is positively associated with RW potential, while the positive association with AI complementarity becomes insignificant when controlling for AI exposure and income. This suggests that cities with jobs more exposed to AI tend to have higher RW potential, but the relationship with AI complementarity is less clear at the city level.

3.1 Preliminary Regression Results Summary

Based on the regression analysis across occupations, industries, states, and cities, the main conclusion is that there is a robust positive association between AI exposure and the potential for RW. In other words, jobs and industries that are more likely to be impacted by AI technologies also tend to be more amenable to RW arrangements.

In some specifications, there is a negative and significant association between AI complementarity (Theta, θ) and RW potential, when controlling for AI exposure (AIOE) and income. This pattern holds at the detailed occupation-level analysis (Table (1)), but also emerges in the industry-state analysis (Table (4)) when including state fixed effects and income controls.

Thus, while jobs and industries with higher AI exposure are more likely to be remote-capable, those with higher AI complementarity are actually less likely to be fully remote-compatible, all else equal. In other words, the tasks and skills that make a job complementary to AI seem to be negatively associated with the ability to perform that job entirely remotely.

This suggests a potential tension between the impact of AI on job tasks and the shift towards RW. Jobs where AI enhances rather than replaces human labor may still require some degree of in-person interaction or physical presence, even if they are in industries or occupations with high overall AI exposure and remote work potential. This nuance is important for understanding the complex ways in which AI and remote work may intersect to shape the future of work. While AI may drive a general shift towards more remote-compatible jobs, the specific jobs where human-AI collaboration is most productive may be less amenable to fully remote arrangements. Policymakers and business leaders will need to consider these complexities when designing workforce strategies and policies in an AI-driven economy.

4 Employment Dynamics

Does exposure to AI, complementarity to AI and feasibility to RW explain employment changes?

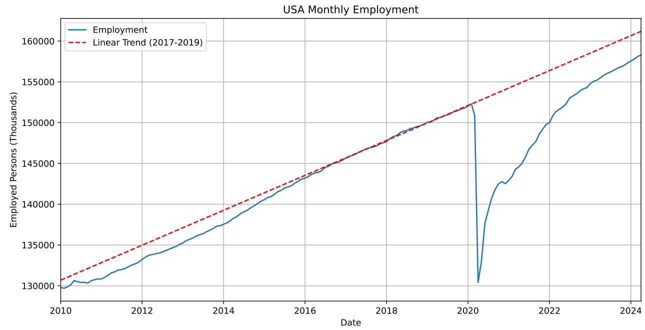
Let the employment in occupation i at time t be $E_{i,t}$, so the growth rate is $\triangle E_i = \frac{E_{i,t}}{E_{i,t-1}} - 1$. So[2]

$$\triangle E_i = \alpha + \beta_1 \text{AIOE}_i + \beta_2 \theta_i + +\beta_3 \text{RW}_i + \varepsilon_i \tag{1}$$

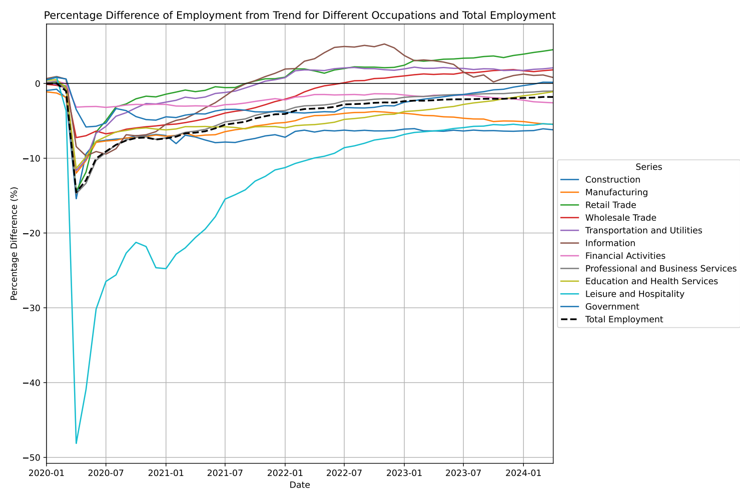
Table 6: Employment Dynamics: Across Occupations, 2022-2023

	Dependent variable:					
	Relative Employment Change, Percent Change					
	(1)	(2)	(3)	(4)	(5)	(6)
AIOE	0.01**			0.01*		0.01*
	(0.004)			(0.004)		(0.01)
Theta		0.05		0.04	0.05	0.03
		(0.05)		(0.05)	(0.05)	(0.05)
REMOTE			0.01		0.01	−0.01
			(0.01)		(0.01)	(0.01)
Constant	−0.01*	−0.04	−0.01*	−0.03	−0.04	−0.02
	(0.004)	(0.03)	(0.005)	(0.03)	(0.03)	(0.03)
Observations	695	695	698	695	695	695
R^2	0.01	0.002	0.001	0.01	0.003	0.01
Adjusted R^2	0.004	0.0003	−0.0004	0.004	−0.0004	0.003
Note:				*p<0.1; **p<0.05; ***p<0.01		

[2]In turn, to this growth rate, subtract the economy wide aggregate employment growth rate. For ease of notation I use E_i to represent the occupation employment growth rate, net of the aggregate growth rate.



(a) Aggregate Employment: Dynamics After COVID-19

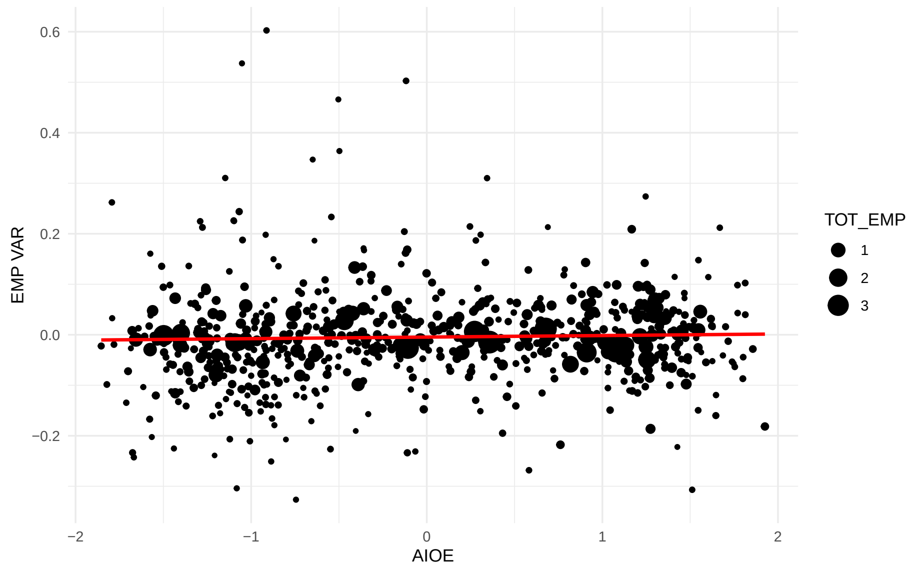


(b) Occupation Dynamics After COVID-19: Difference with trend

Figure 5: Employment Dynamics After COVID-19

Source: Employment data from FRED. Linear trend using 2017-2019 data for both (a) and (b).

Figure 6: Employment Dynamics and AI Exposure Across Occupations, 2022-2023



Source: Employment data from BLS. AI exposure estimates from Felten et al. (2023)

5 Conclusion

TBC

References

Acemoglu, Daron, "The Simple Macroeconomics of AI," Technical Report, National Bureau of Economic Research 2024.

Baldwin, Richard and Toshihiro Okubo, "Are software automation and teleworker substitutes? Preliminary evidence from Japan," *The World Economy*, 2024, *47* (4), 1531–1556.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying, "Does working from home work? Evidence from a Chinese experiment," *The Quarterly journal of economics*, 2015, *130* (1), 165–218.

Brynjolfsson, Erik, Danielle Li, and Lindsey R Raymond, "Generative AI at work," Technical Report, National Bureau of Economic Research 2023.

Dingel, Jonathan I. and Brent Neiman, "How Many Jobs Can be Done at Home?," *Journal of Public Economics*, 2020, *189*, 104235.

Eloundou, Tyna, Sam Manning, Pamela Mishkin, and Daniel Rock, "Gpts are gpts: An early look at the labor market impact potential of large language models," *arXiv preprint arXiv:2303.10130*, 2023.

Felten, Edward, Manav Raj, and Robert Seamans, "Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses," *Strategic Management Journal*, 2021, *42* (12), 2195–2217.

Felten, Edward W, Manav Raj, and Robert Seamans, "Occupational heterogeneity in exposure to generative ai," *Available at SSRN 4414065*, 2023.

Hansen, Stephen, Peter John Lambert, Nicholas Bloom, Steven J Davis, Raffaella Sadun, and Bledi Taska, "Remote work across jobs, companies, and space," Technical Report, National Bureau of Economic Research 2023.

Noy, Shakked and Whitney Zhang, "Experimental evidence on the productivity effects of generative artificial intelligence," *Science*, 2023, *381* (6654), 187–192.

Pizzinelli, Carlo, Augustus Panton, Marina Mendes Tavares, Mauro Cazzaniga, and Longji Li, "Labor Market Exposure to AI: Cross-country Differences and Distributional Implications," Technical Report, International Monetary Fund 2023.