The Impact of Artificial Intelligence on Wages and Wage Inequality

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Master of Science

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Purpose/Motivation: Artificial Intelligence (AI), one of the most influential general-purpose technologies today (Felten et al., 2021), is expected to have far-reaching impacts on the economy and the labor market, both today and in the future (Cheng et al., 2024). Because of the rapid technological progress over the past decade (Acemoglu et al., 2022) and limited research in this context (Pereira et al., 2023), opinions on whether AI will have positive or negative effects vary widely. On the one hand, AI is perceived as a threat that may replace human tasks, reduce wages, and potentially lead to job loss (Occhipinti et al., 2025). On the other hand, AI can complement human labor by increasing productivity, which may ultimately translate into higher wages (Balsmeier & Woerter, 2019). As AI technologies are increasingly able to automate non-routine tasks, this raises the question whether established theories of technological change remain applicable to explain possible labor market effects. While a small number of studies suggest a positive relationship between AI and wages (Engberg et al., 2025; Felten et al., 2019), the empirical evidence remains limited and inconsistent. Therefore, this thesis addresses this gap and examines how AI occupational exposure (AIOE) affects wages and whether this relationship depends on occupational task composition and industry-level AI adoption.

Theories/Hypotheses: Building on the Routine-Biased Technological Change (RBTC) theory (Autor et al., 2003) and the Task-Based Model (Acemoglu and Autor, 2011), this study argues that the wage effects of AI depend not only on the degree of occupational AI exposure but also on the task composition of occupations. Since AI is expected to complement employees performing predominantly non-routine tasks while substituting routine tasks (Huang & Rust, 2018), the relationship between AIOE and wages should vary across occupations. Beyond task routineness, the realization of AI-related productivity gains or substitution effects depends on whether AI technologies are actually adopted in the workplace. Employees working in industries with higher AI adoption are expected to benefit more from AI occupational exposure than employees in industries with lower AI adoption. Accordingly, if AI predominantly complements rather than substitutes employees during the study period,

higher AIOE should be associated with higher wages. Consequently, the following hypotheses were tested.

> H1: Task routineness moderates the relationship between AI occupational exposure and wages, such that the association becomes stronger in non-routine occupations (H1a) and weaker in routine-intensive occupations (H1b).
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> H2: Industry-level AI adoption positively moderates the relationship between AIOE and wages, such that the association is stronger in industries with higher AI adoption rates.

Approach/Methodology: To answer these research questions, I conducted a secondary analysis of the German labor market between 2013 and 2023. The analysis combined data from the SOEP, O*NET, the AI Occupational Exposure (AIOE) index by Felten et al. (2021), and the industry AI adoption share by Rammer et al. (2024). Overall, the study comprised 92,526 person-year observations. I analyzed the relationship between AIOE and wages with OLS regression models and further examined the moderating effects of task routineness and industry-level AI adoption.

Findings: The results show that in general, employees in occupations with higher AIOE earn more compared to employees in occupations with lower AIOE. A one standard deviation increase in AIOE is associated with a wage premium of approximately 18.53%. Furthermore, H1 is supported, as employees in non-routine intensive occupations benefit from a higher wage premium, while the wage premium decreases with increasing routine intensity. In contrast, H2 is only supported for industries in the highest AI adoption tertile. This indicates that industry-level AI adoption share moderates the relationship only above a certain threshold. Moreover, there is no significant effect on overall wage inequality. Nevertheless, AIOE is associated with a widening wage gap between the 10th and 90th percentiles.

Research Limitations: The findings cannot be interpreted causally because of potential self-selection, reverse causality, and omitted variable bias. In addition, the study did not distinguish between AI as a complement or substitute for human labor. Consequently, it remains unclear whether the observed wage premiums reflect productivity gains from AI complementing employees or selection effects.

Research Implications: The results provide empirical support for the Task-Based Model and the Routine-Biased Technological Change theory by suggesting that AI primarily acted as a complementary technology rather than a substitute for human labor in the early phase of AI adoption. At the same time, the rapid progress of generative AI increasingly challenges the

distinction between routine and non-routine tasks, which represents a core assumption of these frameworks. Consequently, future research should re-evaluate which tasks AI complements or substitutes as AI capabilities continue to evolve, and how these developments affect labor market outcomes.

Practical Implications: The positive effect of AIOE on wages suggests that occupations with higher AI exposure are gaining value in the labor market compared to less exposed occupations. Therefore, organizations should invest in AI-related skills and provide opportunities for employees to integrate AI effectively in their daily tasks. At the same time, employees in routine-intensive occupations should be offered upskilling and job redesign opportunities to secure their long-term employment.

Contribution: This thesis contributes to the literature on AI and labor market outcomes by providing empirical evidence that is consistent with the Task-Based Model and the Routine-Biased Technological Change theory during the early phase of AI adoption in Germany. In addition, it highlights the importance of occupational task composition in explaining heterogeneous wage effects.

Paper type: Empirical

Further readings:

Felten, E., Raj, M., & Seamans, R. (2021). Occupational, industry, and geographic exposure to artificial intelligence: A novel dataset and its potential uses. *Strategic Management Journal*, 42(12), 2195–2217. https://doi.org/10.1002/smj.3286

Cnossen, F. (2025). Tasks, wages and new technologies. *Industrial Relations: A Journal of Economy and Society*, *64*(3), 434–457. https://doi.org/10.1111/irel.12380

Engberg, E., Koch, M., Lodefalk, M., & Schroeder, S. (2025). Artificial intelligence, tasks, skills, and wages: Worker-level evidence from Germany. *Research Policy*, *54*(8), 1-14. https://doi.org/10.1016/j.respol.2025.105285

Fossen, F. M., & Sorgner, A. (2022). New digital technologies and heterogeneous wage and employment dynamics in the United States: Evidence from individual-level data. *Technological Forecasting and Social Change*, *175*, 1–17. https://doi.org/10.1016/j.techfore.2021.121381