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ORIGINAL ARTICLE

Tasks, wages and new technologies[1]

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Abstract

This paper addresses the role of technology in shaping worker-level task prices, exploiting within-occupation variation using a unique survey linked to administrative data for over 180,000 Dutch workers between 2014 and 2020. Nonroutine abstract and interactive tasks are related to wage premia, and routine tasks to wage penalties. However, these task returns vary according to exposure to the types of (new) technology, such as computers, robots and artificial intelligence. Overall, wages are higher in technology-intensive industries, but newer technologies target non-routine tasks differently. This may have profound implications for the nonroutine wage premium given the rise of artificial intelligence.

INTRODUCTION

The technological progress observed in recent decades has led to increased efficiency in the execution of programmable and rule-based activities. While this advancement has proven advantageous for individuals performing tasks where humans have a comparative advantage, such as problem-solving, creativity, and interactive activities, it has adversely affected those in routine-intensive occupations, who have seen their tasks replaced. A large body of literature has documented how the decline of routine-intensive, middle-skilled jobs can be explained by the rise in the adoption of various technologies (Autor et al., 2003; Autor & Dorn, 2013; Goos et al., 2014; Van den Berge & Ter Weel, 2015; Terzidis & Ortega-Argilés, 2021). A significant question in this field pertains the worker-level dynamics of routine-biased technological change (RBTC), specifically understanding how technology and tasks interact in shaping the formation of wage inequalities.

There are two main difficulties in understanding the role of tasks and technologies in wage formation on the individual level. First, within very similar occupations, not all workers

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perform the same tasks. This may be related to differences in skill or due to adaptations to technological change (Dauth et al., 2021; Nikolova et al., 2023; Spitz-Oener, 2006). Often-used measures of tasks that rely on occupational task descriptions cannot capture the variation that exists within occupations, which poses empirical limitations in estimating the returns to tasks (Arntz et al., 2017; Autor & Handel, 2013; Lewandowski et al., 2022; Spitz-Oener, 2006). Second, most literature on technology and labor markets conflates different types of technologies, assuming all have similar automation properties. However, each type of technology changes the organization of work in its distinctive way. Endeavors such as those by Webb (2019), Felten et al. (2019) and Prytkova et al. (2024) develop indicators of exposure to technology and find substantial variation between occupations affected by different types of technology. For instance, physical tasks are more exposed by robotic technologies, computer-based software solutions can substitute for many routine tasks, and AI is predominantly used for non-routine cognitive analytic tasks in the higher end of the wage distribution (Webb, 2019).

This paper is the first to explicitly estimate task returns across different technologies while allowing for within-occupation variation. To do so, the analysis relies on a large survey of over 180,000 workers that measures worker-level tasks, which allows for explaining within-occupation variation in tasks across individuals and across sectors that differ in technology adoption. By linking the survey data to register data on the wages of each respondent, the analyses can contribute to the fundamental issue of how wage inequalities are shaped by the (interaction between) tasks and technology adoption in the workplace. Of specific interest are task prices in the context of several types of (new) technologies: computers, robots, and artificial intelligence.

The theoretical underpinning of the literature on routine-biased technological change is based on the task approach to labor markets, which posits that each job can be perceived as a bundle of activities, and each of these activities faces a certain risk of substitution by technology. Hence, studying the tasks that people perform helps in understanding the employment growth in some and the decline in other occupations. A growing body of research highlights the limitations to the task approach (Arntz et al., 2017; Autor & Handel, 2013; Lewandowski et al., 2022; Spitz-Oener, 2006), with one of the biggest challenges being in the measurement of tasks: what is it that people actually *do* in workplaces? Tasks are typically measured through two main methods: either relying on occupational dictionaries or by using surveys, each with its inherent limitations. Although occupational dictionaries, such as O*NET or its predecessor DOT, provide an image of the task content of the entire labor market, survey data collected from individual workers allow for substantial heterogeneity within occupations. Both measures have their imperfections, but one of the main benefits of using worker-level survey data is that it allows for a better view of the micro-level dynamics in tasks—which is of particular interest to the present study.

This paper extends the literature on estimating task prices at the worker level, aligning with studies by Autor and Handel (2013), Cassidy (2017) and De La Rica et al. (2020), who show that tasks significantly explain wage variation in the US, Germany, and OECD countries, respectively. However, none of these papers so far have explicitly modeled differences in the exposure to (types of) technology in understanding these wage inequalities.

Other studies use within-occupation variation to study task differences over time or across workers, by country or industry. For example, Marcolin et al. (2016), De La Rica et al. (2020) and Lewandowski et al. (2022) develop individual-level task measures, revealing substantial within-occupation variation and significant cross-country differences in routine intensity, linked to lower education and skills. Other studies also emphasize within-occupation variation. Autor and Handel (2013), Arntz et al. (2017), and Stinebrickner et al. (2018) show considerable task variation within occupations, with Arntz et al. (2017) noting greater variation in jobs more exposed to task replacement. Spitz-Oener (2006) and Akçomak et al. (2016) find that skill requirements in occupations increase over time, which can be attributed to computerization, and Nikolova et al. (2023) show that the adoption of robots specifically also leads to task changes, by reducing the manual content of work.

This paper's main contribution is that it is the first to estimate task prices in direct relation to exposure to different types of (new) technology, such as computers, robots, and artificial intelligence. To do this, this paper constructs new worker-level task indices for routine, abstract and social tasks using a nationally representative large Dutch survey covering over 180,000 workers. To my knowledge, this is the largest survey to be used for measuring worker-level tasks in the literature. Due to the sample size, there is significant variation within occupations, even at the 4-digit level. The worker-level data are enriched with industry-level data on technology use from Netherlands Statistics to identify task returns in the presence of different types of technology.

The unique data set reveals several key findings. First, consistent with the extant literature, there is a routine wage penalty and an abstract wage premium. To understand the role of technologies in wage formation, further analysis shows task prices differ under differing exposure to technology. Moreover, they differ across the interaction with different types of technology: workers with abstract tasks receive a stronger wage benefit from working with technology, but this benefit is no longer present in the interaction with more advanced new technologies, such as artificial intelligence. This provides early suggestive evidence that aligns with recent models by Bloom et al. (2024) and Autor (2024), which predict that as AI can substitute for more complex, abstract work, the wage inequalities between routine and non-routine work may decrease. Nevertheless, a routine wage penalty is present in interaction with all types of technologies, including AI. A test on sorting on comparative advantage following Autor and Handel (2013) reveals that these returns cannot be fully attributed to a skill-bias in the selection into routine or nonroutine tasks. Therefore, the results provide novel insights into the role of technologies in shaping task prices.

CONCEPTUAL FRAMEWORK

The paper aims to explore how job tasks are rewarded in the labor market, specifically concerning exposure to various types of technologies. The conceptual framework proposed here introduces a model of task prices that exploits industry-level variation in technology adoption. It combines insights from existing literature on routine-biased technical change to create industry-specific production functions, following Cortes (2015) and specifically introduces worker-level heterogeneity, following Autor and Handel (2013).

Technology adoption

Not all industries adopt technological advancements at the same pace, leading to varying levels of innovation adoption across sectors. This discrepancy is evident in the integration of new technology within current production processes across industries. Factors such as uncertainty, sunk costs, firm age and size, export intensity, and regional spillover effects may contribute to these fluctuations in adoption rates (Haller & Siedschlag, 2011). For instance, while Information Technology (IT) is often considered a general-purpose technology, its adoption has not matched that of electricity during the 19th and early 20th centuries (Jovanovic & Rousseau, 2005). Although IT diffusion has been swift in certain sectors, others have been slower to embrace it. These disparities stem from the compatibility of each industry's production methods with technological substitution or enhancement. The automation of routine tasks by computers has accelerated the integration of Information and Communication Technology (ICT) in industries heavily reliant on such tasks (Autor et al., 2003). Industries historically employing a significant portion of routine labor have thus experienced faster technology adoption compared to those with less routine-intensive operations, potentially resulting in present-day discrepancies in technology levels based on the past routine work levels.

Robotic technologies also see uneven adoption, even within manufacturing sectors, leading to differences in routine manual task replacement within occupations and between industries (Nikolova et al., 2023). The adoption of one of the newest technologies, Artificial Intelligence (AI), varies considerably by industry, city, and firm type and cannot only be explained by pre-existing levels of routine intensity of the production process (McElheran et al., 2024). This paper refrains from analyzing the reasons behind varying technology adoption levels across industries, focusing instead on examining individual workers' behavior as they allocate themselves across industries and task bundles. The model assumes technology adoption at the industry level is exogenously determined to the worker, implying that workers do not influence technology adoption levels within an industry; instead, it is firms that primarily drive technological advancement (Borghans & ter Weel, 2007; Entorf et al., 1999).

Production

The model begins with the premise that computer capital complements nonroutine tasks while substituting routine tasks, as has become customary in this literature following (Autor et al., 2003). This assumption yields a production function where routine labor and computer capital are perfect substitutes for executing routine tasks, while nonroutine tasks can only be executed by nonroutine labor.[1]

Within this framework, each industry j generates a unique product q_j, using a mix of routine and nonroutine tasks. Routine tasks are executable by both computer capital κ and routine labor r, while nonroutine tasks exclusively rely on nonroutine labor n. The production function, following a CES (Constant Elasticity of Substitution) structure, is expressed as:

$$q_j = \left[\left(\kappa_j r_j\right)^{\frac{\sigma_j - 1}{\sigma_j}} + n_j^{\frac{\sigma_j - 1}{\sigma_j}} \right]^{\frac{\sigma_j}{\sigma_j - 1}} \tag{1}$$

Here, $\sigma_j = \frac{1}{1-\rho_j}$ is the industry-specific elasticity of substitution and ρ_j the substitution parameter. κ_j is exogenously given and available at no cost, and may therefore also be considered as a technology parameter, following (Cortes, 2015).[2]

The wage per efficiency unit for task $\tau \in \{r, n\}$ and industry j is denoted as $\lambda_{\tau j}$. Assuming competitive industries, wages equal the marginal product of labor, enabling the derivation of relative labor demand for routine tasks:

$$\frac{r_j}{n_j} = \kappa_j^{\sigma_j - 1} \left(\frac{\lambda_{rj}}{\lambda_{nj}} \right)^{-\sigma_j} \tag{2}$$

[1]An alternative possibility is presented by Bloom et al. (2024), who propose a nested CES function where older technologies such as robots substitute for low-skill labour, artificial labour substitutes for high-skill labour and high-skill labour is also substitutable for low-skill labour. When one would swap low-skill work for routine tasks and high-skilled work for abstract tasks, such a model could explain how artificial intelligence decreases the wage inequality between relatively abstract and relatively routine-intensive workers, under the assumption that AI is more substitutable for abstract workers than routine workers are for abstract workers (Bloom et al., 2024). In this model, AI is not treated as a different technology.

[2]While Autor et al. (2003) models technical change as an exogenous decrease in the price of capital, this model, in line with Cortes (2015), represents technological change as an exogenous increase in the stock of computer capital, κ_j. This is also governed by empirical considerations, as it is more intuitive to assess complementarity between computers and tasks by measuring actual technology use rather than its price.

An exogenous increase in technology, represented by an improvement in κ_j, leads to a decrease in the relative demand for labor performing routine tasks, given $\sigma_j < 1$. Of particular interest for the current paper is whether the effect of different types of technology κ_j is associated with different effects on the demand for routine tasks, and thus ultimately on the wage inequality between routine and nonroutine jobs.

In the long run, task prices are expected to equalize across industries as workers migrate to higher-paying industries. However, short-term variations in task prices can occur due to several factors, and in particular for new technologies. First, task prices are not directly observable, as each occupation is a bundle of different tasks and different industries may offer different bundles. It may take considerable time (and training) for workers with a lower-paying bundle of tasks to switch to an industry and task bundle that has higher rewards. Second, the demand for particular tasks is changing due to technological change and since that process varies across industries, there is scope for industry-specific changes in task prices. Third, the supply of specific tasks can also be constrained in the short run, as training additional workers with particular qualifications takes time.

Worker heterogeneity and empirical implementation

Each occupation involves a bundle of tasks, combining both routine and nonroutine elements. Consequently, a worker's productivity, or marginal product, isn't simply determined by λ_{rj} or λ_{nj}. Moreover, workers possess differing proficiencies in various tasks; some excel at nonroutine tasks while others are more adept at routine ones. This insight motivates a model of self-selection as first proposed by Autor and Handel (2013), drawing on Roy's model of self-selection (Roy, 1951). Since workers aim to maximize income, they tend to gravitate toward roles where they can optimize their returns based on their task-specific abilities.

Following Autor and Handel (2013), workers exhibit varying proficiencies or skills across different tasks, which we can represent as a vector of task efficiencies for worker i, denoted as $\Phi_i = \{\phi_{i1}, \phi_{i2}, \ldots, \phi_{iT}\}$. Each element of Φ_i quantifies the efficiency of worker i at task τ, where τ can be either routine or nonroutine. This vector can be conceptualized as a person's reservoir of human capital, with their efficiency in each task being influenced by factors such as human capital investments, innate abilities, or a combination thereof.

Referring back to the industry-specific CES production function, we understand that each product is manufactured using a combination of labor and capital. Assuming that worker i contributes to industry j, their wage, based on their marginal product, can be approximated as:

$$w_i = \alpha_j + \lambda_{rj}\phi_{ir} + \lambda_{nj}\phi_{in} + \mu_i \tag{3}$$

Here, $\lambda_{\tau j}$, where τ represents either routine or nonroutine tasks, signifies the task-specific wage returns in industry j, with α_j denoting an industry-specific task price and μ_i representing a worker-specific error term.

It's worth noting that a worker's wage is not influenced only by their proficiency in specific tasks but also by the production process of the industry they are employed. As per the labor demand function, $\lambda_{\tau j}$ encompasses both the level of technology, represented by κ_j, present in the industry's production process and the overall (non)routine task intensity of the industry. Thus, task prices, and consequently, individual wages, rely on the mix of routine and nonroutine tasks employed in the industry, as well as the level of computer capital.

The data used in this paper provide the opportunity to, at least, partly disentangle the roles of worker sorting and technology that together shape the wage structure. Two things are to be considered. First, if workers sort into tasks based on absolute ability, i.e. routine tasks are considered simpler, the return to routine tasks captures the fact that routine workers have lower productivity in general, and thus reflects a skill return, rather than a task return. However, should workers sort according to comparative advantages, routine tasks should be rewarded more in industries or occupations that use that task intensively.

To overcome this, Autor and Handel (2013) propose a test of a model of comparative advantage. Sorting on comparative advantage would relate to the empirical observation of nonzero covariances between industry- or occupation-level task returns and the task endowments of workers who self-select into these industries (Autor & Handel, 2013). To recover these covariances, one can estimate an augmented version of the Mincer equation where industry- or occupation-level task means $\overline{R}_j$ and $\overline{N}_j$ are interacted with worker-level task inputs:

$$\ln w_{ij} = \alpha + \beta_N N_i + \beta_R R_i + \delta_N \overline{N}_j + \delta_R \overline{R}_j + \gamma_N N_i \times \overline{N}_j + \gamma_R R_i \times \overline{R}_j + e_{ij} \quad (4)$$

Two cases emerge that make different predictions on the signs of the interaction terms γ_N, γ_R in this equation (Autor & Handel, 2013). The first case is one of *comparative advantage*, where workers positively self-select into each bundle of tasks. In terms of the data presented in this paper, this would be when a worker who performs relatively more routine-intensive tasks than the average worker, earns more when they work in an occupation or industry where the routine intensity of work is high. This can occur when the correlation between worker abilities across tasks is sufficiently low: workers who can perform abstract tasks are not necessarily also productive in routine tasks, and vice versa. Formally, this implies that $\gamma_N, \gamma_R > 0$.

The other case is one where the distribution of skills across the population of workers is characterized by *absolute advantage* – that is, workers who excel at task 1 also excel at task 2 – then positive self-selection on task 1 into industry j must imply negative self-selection on task 2 into industry j' and vice versa. For instance, if nonroutine tasks are simply more complex tasks than routine tasks, and they require the same skill but at a higher complexity, one could observe positive self-selection of workers in nonroutine tasks and negative self-selection in routine tasks. In that case, the task coefficients are more likely to pick up a general ability bias. In the regression coefficient, absolute advantage would be picked up in the fact that γ_N is positive, but that γ_R might be negative.

Second, to understand the technology element in wage formation, a more nuanced understanding of task prices can be obtained by regressing the technology inputs explicitly. To observe the complementarities between the level of computer capital K_j adopted in an industry and the tasks of the workers in that industry, we can estimate:

$$\ln w_{ij} = \alpha + \theta_K K_j + \sum_{T \in (N,R)} \left[\beta_T T_i + \vartheta_T K_j \times T_i\right] + e_{ij} \quad (5)$$

Here, T_i represents either nonroutine or routine tasks at the worker level. This approach offers a novel application of the Mincer equation in the context of Routine-Biased Technological Change (RBTC). Unlike conventional models where workers are assumed to sort into fixed occupations, this paper underscores the variability of tasks within occupations and how workers contribute their tasks to industries, optimizing their returns. Consequently, we expect to observe a positive and higher return to abstract work in industries with high ICT intensity, while routine work should yield lower task returns in such settings. Additionally, ICT capital should generally benefit all wages, as κ positively influences wages in the equations for $\lambda_{\tau j}$ but the effect of κ is expected to vary across different types of technologies, as well as between types of tasks (nonroutine versus routine).

DATA

This paper takes advantage of data from the Netherlands Working Conditions Survey (NEA) and data on ICT use in industries from Netherlands Statistics.

The NEA is a nationally-representative of workers aged between 15 and 75 of which the analysis sample consists of the waves in 2014, 2016, 2018 and 2020. NEA polls between 35,000 and 60,000 workers each year. Surveys are sent to people's home addresses and can be either filled out online or using a paper version. The individual-level task measurements in this paper are based on several questions from the working conditions section. One benefit of this survey is that it asks workers both for their job tasks and their occupation, creating data suitable for understanding within-occupation variation in tasks. Moreover, NEA contains demographic variables such as education level, age, and gender, which are not self-reported but originate from census data. Descriptive statistics on these demographic variables for the full sample, and by gender and education level are provided in Panel A of Table 1.[3]

The primary advantage of using NEA data is its integration into the microdata of Statistics Netherlands, allowing for the retrieval of data on income and employment. By matching survey data with this administrative data, more accurate income information is obtained compared to self-reported surveys (Abowd & Stinson, 2013; Meyer & Mittag, 2019a, 2019b). This allows for a direct link between a person's tasks and their hourly wage, which is retrieved from tax records (POLISBUS) data. These data include monthly information on hours worked, total wages, and contract types.[4] In the NEA, respondents are asked to report on the job where they spend the most hours. To match a respondent to a specific job, the job with the highest contracted hours during the survey period is selected. The hourly wage is calculated by dividing the total contract wage by the total contract hours and then applying a log transformation.[5] Descriptive statistics on the log hourly wage for the full sample, and by gender and education level are provided in Panel A of Table 1.

This paper uses four pooled cross-sections from NEA and excludes respondents who are older than 65, those who do not have the main labor market status "employer" during the survey, and those with missing data on task measures or demographic variables. The final sample covers 183,686 workers.

Tasks

In creating the task measures, this paper follows the main framework behind studying tasks concerning technological progress: machines can substitute for workers who perform limited and well-defined sets of tasks. At the same time, it complements workers in carrying out creative and problem-solving tasks Autor et al. (2003), an assumption that might well be very different for artificial intelligence but should at least still hold for all other technologies (Autor, 2024). Following Acemoglu and Autor (2011), routine tasks are 'procedural, rule-based activities to which computers are well-suited', whereas nonroutine tasks are 'activities that

[3]The data are made nationally representative due to the inclusion of sampling weights, provided by Statistics Netherlands. The weight coefficients are constructed using poststratification. Stratifications used are 1. gender x age cohort x migration status, 2. industry, 3. region x urban and 4. gender x age cohort x level of education. The sampling weights are used in the final estimations. See Hooftman et al. (2018) for further explanations.

[4]Contract types are either tenured or temporary. A tenured contract covers workers with indefinite contracts, interns, directors/major shareholders (directeur-grootaandeelhouder or DGA in Dutch), and individuals employed under the Sheltered Employment Act (WSW in Dutch). Temporary contracts apply to temporary employees, sub-contracted, or on-call employees (uitzendkracht and oproepkracht in Dutch, respectively).

[5]For this, the variables *sbasisloon* and *sbasisuren* are used.

TABLE 1 Descriptive statistics.

	By gender					By level of education						
	Full sample		**Male**		**Female**		**Low**		**Middle**		**High**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
A. Wage and demographics												
Log hourly wage	2.87	0.55	2.96	0.56	2.79	0.52	2.44	0.59	2.77	0.47	3.16	0.43
Female	0.49	0.50	0	0	1	0	0.46	0.50	0.47	0.50	0.52	0.50
Age	42.52	14.04	43.78	13.98	41.21	13.97	41.96	17.44	42.65	14.19	42.57	12.20
Education												
Low	0.17	0.38	0.18	0.39	0.16	0.37	1	0	0	0	0	0
Middle	0.40	0.49	0.41	0.49	0.39	0.49	0	0	1	0	0	0
High	0.42	0.49	0.39	0.49	0.44	0.50	0	0	0	0	1	0
B. Tasks												
Worker-level												
Routine	0.00	1.00	−0.13	0.94	0.13	1.04	0.38	1.08	0.09	1.01	−0.26	0.87
Abstract	0.00	1.00	0.10	0.99	−0.09	0.99	−0.58	1.03	−0.12	0.96	0.38	0.85
Social*	0.00	1.00	−0.01	1.03	0.03	0.97	−0.52	1.04	0.03	1.01	0.19	0.90
Industry-level												
Routine	−0.02	0.32	−0.08	0.32	0.05	0.30	0.12	0.33	0.01	0.33	−0.10	0.27
Abstract	0.02	0.35	0.02	0.35	0.02	0.36	−0.21	0.35	−0.05	0.33	0.19	0.28
Social	0.03	0.24	−0.01	0.24	0.06	0.23	−0.07	0.29	0.01	0.24	0.08	0.19
C. Technology												
Worker-level												
Computer use	−0.02	1.01	−0.01	1.02	−0.04	1.00	−0.70	0.95	−0.15	1.02	0.37	0.83

TABLE 1 (Continued)

	Full sample		By gender				By level of education					
			Male		Female		Low		Middle		High	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Industry-level												
Computer use (NEA)	−0.01	0.51	0.06	0.51	−0.09	0.50	−0.29	0.46	−0.08	0.51	0.16	0.47
Robot (CBS)[a]	5.66	8.91	7.57	10.44	3.50	6.08	5.85	9.23	5.87	9.24	5.24	8.22
AI (CBS)[b]	13.72	7.13	14.23	7.99	13.16	5.98	11.55	5.21	12.58	6.30	16.20	8.12
Internet (CBS)[a]	72.88	18.83	72.12	18.07	73.74	19.62	62.65	18.22	70.69	18.17	81.61	16
Big Data (CBS)[a]	25.16	7.97	25.65	8	24.61	7.90	24.06	6.38	24.29	7.54	26.93	8.96
N	183,686		93,881		89,905		31,908		73,724		76,349	

[a] Only available in 2018 and 2020.
[b] Only available in 2020.
* should be an a (only available in 2018 and 2020).
Source: Author's calculations using NEA and CBS Statline data. Technology use indicators as defined in Appendix Table A2.

require problem-solving, intuition, persuasion and creativity'. The main nonroutine tasks used in this study refer to nonroutine cognitive tasks, but some additional analyses also include a measure of nonroutine interactive tasks.

The analysis relies on five items from NEA to construct an abstract task measure: (1) In your work, are you required to think of solutions to do certain things? (2) Does your job require learning new things? (3) Does your work require creativity? (4) In my job, I make a clear contribution to improving products or services; (5) In my job, I get the time to develop new ideas. This reflects that nonroutine cognitive tasks require problem-solving and creative skills, where workers are stimulated to be part of the creative process: improving products, coming up with new ideas and learning new things. Cronbach's Alpha is 0.77, and an index is created through polychoric principal component analysis (Olsson, 1979), of which the first component that explains 59% of total variation and has an Eigenvalue of 3.0 is used to construct an index.[6]

The measure of routine intensity uses the following questions: (1) Are you doing work where you are required to make repetitive movements? (2) Can you decide the sequence of your tasks? (3) Can you decide the speed of your tasks? and (4) Can you decide how you execute your work? These inputs reflect the explicit procedure characteristic of routine tasks (Autor et al., 2003). The first component of the polychoric PCA explains 0.65 of total variation, its Eigenvalue is 2.6 and Cronbach's alpha is 70%.[7]

Although the main measure for nonroutine-intensity is abstract tasks, in 2018 and 2020, the NEA questionnaire included items on interactive tasks, which can be used for the construction of another nonroutine task measure, that are used in some additional analyses. Four items are used in the construction of a social task index. (1) How often are you in touch with people where you are actually meeting in person? (2) How often are you in touch with people on the telephone or digitally? (3) Are you managing employees? (4) Does your work pace depend on the number of clients that ask questions, place orders or contact you? Of the three, this index is the least reliable, as Cronbach's alpha is 0.20, and the first component explains 33% of total variation, which has an Eigenvalue of 1.3.[8]

The indices are weighted using the NEA's sampling weights to ensure representativeness and are standardized for easier interpretation. The correlations Table 2 shows that routine tasks correlate negatively with both abstract and social tasks, while abstract and social tasks correlate positively with each other, as would be expected.

Table 3 compares NEA-based measures with three other sources from the literature. The NEA routine task measure correlates 62% with the routine task index of Goos and Salomons (2009) and 81% with their abstract task index. Service tasks correlate 78% with social tasks. Mihaylov and Tijdens (2019) and O*NET-based task measures of Hardy et al. (2018) following Acemoglu and Autor (2011) distinguish between routine manual and cognitive tasks; the NEA measure aligns more with routine manual tasks. Abstract

[6]Standard PCA relies on Pearson correlations, which assumes that all variables are normally distributed. This poses a problem for the variables proposed here, which have a discrete scale. Also, one would need to assume that the distance between all the answers is equal, and thus that the step from 'no' and 'yes, sometimes' and 'yes, sometimes' and 'yes, often' is the same (Bond & Lang, 2018). To solve this, one can create an index using PCA based on polychoric correlation, which assumes the variables are ordered measurements of an underlying continuum (Olsson, 1979). This makes it better suited for creating an index using categorical variables.

[7]Table S1 reveals that for routine tasks, only 15% of respondents report no autonomy over job decisions, and 50% do not make repetitive movements, indicating low routine intensity for most. Although the focus of this paper is on relative scales, it is important to keep these levels in mind.

[8]For comparison, in the study by Autor and Handel (2013), their survey-based routine index dataset explains 56% of the variation in the included variables. Conversely, the routine index of Nikolova et al. (2023), utilizing EWCS data, accounts for 37%. In terms of abstract indices, Autor and Handel's index explains 41%, while that of Nikolova et al. (2023) matches at 37%. Regarding social indices, Nikolova et al. (2023) captures 47% of the total variance, with no equivalent index available for comparison in Autor and Handel's study.

TABLE 2 Correlations between main task and technology variables.

Variables	Worker-level (1)	(2)	(3)	(4)	Industry-level (5)	(6)	(7)	(8)	(9)
Worker level									
(1) Routine	1.000								
(2) Abstract	−0.407	1.000							
(3) Social	−0.156	0.311	1.000						
(4) ICT use	−0.309	0.291	0.309	1.000					
Industry level									
(5) ICT use	−0.262	0.254	0.114	0.517	1.000				
(6) Robot use	−0.074	0.020	−0.075	0.025	0.055	1.000			
(7) AI use	−0.154	0.185	0.055	0.373	0.711	−0.029	1.000		
(8) Big Data use	−0.082	0.079	0.047	0.275	0.520	−0.191	0.797	1.000	
(9) Internet use	−0.223	0.287	0.115	0.385	0.716	−0.255	0.477	0.256	1.000

Source: author's calculations using NEA data. All corrrelations are significant at the 1% level.

TABLE 3 Correlations between tasks measures and other research.

Source	Routine		Abstract		Social	
Goos and Salomons (2009)	Routine	0.62	Abstract	0.81	Service	0.78
O*NET (Hardy et al., 2018)	Routine manual	0.57	Nonroutine cognitive analytical	0.74	Nonroutine cognitive interpersonal	0.52
	Routine cognitive	0.27	Nonroutine cognitive personal	0.54	Nonroutine manual interpersonal	0.56
Mihaylov and Tijdens (2019)	Routine manual	0.39	Nonroutine abstract	0.71	Nonroutine interactive	0.56
	Routine cognitive	0.08				

Source: Author's calculations using NEA data.

tasks in this paper overlap 70% with nonroutine cognitive analytical tasks from ONET and Mihaylov et al. Social tasks show moderate correlations (52–56%) with both nonroutine cognitive interpersonal and manual interpersonal tasks. These comparisons suggest that the NEA-based measures effectively capture job interactivity, with correlations comparable to other literature.

Technology

Relies on two sources for technology data. The first measure of technology is constructed following the NEA item on daily computer use (in hours), which can refer to a smartphone, tablet, laptop or desktop computer. By averaging and standardizing this measure by industry-year, a clear understanding of the extent of ICT usage in the industry is obtained. The computer use data highlight the significant differences between industries in the adoption of computers and their software, see Figure 1.

Besides technology indicators based on the worker-level survey data, this paper also exploits industry-level measures based on firm-level surveys to identify the use of new and different

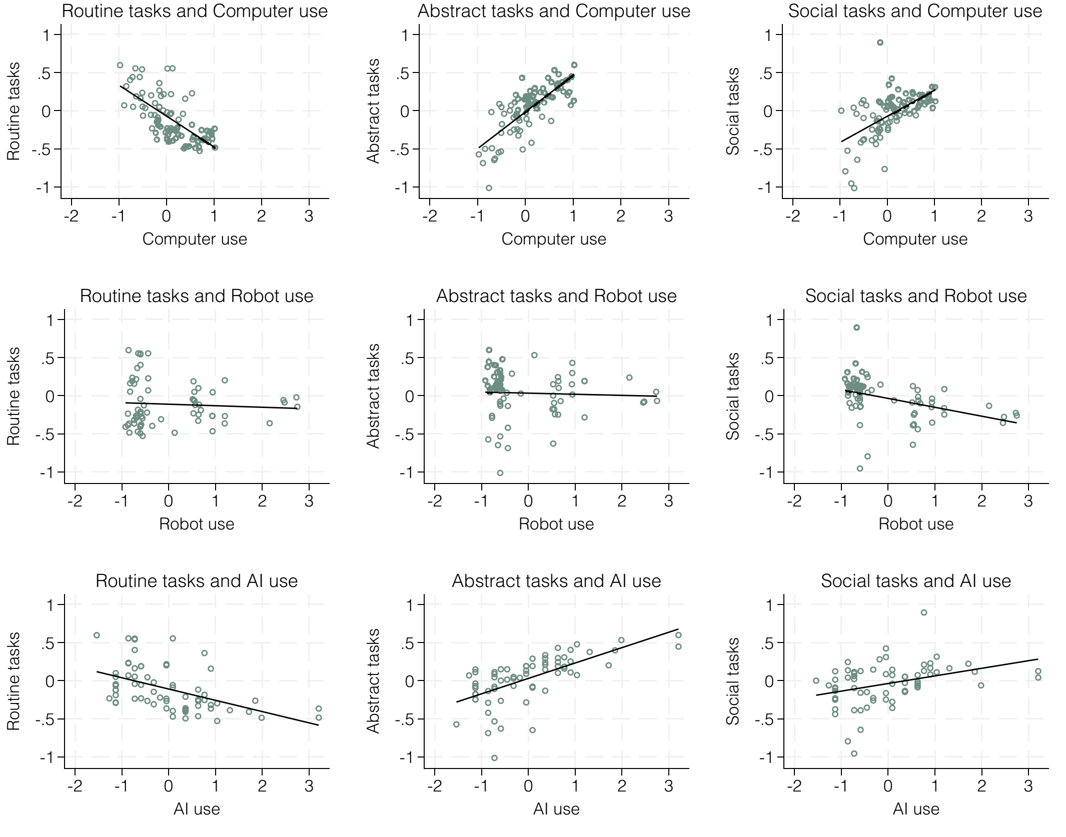

FIGURE 1 Average worker-level task measures and industry-level technology adoption. *Source*: All industry-level technology adoption measures apart from ICT are based on CBS data. Worker-level task and computer data are based on authors' calculations using data from NEA 2014, 2016, 2018 and 2020. Social tasks are only based on surveys in 2018 and 2020. Computer use is available from 2014 to 2020 with two-year intervals and is based on respondents' answers in NEA on the number of hours spent behind a computer. Robot data are available for 2018 and 2020 and AI adoption is only available in 2020. All task measures are standardized across the population to have a mean zero and a standard deviation of one and then averaged across industries.

types of technology. The survey "ICT Use by Businesses" conducted annually by CBS measures the automation and application of information and communication technology (ICT) in Dutch companies. Among others, it covers internet usage, e-commerce, software, big data analytics, robots, artificial intelligence, and ICT security incidents and measures. The survey targets over 1.1 million companies with at least one employee since 2021, and at least two employees in 2020. Data are collected both comprehensively from companies with 100+ employees and through a sample for smaller companies, with results published directly without adjustments. Data accuracy is ensured through consistent individual-level checks, aggregation comparisons with previous years, and validation using economic trends. The survey's findings are published in CBS's Statline tables and are publicly accessible.

From this survey, two indicators are used for the main analysis, and two other ones are selected for additional robustness tests. First, the share of firms in an industry that have utilized one or more industrial or service robots. The use of robotics involves industrial robots that are automatic, reprogrammable manipulators for industrial applications, and service robots that operate autonomously in complex environments, excluding software robots and 3D printers. Second, the percentage of companies that employ one or more AI technologies from a pre-specified list. In the CBS survey, Artificial Intelligence (AI) refers to systems that exhibit intelligent behavior by analyzing their environment and taking actions to achieve specific goals with a degree of autonomy, whether software-based (e.g., speech and facial recognition systems) or embedded in devices (e.g., autonomous robots like self-driving cars and drones).

For additional robustness tests, two other proxies for technological intensity are also selected: internet and big data analytics. The former contains the percentage of workers in an industry that regularly use a computer with internet access for their tasks and the latter measures the percentage of firms that rely on big data analysis in their production. Big data encompasses information from users' electronic activities and inter-device communication, characterized by large volumes and diverse formats, analyzed using techniques and software tools to understand processes and inform decision-making. Statistics on both measures are presented in the Table S2. Conceptually, big data analytics are more like AI than simpler software technologies (such as spreadsheet software) because they automatically analyze large, diverse data sets to make or inform decisions that humans cannot perform, thus reducing the added value of abstract tasks for many workers except those directly working with Big Data.

Table 2 presents the correlations between the task measures and the technology variables on the worker level. The strongest correlation exists between AI and computer use (0.711). Importantly, it does not seem to be the case that technology-intensive industries adopt all technologies equally: there are clear patterns of co-adoption of certain combinations of technologies but not of others. For instance, there is a negative or close-to-zero association between robots and all other types of technology.

Interesting patterns emerge when examining the tasks performed in the presence of technologies, which are visualized in Figure 1. All technologies show the expected trends: more technology-intensive industries have fewer routine tasks and more abstract and social tasks. However, the strength of these correlations varies significantly. For example, the correlation between abstract tasks and internet use is 28.7%, but it drops to only 7.9% with big data analysis. Industries utilizing at least one AI technology also engage in social tasks, although this correlation is much weaker compared to the correlation between social tasks and ICT use. The notable outlier is robotic technologies. Among all technologies, robots have the weakest correlation with tasks, as illustrated before in 1 using industry averages. Moreover, the association between robots and social tasks is even negative. If one considers the finding by Webb (2019) of the overlap between tasks and robotic technologies, and the empirical evidence of task adjustment to robots in Nikolova et al. (2024), it seems that robotic technologies operate in ways distinctly different from more software-related technologies (such as internet and big data analysis) as well as from artificial intelligence.

Explaining task differences

Most analyses of job tasks consider them at the occupation level. However, a significant advantage of NEA's individual-level task measures is their ability to explore the variability of job tasks within occupations and how this variability is systematically related to both worker, job and industry attributes. This subsection analyzes the role of human capital, demographic attributes and occupation- and industry characteristics in determining individual-level tasks. Of specific interest are the signs of the technology indicators to see how these determine tasks. The regression takes the following form:

$$T_{ijk} = \beta_0 + \beta_1 S_i + \beta_2 D_i + \gamma_j + \sum_{1}^{k} \kappa_k + \mu_s + \varepsilon_i \tag{6}$$

where the variable S_i includes education level dummies, D_i is a vector of demographic characteristics age and sex, γ_j is a vector of 4 digit occupation dummies, κ_k captures the level of technology adoption in sector k. The results of this descriptive OLS regression are presented in Table 4.

Columns (1), (4) and (7) provide a regression with demographic characteristics on routine, abstract and social tasks, respectively. Overall, women have more routine-intensive jobs, and education is negatively associated with routine intensity. Young people are more likely to perform routine tasks and less likely to perform abstract and social tasks. Columns (2), (5) and (8) include 4-digit occupation dummies. Although the coefficient sizes are reduced for all demographic variables, and the explained variation increases to ~30%, these detailed occupations still cannot fully explain the individual-level variation in tasks.

The technology parameters document an interesting pattern. For this, we observe columns (3), (6) and (9), which include all technology types – except AI – for the survey years 2018 and 2020. Industries that adopt relatively more robots and internet technologies generally use less routine labor, whereas big data analysis is associated with more routine-intensive work. Robots have no impact on abstract tasks, but a significant negative association with social tasks (Nikolova et al., 2023). Computer use is positively associated with abstract tasks and with social tasks, but negatively with routine tasks (although insignificant when including all other technology types). The effect sizes are small, nevertheless, they highlight important differences in the use of (non-)routine labor depending on the type of technology, a finding that substantiates the use of industry-specific production functions as an underlying framework for understanding wage differences between individual workers.

RESULTS

Tasks and wages

For the baseline descriptive cross-sectional equation, the following OLS regression is estimated for log hourly (monthly) wage $\ln w_{ij}$ of individual i in industry j as follows:

$$\ln w_{ij} = \beta_0 + \sum_{1}^{\tau} \beta_{\tau 1} T_{ij} + X_i \beta_3 + Z_j \beta_4 + \varepsilon_j + \mu_s \tag{7}$$

where T_{ij} are the standardized task scales, X_i is a vector of demographic controls (education, age, age^2, gender and migration background) and Z_j is a vector of job-related covariates (occupation and industry), ε_i and μ_s are the worker-specific error-term and the error term for a dummy of the

TABLE 4 OLS regressions of task indices on demographic variables and technology parameters.

	Routine			Abstract			Social		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Female	0.25***	0.14***	0.14***	−0.21***	−0.15***	−0.16***	0.01	−0.06***	−0.10***
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)
Ref.cat.: Primary educ.									
High school	−0.10***	−0.07***	−0.01	0.17***	0.07***	0.04	0.37***	0.20***	0.21***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
Middle educated	−0.30***	−0.13***	−0.08***	0.52***	0.18***	0.13***	0.78***	0.42***	0.43***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
Bachelor	−0.56***	−0.23***	−0.17***	0.93***	0.25***	0.19***	0.88***	0.43***	0.42***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
Master/PhD	−0.75***	−0.31***	−0.25***	1.09***	0.34***	0.30***	0.93***	0.43***	0.40***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)
Age	−0.07***	−0.03***	−0.03***	0.06***	0.02***	0.02***	0.05***	0.05***	0.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Age^2 \times 100$	0.06***	0.03***	0.02***	−0.07***	−0.03***	−0.02***	−0.07***	−0.06***	−0.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Technology: industry-level									
Computers		−0.04***	−0.04*		0.08***	0.04**		0.00	0.02
		(0.01)	(0.02)		(0.01)	(0.02)		(0.01)	(0.02)
Robots			−0.03***			−0.01			−0.04***
			(0.01)			(0.01)			(0.01)
AI			0.01			0.00			−0.01
			(0.01)			(0.01)			(0.01)
Constant	1.78***	0.92***	0.12**	−1.85***	−0.46***	−0.37***	−1.71***	−0.83***	−0.77***
	(0.02)	(0.10)	(0.05)	(0.02)	(0.11)	(0.05)	(0.03)	(0.18)	(0.05)

TABLE 4 (Continued)

	Routine			Abstract			Social		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Observations	183,686	183,686	36,549	183,686	183,686	36,549	104,211	104,211	35,106
R-squared	0.130	0.287	0.340	0.165	0.320	0.351	0.084	0.275	0.310
Survey years	'14-'20	'14-'20	'20	'14-'20	'14-'20	'20	'14-'20	'14-'20	'20
Occ dummies (4 digit)	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

***$p<0.01$, **$p<0.05$, *$p<0.1$ Robust standard errors in parentheses. Technology use indicators as defined in Appendix Table A2. All regressions contain survey year dummies and a dummy if education is "unknown." Columns (3), (6) and (9) also include covariates for the share of firms using big data analysis, and the share of workers using internet.

TABLE 5 OLS regressions of log hourly wage on worker-level tasks.

	2014–2020				2018–2020
	(1)	(2)	(3)	(4)	(5)
Routine	−0.126***	−0.029***	−0.026***	−0.018***	−0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Abstract	0.177***	0.082***	0.068***	0.037***	0.032***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Social					0.026***
					(0.001)
Demographic		X	X	X	X
Industry dummies (2 dgt)			X	X	X
Occ. dummies (4 dgt)				X	X
Observations	183,686	183,686	183,686	183,686	104,211
R-squared	0.227	0.647	0.680	0.726	0.722

***$p<0.01$, **$p<0.05$, *$p<0.1$ Robust standard errors in parentheses.

year of the survey *s*, respectively. Including basic socio-demographics partly accounts for selection on observables.

The results are presented in Table 5. Columns (1) to (4) present results from the 2014–2020 surveys, excluding social tasks, and the final column includes social tasks, which were only surveyed consistently in 2018 and 2020. As the task indices are all standardized by year for the entire population with zero mean, and a standard deviation of one, the coefficients can be interpreted as the relationship between a one-standard deviation change in routine work on the log of hourly wages. Because sampling weights are included in each regression, the results are representative of the Dutch population.

The first estimation shows that routine work is associated with lower wages: one standard increase in routine intensity is followed by a decline in hourly wages of approximately 12.6%, in the absence of any industry and demographic controls. The raw wage premium for abstract work is 17.7%. In column (2), education controls and other demographic variables are added to the specification. The signs of the routine and abstract coefficients do not change but are reduced in size by roughly half, indicating some selection on demographics into tasks.

In addition, columns (3) and (4) add 86 2-digit industry dummies and 487 4-digit occupation dummies, respectively. The goal is to see the extent to which occupational averages capture the effect of individual-level tasks. If both the worker-level coefficients would turn insignificant, this would make the use of such data superfluous in the presence of occupation-level data. Although both coefficients are reduced in size, they are still highly significant. Within narrowly defined occupations and industries, there is still a wage penalty of nearly 2% for routine tasks and a premium of 3.7% for abstract tasks. Column (5) then also includes social tasks. Although including social tasks decreases the coefficient size of abstract tasks to a small degree, they are both still significant, and thus capture distinct elements of nonroutine work. Here, consistent with the literature, social tasks also have a wage premium, of approximately two and a half per cent, again accounting for 4-digit occupation controls.[9]

[9]To provide some context: in Autor and Handel (2013) the routine task return is −3% and 7% for abstract tasks. For De La Rica et al. (2020) its −2.4% and 2.6% for routine and tasks respectively, and Nikolova et al. (2023) find a routine task return of −1.8%, an abstract return of 4.5% and a social return of 1.6%, with similar covariates.

TABLE 6 OLS Regression on tasks and task means across occupations and industries.

	Mean calculated at the					
	Occupation-level				Industry-level	
	(1)	(2)	(3)	(4)	(5)	(6)
Routine individual	−0.018***	−0.027***	−0.017***	−0.031***	−0.018***	−0.020***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Abstract individual	0.041***	0.041***	0.035***	0.036***	0.038***	0.037***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Routine mean	−0.018***	−0.007***	0.001	−0.005**	−0.050***	−0.045***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)	(0.005)
Abstract mean	0.225***	0.230***	0.212***	0.216***	0.119***	0.120***
	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.005)
Routine × Routine mean		0.065***		0.071***		0.049***
		(0.002)		(0.001)		(0.003)
Abstract × Abstract mean		0.009***		0.008***		−0.007***
		(0.002)		(0.001)		(0.002)
Constant	0.885***	0.847***	0.878***	0.843***	1.014***	1.012***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.030)	(0.030)
Observations	183,686	183,686	183,686	183,686	183,686	183,686
R-squared	0.702	0.704	0.700	0.705	0.717	0.718
Occ dummies	2 dgt	2 dgt	4 dgt	4 dgt	4 dgt	4 dgt

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$ Robust standard errors in parentheses. All regressions adjust for survey year dummies, the level of education, sex, age and age squared.

To examine whether these task prices are driven by specific periods or different in the Covid-19 year, Table S3 presents the baseline regression with the full set of controls for each survey year. The size and signs of the task coefficients exhibit only slight variations over the years.[10]

Sorting on comparative advantage

To partly overcome the issue of non-random sorting of workers into industries and occupations, this section presents a similar method as Autor and Handel (2013) as discussed in the conceptual framework section.

Table 6 presents the empirical results of estimating Equation (4). Similar to Autor and Handel (2013), the table presents mean values at both the 2-digit (51 occupations) and 4-digit (487 occupations) levels. Additionally, to test for similar sorting patterns into industries, the estimations also include industry means and their interactions with worker-level tasks. Including occupation- and industry-level averages in columns (1), (3) and (5) does not alter the main task coefficients' signs and sizes drastically. For a test of comparative advantage, columns (2), (4),

[10]Notably, there is an observable trend of the abstract wage premium gradually decreasing, from 4% in 2014 to 3.3% in 2020. Further research should examine whether these differences are persistent and robust, but they could indicate a declining wage premium for abstract work and potentially for high-skilled occupations as recently modeled by Bloom et al. (2024), a trend that could continue in the coming years as artificial intelligence becomes more dominant in work organization (Autor, 2024).

and (6) reveal the γ_N and γ_R parameters from Equation 4. The findings support the hypothesis that workers sort according to comparative advantage: although returns for routine tasks are generally negative, they are mitigated by the routine intensity of the occupation or industry. In other words, routine tasks have a relatively higher price in jobs and production processes where such tasks are more prevalent. This pattern holds not only for occupation sorting but also for industry sorting, indicating that certain industries intensively utilize routine tasks and compensate workers accordingly.

Similarly, the coefficient for nonroutine tasks (γ_N) is positive for occupations, although much smaller, indicating that while abstract tasks are somewhat more valued in abstract-intensive occupations, their returns are more widespread across the economy and less specific to particular products or jobs compared to routine tasks. The interaction on the industry-level is negative, although again small in size. It therefore seems that workers performing abstract tasks in somewhat less abstract environments may have higher productivity.[11] These findings suggest that the negative returns to routine tasks cannot be fully driven by ability sorting but rather provide evidence for sorting on comparative advantage. For abstract tasks, the results show evidence for such a sorting pattern on the occupation level, although weaker than for routine tasks, but not on the industry-level. Combined, these results enable further analysis by incorporating technology indicators to examine how different types of wages interact with different types of (new) technologies.

How task prices relate to technologies

To analyze whether part of these differences in task prices can be explained by exposure to (different types of) technology, Table 7 includes the technology parameters for the sample of 2014 to 2020, using only routine and abstract tasks following Equation (5). Column (1) presents the baseline results from column (4) in 5 as reference.

Columns (2) to (4) incorporate industry-level measures of technology. The computer use data are available in all survey years (2014–2020) for all 86 2 digit industries. Robot and AI data are available 68 2 digit industries in 2018–2020 and 2020, respectively. In all instances, workers in more technology-intensive industries earn higher wages. However, notable patterns emerge in the interactions. First, the routine wage penalty is more pronounced in industries utilizing more computers, robots and AI. For abstract tasks, there are modest yet significant additional wage benefits in computer-intensive and robot-intensive industries. Crucially, this abstract wage premium disappears or even turns negative in industries with advanced software technologies like artificial intelligence. Although the full impact of AI is still unfolding, these results align with other research suggesting a diminished benefit for non-routine work in the context of artificial intelligence (Autor, 2024; Bloom et al., 2024; Webb, 2019).

As an additional robustness test, Table S5 includes two additional measures of software-related technologies, as proxied by the importance of internet use and the analysis of big data. Again, workers in software-intensive industries have higher wages, but this is dampened when workers execute routine tasks in such environments, given the negative coefficient of the routine × technology indicators. Interestingly, the interaction coefficient for big data analytics, which indicates more advanced use of information technologies, is negative for abstract tasks as well, just like the results for AI. Table S6 also includes social tasks. Including nonroutine interactive tasks makes the abstract task index insignificant for both big data analysis as well as

[11] Table S4 includes social tasks and their interactions with occupation- and industry averages, showing similar results to nonroutine abstract tasks, with the routine task coefficient remaining unchanged.

TABLE 7 OLS regressions of log hourly wage on tasks and technology indicators.

	Baseline	With technology indicators: Computers	Robots	AI
	(1)	(2)	(3)	(4)
Routine	−0.018***	−0.022***	−0.024***	−0.025***
	(0.001)	(0.001)	(0.001)	(0.002)
Abstract	0.037***	0.039***	0.040***	0.035***
	(0.001)	(0.001)	(0.002)	(0.002)
Technology		0.079***	0.014***	0.014***
		(0.002)	(0.002)	(0.002)
Routine × Technology		−0.023***	−0.005***	−0.009***
		(0.002)	(0.002)	(0.002)
Abstract × Technology		0.004**	0.005***	−0.003
		(0.002)	(0.002)	(0.002)
Constant	0.973***	0.983***	0.714***	0.834***
	(0.031)	(0.030)	(0.015)	(0.021)
Observations	183,686	183,686	75,884	36,549
R-squared	0.726	0.716	0.719	0.713
Occupation dummies	Yes	Yes	Yes	Yes

***$p<0.01$, **$p<0.05$, *$p<0.1$ Robust standard errors in parentheses. All regressions include 2 digit industry and 4 digit occupation fixed effects, and education and sex controls. Computer use is calculated using NEA data, and is a by-year standardized measure of the average daily working hours spent behind a computer. Technology indicators are standardized across industries and sourced from CBS Statline. Robots: Percentage of companies that used robots (2018 & 2020). AI: Percentage of companies that uses one or more AI technologies (2020).

AI, potentially implying that especially nonroutine interactive tasks may be hurt by advancing software and AI capabilities.

Nevertheless, regardless of the type of technology studied here, the routine task penalty is stronger in technology-intensive industries. The impact on abstract tasks is more nuanced and varied. This suggests that newer types of technologies might influence wage inequalities differently compared to previous technological advancements, with a stronger effect on the replacement or change in nonroutine tasks than the displacement of routine tasks. Specifically, social tasks might face greater penalties in the context of these emerging technologies. Further research into these effects is warranted, but the results add further relevance to the growing realization that new technologies may be more targeted toward non-routine tasks (Autor, 2024; Bloom et al., 2024; Webb, 2019).

DISCUSSION AND CONCLUSION

This paper delves into the relationship between job tasks, technology adoption and wage outcomes, leveraging data from the Netherlands Working Conditions Survey (NEA). Covering a span from 2014 to 2020 and encompassing a sample of 183,686 workers, the paper constructs novel survey-based measures for routine, abstract, and social tasks that are consistent with those used in the extant literature. These tasks help understanding how technological advancements interplay with wage dynamics, especially as they capture within-occupation variation that allows us to understand in a more fine-grained manner how workers adapt to technological change.

There are some limitations to the present study. First, although worker-level task data provide a more detailed image of the tasks people perform on the job, they are based on the individual interpretations that may be biased. Second, self-selection into tasks cannot be ruled out fully, and unobservables may play a role in shaping the routine task penalty and abstract wage premium. Third, the data presented here are based on the Netherlands only. Nevertheless, data from the European Working Conditions Survey indicate that the Netherlands is comparable to other (Western) European countries in the size of the routine- and abstract task return (De La Rica et al., 2020; Nikolova et al., 2023).

Keeping the limitations in mind, the presented evidence underscores the complex interplay between tasks, technology, and wages in shaping the modern labor market. Routine tasks, characterized by repetitive and procedural activities, are found to be associated with lower wages, while abstract tasks, demanding problem-solving and creativity, are correlated with higher wages. Moreover, social tasks, involving interaction with others, have a similar wage premium as abstract tasks. These results are in line with comparable studies estimating task prices using worker-level indices, such as De La Rica et al. (2020); Autor and Handel (2013); Nikolova et al. (2023); Stinebrickner et al. (2018). Importantly, additional analyses on an augmented Mincer equation provides evidence for worker-sorting according to comparative advantage, implying that these results cannot only be attributed to an ability bias (Autor & Handel, 2013).

One significant contribution of this paper is that the analysis further examines the interplay between tasks and several (types of new) technologies. Individual-level computer measures reveal that workers with greater computer usage tend to enjoy higher wages, suggesting the productivity-enhancing effect of technology. This offsets the additional wage penalty for performing routine tasks on a computer. At the industry level, technology adoption emerges as both a significant determinant of tasks, as well as wage differentials. Industries characterized by higher technology intensity generally offer higher wages. However, the impact depends on which technology is used intensively in the industry. This highlights the differential impact of technology on workers based on their task profiles, and, importantly, the differential impact of different types of technology.

Notably, industries that adopt advanced software technologies such as artificial intelligence (AI) may not provide additional wage benefits for nonroutine tasks, and in some cases, may even lead to a negative impact. This sheds important light on the potential future interplay between AI as a dominant technology and both the abstract task premium, as well as the high-skill wage premium (Autor, 2024; Bloom et al., 2024). The regression results by survey year presented in this paper hint toward such a direction through a decline in the abstract wage premium over the last decade, although this is a trend that needs to be studied further and could develop differently over the coming years.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Netherlands Statistics. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from https://www.cbs.nl/en-gb/our-services/customised-services-microdata/microdata-conducting-your-own-research with the permission of Netherlands Statistics.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.
Appendix S1.

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