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Impact of Robots and Artificial Intelligence on Labor and Skill Demand: Evidence from the UK

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Abstract

Over the past four decades, automation technologies have replaced routine tasks performed by medium-skilled workers, and contributed to increased labor market polarization. With the advent of artificial intelligence, this dynamic may have shifted, extending task substitution to non-routine tasks performed by high-skilled workers. Using textual analysis and descriptions of technology found in patent texts, we construct novel occupational exposures to robot and artificial intelligence technologies. These occupational exposures are then used to analyze changes in labor and skill demand over the last decade in the United Kingdom. We find that the middle part of the income distribution is primarily exposed to robot technology, while exposure to artificial intelligence increases monotonically across income percentiles. Second, we find that exposure to robots is strongest among high school dropouts and declines monotonically with education, while artificial intelligence automation has a limited impact on the same workers, with a pronounced exposure among college graduates. Third, our findings suggest asymmetric effects of automation technologies across skill groups. Robot automation reduces demand for low-skilled workers, while AI technology shifts demand away from high-skilled workers, with the direct effects consistently negative despite the presence of several compensating mechanisms. Finally, a joint estimation of the effects of robot and AI automation shows that robot automation is positively associated with an increase in demand for skilled workers, while AI automation is weakly associated with a decrease in demand for skilled workers. These patterns indicate structural changes in the labor market, with important implications for wage inequality and the future of work.

Keywords: Automation, Artificial Intelligence, Patents, Robots, Skill Demand

JEL Classification: J30 , O14 , O15 , O33

1 Introduction

New technologies such as robots and artificial intelligence (AI) have revolutionized the production process in many ways. Annual global installations of industrial robots almost quintupled between 2000 and 2019 (Jurkat, Klump, & Schneider, 2022). The picture is even more staggering when we look at the development of AI technologies in general. Zhang et al. (2021) find that the number of peer-reviewed AI publications has increased almost twelve-fold over the same period.

Rapid adoption of robots and AI raised concerns about their impact on employment and wages. Recent research indicates that over the last four decades, automation technologies have put downward pressure on wages of low- and medium-skill workers and contributed to a labor market polarization. Autor (2011) documents that since the late 1980s, an employment and wage growth has been concentrated in high- and low-skill jobs in the United States. Similar trend was documented for advanced European countries since at least the mid-1990s (Bachmann, Cim, & Green, 2019; Breemersch, Damijan, & Konings, 2017; Goos, 2018; Goos, Manning, & Salomons, 2009; Salvatori, 2018). Labor market polarization in the United Kingdom (UK) was investigated by Goos and Manning (2007); Montresor (2019); Salvatori (2018) among others. New technologies developed since the mid-80s were able to replace routine tasks, mainly those of middle-skilled workers, and increased the demand for low-skilled service workers and high-skilled workers performing non-routine tasks (Autor, Chin, Salomons, & Seegmiller, 2024; Autor, Levy, & Murnane, 2003). However, recent advances in artificial intelligence brought into attention a set of tasks that have been perceived as non-routine and thus hard or impossible to automate. Autor (2022) argues that due to AI, an expanding set of expert and semi-expert tasks is becoming technologically equivalent to the 'routine tasks' of previous decades that can be well accomplished by machines. An early evidence in Felten, Raj, and Seamans (2019); Gonzalez Ehlinger and Stephany (2023); Svanberg (2023); Webb (2019) suggests that AI is indeed replacing high-skilled non-routine tasks of workers in the production process. Unlike traditional automation technologies deployed over the last four decades, AI technologies may reduce relative skill demand for a broadly defined high-skilled workers. However, as adoption of automation technologies goes hand-in-hand with several compensating mechanisms, the impact of robots and AI on labor demand remains ambiguous and ultimately becomes an empirical question (Arntz, Gregory, & Zierahn, 2019).

Our aim is to address this question and provide new empirical evidence on the role of robots and AI in shaping the labor demand and relative demand for skills over the last decade in the United Kingdom. In particular, what we do in this paper is following. First, we construct novel occupational exposures to robot and artificial intelligence technologies for 3-digit level UK Standard Occupational Classification (SOC) 2010. Second, we explore how these exposures are scattered across skill distribution by educational level and 2-digit SOC 2010 occupations, and across wage percentiles. Then we estimate a direct displacement effect of robots and AI on labor demand over the period 2010 - 2020. Finally, we estimate effects of robots and AI on relative demand for skills.

In principle, our methodology relies on the similarity between tasks performed by workers across different occupations and the descriptions of patents. By examining the extent to which these two domains overlap, as argued by Autor et al. (2024), we can measure exposure to automation from new technologies. Furthermore, Autor et al. (2024) demonstrate that this approach effectively isolates the automation effects of new technologies from their augmentation effects in relation to changes in labor demand.

Autor et al. (2024) show that although automation and augmentation exposures are positively correlated across occupations, each has significant explanatory power when considered individually. Specifically, automation tends to be labor-displacing, while augmentation is labor-reinstating. In this context, it is possible that our estimates of displacement effects are weakened by the concurrent augmentation of workers through the same technological advances, thereby representing a lower bound of the true displacement effect.

Using these novel measures of occupational exposure to robots and AI automation technology developed in this paper, we observe distinct patterns of exposure across demographic and socioeconomic groups. Robot exposure is highest among individuals with lower education levels, particularly high school dropouts, and decreases monotonically as education levels increase. In contrast, workers with less education are the least exposed to automation by AI technology, while college graduates exhibit the highest levels of exposure to this technology. On average, women face lower exposure to automation technologies compared to men across all educational groups.

Our analysis reveals that the middle-income distribution is primarily exposed to robot technology, while exposure to AI technology increases monotonically across income percentiles, aligning with broader findings in the literature. These results highlight the asymmetric effects of automation technologies across skill groups: robot automation reduces demand for low-skilled workers, while AI technology shifts demand away from high-skilled workers. Notably, the direct effects of automation on labor demand are consistently negative, despite the presence of several compensation mechanisms. When jointly estimating the effects of robot and AI automation, we find that robot automation is positively associated with increased demand for skilled workers, whereas AI automation is weakly linked to a decline in skill demand, predominantly affecting skilled workers. These findings underscore the asymmetric impacts of these technologies on labor markets, pointing to structural changes with significant implications for wage inequality and the future of work.

The rest of the paper is organized as follows. Section 2 provides the literature review and describes our contribution to the existing literature. The theoretical background and mechanisms tested in the empirical analysis are described in Section 3. Section 4 describes the construction of occupational exposures to robot and AI technology, discusses the data used to measure labor market outcomes over the last decade in the United Kingdom, and provides the specification of the empirical model. Section 5 provides a descriptive analysis of occupational exposures across the skill distribution and compares them with other estimates of exposure to these technologies by other authors. In addition, this section relates the occupational exposures to decade-long changes in labor market outcomes. Finally, Section 6 concludes and summarizes the main results.

2 Literature Review

The natural starting point for modeling the impact of technological change on labor market is the canonical task-based model (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2019, 2022). It is based on the notion of 'tasks' as units of work that can be accomplished by workers or machines. In task-based models, technological progress is shifting a set of tasks performed by a capital away from labor and creating demand for tasks in which labor has comparative advantages. Therefore, it is important to specify what kind of tasks automation technologies can accomplish. Using the terminology of Autor et al. (2003), it is common to refer to automatable tasks as routine. What makes tasks routine is that they follow codifiable and explicit rules, which could be executed more cost-effectively by machines. In the task-based model, new technologies directly replace routine production or clerical tasks often performed by middle-skilled workers. However, technologies also reinstate labor by creating new tasks and by increasing the quality and productivity of, mainly, high skilled labor in existing tasks (Autor et al., 2024).

Assessing the impact of automation on the labor market requires proper measurement of automation technologies. A dominant share of the literature employs various proxies for automation, such as the share of routine tasks in job descriptions within an industry as a proxy for amenability to computerization (Autor, Katz, & Kearney, 2008; Autor et al., 2003; Goos & Manning, 2007); firm-level surveys on the use of computers in the workplace or investments in computer capital (Autor et al., 2003; Beaudry, Doms, & Lewis, 2010); and, finally, the number of robots used in production (Acemoglu & Restrepo, 2020a; Graetz & Michaels, 2018). A growing, yet smaller share of the literature utilizes patent metadata or patent grant text related specifically to automation *per se* (Mann & Püttmann, 2023), or directly to labor automation with relevance to job descriptions (Autor et al., 2024; Prytkova, Petit, Li, Chaturvedi, & Ciarli, 2024; Webb, 2019).

An economic development in previous decades has been driven by 'traditional' automation technologies such as computers, computer controlled machines (CNC machines), industrial robots, digital technologies, and more recently by 3D printers. Recent advances in artificial intelligence brought into attention a set of tasks that have been perceived as non-routine and thus difficult or impossible to automate. Autor (2022), among others, raised a natural question whether AI fundamentally changes the previously established relationship between technological change, labor demand, and inequality across different skill groups of workers — and if so, how do we characterize and explore these changes analytically and empirically? As adoption of automation technologies goes hand-in-hand with several compensating mechanisms, the impact of robots and AI on employment and wages remains ambiguous and ultimately becomes an empirical question (Arntz et al., 2019). Autor (2022) outlines several scenarios of potential impacts of further advances in AI on labor market. He hypothesises that AI could accelerate the process of task automation, and labor share will decline even further. On top of it, AI will reshape the sets of tasks that are automated and augmented with more high-skill bias inherent in these technologies. Current semi-expert tasks will be increasingly substituted. Recently, Bloom, Prettner, Saadaoui, and Veruete (2023) developed an industry level tractable model that aims to capture and analytically explore the distinct features of robot and AI technology. In the core of the model, robots substitute for low-skilled workers, and AI substitutes for high-skilled workers. They derived conditions under which the use of AI would reduce the college skill premium. They hypothesize that, *ceteris paribus*, an increasing use of AI reduces wage inequality between high-skilled and low-skilled workers as long as AI is more substitutable for high-skilled workers than low-skilled workers are for high-skilled workers. Early evidence in Felten et al. (2019); Gonzalez Ehlinger and Stephany (2023); Svanberg (2023); Webb (2019) suggests that AI is indeed replacing high-skilled non-routine tasks of workers in the production process.

Employment polarization, as documented by Goos, Manning, and Salomons (2014), is also evident across European countries. Between 1993 and 2010, significant employment growth occurred in high-education, high-wage occupations and low-education, low-wage roles, particularly in personal services. In contrast, traditional middle-tier jobs in production, operations, clerical support, and sales experienced a notable decline, both in Europe (Goos et al., 2014) and in the United States (Autor, 2014). The long-standing presence of robot technology, combined with the emergence of AI technologies, could help explain the labor market polarization observed within countries.

There is a growing literature that addresses these questions by measuring the exposure of occupations and industries to AI and other emerging technologies and exploring their implications for the European labor market. European regional employment dynamics between 2011 and 2018, driven by AI exposure indicators (Felten et al., 2019), is studied by Guarascio, Reljic, and Stöllinger (2023). Their findings suggest that, on average, AI exposure has a positive impact on regional employment that points to the prevalence of complementarity effects of recent AI technologies. However, an interaction of robot technology with AI technologies indicates a negative employment effects over this period. Jestl (2024) explores the role of industrial robots and ICT on regional employment in EU countries over the years 2001–2016. He provides evidence of weak effects on total regional employment dynamics. In line with other studies, he shows that robots had a negative employment effects in local manufacturing industries, but positive effects in non-manufacturing industries. Prytkova et al. (2024) used approximately 200 thousand Derwent patents filed between 2012 and 2021 to identify 40 clusters of emerging digital technologies. They calculated the exposure of 4-digit ISCO-08 occupations and 3-digit NACE Rev. 2 industries to these emerging digital technologies. These technologies may substitute or complement labor as the exposure scores are neutral regarding the relationship between technology and labor. They study the effects of these digital technologies on European regional employment (employment-to-population ratio) over the period 2012–2019 for a sample of NUTS-2 regions in 32 European countries. Their empirical results show that these technologies generally have a positive effect on the employment-to-population ratio. Their findings suggest heterogenous impacts across different digital technologies. This points out that focusing solely on specific technologies may overlook the broader positive employment effects arising from complementarities among diverse digital technologies.

There is a rich evidence on labor market polarization in the United Kingdom and the role played by traditional automation technologies in this process, but a more recent evidence on the role played by AI is one of the gaps in the literature. Goos and Manning (2007) documents job polarization in the United Kingdom since the mid-1970s. They show that job polarization can account between one-third and one-half of the increase in UK wage inequality between the 1970s and 1990s. Salvatori (2018) replicates and extends the analysis for two more decades to 2009. He documents that the main feature of the labor market polarization process in the UK has been a shift in employment towards high-wage occupations, which have gained 80 % of the employment share lost by middle-skilled occupations. Contrary to previous evidence, he argues that supply-side factors, rather than technology, have played the major role in this development. The proportion of UK people with university degree doubled between 1993 and 2006 and tripled by 2016. Over the same period the college wage premium have not changed. Without very unreasonable assumptions, such as almost perfect substitutability between unskilled and skilled workers, skill biased technological change model cannot account for this phenomena. Blundell, Green, and Jin (2022) argue that the shift in organization form is the main channel through which more educated workers benefit from technological change since human capital investment gives workers greater ability to deal with increased change and decision making and makes them relatively more productive. Montresor (2019) confirms the fundamental role of technology in hollowing out of middle-skilled employment but finds no effect of technological exposure on top skilled occupational employment changes over the period 1993 – 2014. Stansbury, Turner, and Balls (2023) provides a more nuanced evidence on wage premium since 1997. They document that wage premium in the UK declined in all regions apart from London. In a contrast to other degrees, they show that wage premium for university level STEM skills has hardly fallen and even, in some regions, has risen. The impact of robots on the UK labor market has been studied recently by Kariel (2021). In this study, UK-eligible patent data related to robots and automation at a sectoral level are used to construct a local labor market exposure to automation innovations. The results show that industrial robots have directly replaced workers in some manufacturing industries and areas. On the other hand, services have experienced an increase in employment in response to higher robot exposure.

Building upon the theoretical and empirical context established earlier, the primary objective of this paper is to investigate the role of industrial robots and AI technologies in shaping labor and skill demand in the United Kingdom. An impact of automation technologies remains under-explored outside the US, as emphasized by Restrepo (2023). This disparity arises primarily from data limitations, both in terms of labor market outcomes and detailed descriptions of task content across occupations. Specifically, the United Kingdom lacks harmonized datasets such as the Integrated Public Use Microdata Series (IPUMS), the Dictionary of Occupational Titles (DOT), and the Occupational Information Network (O*NET). Although substitutes exist—such as the New Earnings Survey and the Annual Population Survey (APS)—their scope is limited because they rely on the UK Standard Occupational Classification (SOC) framework, which aggregates data at the occupational and industry levels. Similarly, while the UK SOC provides descriptions of task content within occupations, it lacks the level of detail offered by DOT or O*NET, making it a less comprehensive but still useful substitute for analyzing task-level landscape. Due to these constraints, previous research has relied on proxies for technological progress, such as routine task content or exposure to automation technologies, mapped from the US SOC to the UK SOC occupational classification. However, a critical limitation is the absence of a clear, unambiguous mapping between the US SOC (augmented by task-level data from O*NET) and the UK SOC or other comparable systems.

This paper makes several contributions to the literature. First, it builds on the growing body of research that measures technological progress using patent text as a proxy for innovation activity (Autor et al., 2024; Dechezleprêtre, Hémous, Olsen, & Zanella, 2021; Mann & Pozzoli, 2022; Prytkova et al., 2024; Webb, 2019). By applying state-of-the-art textual analysis techniques, we extend Autor et al. (2024)' notion that automation innovations substitute for specific occupational tasks. Using weighted averages of word embeddings, we capture the semantic relationship between patents and occupational tasks by measuring their proximity in embedding space. These techniques enable us to construct UK-specific measures of occupational exposure to automation technologies as a count of patents that are likely to be close substitutes for occupational tasks performed within occupations.

Second, we adopt a dictionary-based approach inspired by Webb (2019) and Dechezleprêtre et al. (2021) to distinguish between robots and AI. This distinction enables us to explore their differing impacts on worker displacement across sectors with varying skill intensities. By examining occupational exposure to robots and AI within industries, we analyze their predicted effects on labor demand—proxied by the wage bill—and extend Autor et al. (2024)' theoretical model to the UK context. This allows us to empirically verify the predicted impact of automation as a technology-specific measure that predominantly affects one sector more than the other. Our measure of occupational exposure is conceptually distinct yet complementary to existing measures of automation technologies. Mann and Püttmann (2023) focus on industry-level automation exposure by quantifying the intensity of automating patents and their probabilistic links to industries over time, while Prytkova et al. (2024) construct both industry- and occupational-level measures but remain agnostic about whether technologies automate or augment labor. In contrast, we account for the assumption, consistent with Autor et al. (2024), that automation technologies have a negative effect on labor demand, as posited in this stream of literature. Furthermore, unlike Prytkova et al. (2024), we focus specifically on robotics and AI, which have been shaping labor markets since the 1980s, rather than on emerging technologies documented in patents over the past decade.

Our approach also differs from expert-driven evaluations of task-technology overlap, such as task-level susceptibility to machine learning by Frey and Osborne (2013), or crowd-sourced survey datasets linking AI applications to workplace activities, as in Felten et al. (2019). While these studies, like ours, focus on occupational exposure, our methodology is based on textual analysis of patents and occupational descriptions, enabling a more nuanced assessment of task substitution and augmentation.

Third, our study advances the literature examining the labor market impacts of automation and AI technologies. While prior research, such as Acemoglu and Restrepo (2020a), Graetz and Michaels (2018), and Krenz, Prettner, and Strulik (2021), focuses on local labor market effects using instruments like Bartik (1991), we adopt occupational exposure measures and directly link them to changes in labor and skill demand, as demonstrated by Webb (2019) and Autor et al. (2024). Additionally, by explicitly distinguishing between robots and AI, we provide empirical evidence on their distinct impacts across sectors and worker skill levels.

Finally, we contribute to the emerging field of AI exposure measurement, which has predominantly relied on expert judgment (Brynjolfsson, Rock, & Syverson, 2019; Felten et al., 2019), patent-based substitution measures (Webb, 2019), semantic similarity between occupational tasks and AI-related technologies (Prytkova et al., 2024), or firm-level job postings data (Alekseeva, Azar, Gine, Samila, & Taska, 2021). Our work aligns with this literature while introducing a complementary methodology to analyze occupational exposure to automation in the UK.

3 Theoretical model

The task-based framework is built around the understanding that the production requires the completion of a range of tasks (Acemoglu & Restrepo, 2019). These tasks can be performed either by labor or capital. The allocation of tasks to these factors then determines the task content of production. Automation as a specific kind of technological progress shifts the allocation of tasks performed by labor towards capital. In this way, we observe direct displacement effects of automation. However, new technologies create new tasks in which labor has comparative advantages which reinstates labor and creates new work. Further, an increase in productivity due to automation increases value added and this raises the labor demand from non-automated tasks. Moreover, automation in one sector may reallocate economic activity towards other sectors that is referred to as the composition effect. An increase in income and exogenous demand shifts further alter the demand for labor. Therefore, overall labor market outcomes of automation are hard to predict and isolate.

Building on this foundations, we use the theoretical framework introduced by Autor et al. (2024), which models an economy with two sectors: a skill-non-intensive sector (U) and a skill-intensive sector (S). Production in each sector combines tasks, intermediates, capital, and labor. Automation plays a central role in this model, as it shifts the threshold of tasks performed by capital, thereby altering the labor share and employment distribution across sectors (see Acemoglu and Restrepo (2018)).

Since we consider two distinct automation technologies, each may predominantly affect different sectors. Specifically, we assume that robots predominantly impact the skill-non-intensive sector (U), while AI primarily affects the skill-intensive sector (S). In Autor et al. (2024), the technology is treated as a single unified concept, without differentiation between its sectoral impacts. Therefore, we propose a new proposition to test in this paper, complementing the propositions derived in Autor et al. (2024), particularly in terms of changes in skill demand.

Proposition 1. *Automation in sector U, through the adoption of robot technology—reduces the wage bill in that sector, with displaced workers moving into sector S. This results in the reduction of the wage bill in sector U and an increase of the wage bill in sector S, while the following inequality holds:*

$$\left|\frac{\partial \, Wage\ Bill_U}{\partial I_U}\Delta I_U\right| > \frac{\partial \, Wage\ Bill_S}{\partial I_U}\Delta I_U, \tag{1}$$

leading to a net decline in the economy-wide wage bill:

$$\frac{\partial \, Wage\ Bill}{\partial I_U}\Delta I_U < 0. \tag{2}$$

Similar conditions apply when automation occurs in sector S, through the adoption of AI technology. In this case, displaced workers move to sector U, but the overall wage bill still declines:

$$\frac{\partial \, Wage\ Bill}{\partial I_S}\Delta I_S < 0. \tag{3}$$

The model assumes that automation in sector U expands the range of tasks performed by capital (I_U, as discussed in Acemoglu and Restrepo (2018)), reducing the demand for labor in that sector. Displaced workers, both high- and low-skilled, reallocate to sector S, increasing the labor supply there. The resulting changes in wage bills are as follows: the wage bill in sector U decreases due to reduced labor demand, while the wage bill in sector S rises as it absorbs the displaced workers.

However, sector S's capacity to absorb workers is constrained by several factors. Sector S is less labor-intensive than sector U, relies more heavily on high-skilled labor, and faces constraints such as fixed capital stocks and diminishing marginal returns to labor. These constraints limit sector S's ability to accommodate the influx of workers, particularly low-skilled workers.

These theoretical predictions are tested empirically by estimating Equation 5 (Section 4.3), where we measure the overall change in the wage bill across occupations employed in both sectors. Detailed formulations, equilibrium conditions, and technical derivations supporting Proposition 1 are provided in Appendix B.

4 Data and Methods

This section introduces the construction of occupational exposure to robot and AI technology, discusses the data used to measure labor market outcomes over the last decade, and formulates empirically testable hypotheses.

4.1 Creation of UK-specific measure of automation exposure

To identify task inputs of each occupation, we utilize the task descriptions from the UK Standard Occupational Classification 2010 (UK SOC 2010), consisting of 363 occupations (Office for National Statistics, 2010). An example of the task inputs in the UK SOC (2010) is provided for two occupations in Table A1. Consistent with prior research by Autor et al. (2024); Kogan, Papanikolaou, Schmidt, and Seegmiller (2021); Webb (2019), we measure innovation (technological progress) using patent data. Our search is confined to a universe of patent applications from the Google Patents Public Dataset, considering granted patents between 1980 and 2020. We adopt Webb (2019)'s approach by creating quasi-labeled subsamples of unique patents using predefined keywords related to technology $\tau : \{robot; AI\}$. More specifically, we label a patent as a part of *robot family* if it contains at least one of the following words in the patent title: [robot* $\vee$ mechatroni(c—cs) $\vee$ cyber-physical $\vee$ system $\vee$ computer $\vee$ vision $\vee$ control systems $\vee$ sensor]. *AI family* was created in the same manner, with a following words: [artificial intelligence $\vee$ machine learning $\vee$ neural network $\vee$ deep learning]. This procedure does not guarantee that the label of each patent is unique, but upon a closer examination of the extracted verb-noun pairs of each technology, we can clearly see that they are at least qualitatively different. The resulting dataset includes approximately 1,300,000 worldwide patents published with title and abstract published in English language.

Figure A1 illustrates the exponential growth in the total number of patents across all technology groups over time. Both robot and AI patents first appeared in the 1980s. In the right panel, the growth rates of robot patents follow a pattern resembling linear curves on a logarithmic scale, indicating consistent exponential growth throughout the observed period. In contrast, AI patents have demonstrated growth rates exceeding exponential levels since the 1990s.

A subsequent task involves measuring the semantic similarity between patent descriptions and labor tasks. Recently, large language models such as Bidirectional Encoder Representations from Transformers (BERT) or Generative Pre-trained Transformers (GPT) have attracted considerable attention across a broad research community (see, for instance, an exhaustive treatment of applications in economics in Gentzkow, Kelly, and Taddy (2019)). These models excel in capturing contextual information and understanding sentence-level semantics. In contrast to GloVe (Pennington, Socher, & Manning, 2014), which focuses on word-level representation, sentence transformers outperform in tasks requiring nuanced interpretation of short sentences, as demonstrated by Radford, Narasimhan, Salimans, Sutskever, et al. (2018). Therefore, we harness the semantic representation capabilities of the BERT model, as introduced by Devlin, Chang, Lee, and Toutanova (2018), to obtain dense vectors representing the semantic representation of both patent documents and corresponding job occupation descriptions in the embedding space. Utilizing the attention layers embedded in BERT sentence transformers, known for their contextual comprehension and document vector generation, we intentionally refrained from applying text cleaning measures, such as the removal of stop words, special characters, or lemmatization, to maintain the raw textual content's nuances. We employ the standard cosine similarity measure to measure the semantic relatedness between these dense vectors of the semantic representations.

Subsequently, we create a matrix $X^{\tau}_{p,j}$ of cosine similarity between patent p, occupation j tasks for technology τ. Again, τ : {robots, AI} stands for obtained technology by quasi-labeling each observation in the patent data. Following Autor et al. (2024) we retain the top 15 percent highest textual similarity scores across patent - $p \times$ occupation - j pairs according to:

$$I^{\tau}_{p,j} = 1 \text{ if } X^{\tau}_{p,j} \geq \lambda^{\tau}_{t} \text{ and zero otherwise;}$$

where λ^{τ}_{t} is a threshold based on the similarity distribution illustrated in Figure A2 for technology τ across the period $t : \{1980, 2020\}$. Let $\mathcal{P}^{\tau}$ represent the two sets of patents classified based on technologies τ, and let $\mathcal{O}$ represent the set of all occupations. In the final step, we aggregate the most similar patents that are likely to substitute the occupational tasks within each set of technology in the following way. Specifically, we aggregate patents over the entire time period t for each occupation $j \in \mathcal{O}$ and patent family $\mathcal{P}^{\tau}$ to obtain the cumulative occupational exposure to automation $Aut^{\tau}_{j,t}$ for a given technology τ:

$$Aut^{\tau}_{j,t} = \sum_{p \in \mathcal{P}^{\tau}} \sum_{j \in \mathcal{O}} I^{\tau}_{p,j} \tag{4}$$

We obtain cumulative automation exposure scores, which are characterized by a right-skewed distribution because they represent count values. A correlation matrix of the raw counts across technologies and their changes between the two periods 1980-2000 and 2000-2020 is presented in Figure A3 in the Appendix.

In aggregating the automation exposure score, all automation patents are assigned equal weight, without considering variations in their significance, such as citation counts (as utilized by Mann and Püttmann (2023)) or breakthrough innovation indices (as proposed by Kelly, Papanikolaou, Seru, and Taddy (2021)). While this approach ensures uniformity, it does not account for the differing impact or importance of individual patents. As shown in Autor et al. (2024), taking into account the breakthrough measure of patents yields similar results when later linked to changes in labor demand.

4.2 Measuring wages, labor demand and skill demand

Our primary data source for the UK economy comes from the Annual Population Surveys (APS) for the years 2012 and 2022. The sample size is approximately 200,000 respondents each year. APS encompasses a broad range of topics, but our primary focus is on wages and working hours across demographic groups defined by age, education level, years of experience, gender, nationality, and employment status. We start our analysis in 2012 because the personal income weight has only been available since 2012.

All these demographic characteristics vary across one-digit industrial classifications recorded in UK Standard Industrial Classification (SIC) (2007) and three-digit occupational classifications, recorded in the UK Standard Occupational Classification (SOC) (2010) for 2012 and 2020. After the revision of SOC in 2021, all occupations are recorded in SOC (2020). To obtain consistently defined occupational groups, we use a correspondence Table (Office for National Statistics, 2020), cross-walking SOC 2020 into SOC 2010 classification based on one-to-one mapping. The criterion for selecting an exact match of SOC 2020 to SOC 2010 at the three-digit resolution is that there must be at least 80% of men in Labor Force Survey recorded in the SOC 2020 occupation to be unambiguously matched into the SOC 2010 occupation. This criterion is fulfilled for 90% of cases, and we discarded occupations that do not have an unambiguous match.

Main variable of interest is the wage of workers[1], which is right-censored at the value $a = £788$. We observe a true wage y_{i*} only if the wage is lower than the censoring threshold a. If the wage is above the censoring threshold, we observe only the value of a (see the left panel of Figure A5). Despite the fact that censoring only affects approximately 10% of all observations, in some demographic groups, such as men with a college level of education, it is quite substantial. Trimming the wage distributions at the censoring threshold would necessarily bias our results. Therefore, we conduct a homoscedastic single imputation using the tobit model, based on observable characteristics, as described in Büttner and Rässler (2008), drawing inspiration from code prepared by Dauth and Eppelsheimer (2020). The plotted wage distributions after the wage imputation at the beginning and at the end of the period can be found in Figure A5.

The real wages were obtained by deflating the observed and imputed wages using the Consumer Price Index (2015=100) provided by Office for National Statistics (2024). The wage bill is calculated by summing the product of hourly wages and the ratio of actual working hours to standard full-time hours for all full-time workers. This calculation is performed for each group, where groups are defined by the combination of occupation and industry at a given time period. This approach ensures that the wage bill reflects both hourly earnings and the effective full-time equivalent hours worked within each group.

We measure college and high school skill demand by the college and high school wage bill of full-time workers within the one-digit SIC industry (i) and consistent three-digit SOC occupation (j) cell (referred to as an 'industry-occupation cell'). The wage bill is constructed as the sum of weekly real hourly wages and multiplied by 35 hours per week and 4 weeks per month. We define college workers as those with a university education or more, and high school workers as those with a high school degree or less. Following Acemoglu and Restrepo (2020b), we are interested in the log change of relative skill demand for the period from 2012 to 2022, which is measured as the share of the college wage bill relative to the high school wage bill.

4.3 Empirical specification

First, similar to Autor et al. (2024), we test the impact of a newly constructed measure of exposure to automation technologies on the wage bill, estimating the model specified as follows:

$$100 \times \Delta \log(\omega_{ijt}) = \beta_1 Aut_j^{\tau} + \beta_2 \mathbf{Z}_{i,j,0} + \gamma_i + \delta_j + \varepsilon_{ijt} \tag{5}$$

[1] APS variable gross income that refers to gross weekly pay in the main job.

where the dependent variable, $\Delta \log(\omega_{ijt})$, represents the two five-year stacked changes in the wage bill for an occupation-industry cell between 2012 and 2022. The values of the independent variables are multiplied by 100 so that the changes approximately correspond to average five-year percentage point changes over this period.

The main independent variable of interest, Aut_j^τ, quantifies the inverse hyperbolic sine (IHS)-transformed exposure to automation technology τ in the occupation cell across the period 1980–2020. Here, τ : robots, AI refers to technologies derived from quasi-labeled patents as discussed above.

We iteratively control for multiple exogenous variables, captured by the vector $\mathbf{Z}_{i,j,0}$, which includes the share of high school and college workers, the share of foreign workers, and wage levels at the beginning of the period. Additionally, we control for industry fixed effects (γ_i), and fixed effects for broad occupational categories (δ_j), defined as the one-digit SOC codes, in order to harness the variation within the industries and broader occupational groups. The broad occupational and industry fixed effects help isolate unobserved shocks caused by demographic changes, trade, unionization, and industry-specific events by holding these factors constant.

The main potential source of endogeneity is that firms will choose their research effort in response to labor market developments, such as changes in the wage level of their workers. Thus, the employment and wages of different occupations may drive the innovation process that leads to task displacement by these technologies. These concerns are particularly relevant in the case of demand for technology, such as investment in automation or other measures of direct adoption of new technologies. However, our measures are based on the supply side of new technologies, where research efforts by firms in one industry are less directly linked to adoption in another industry or occupation-industry cell. Using breakthrough patents as instruments for our exposure measures (similar to Autor et al. (2024)) could further mitigate the potential endogeneity, but we leave this for further research. The results presented in Autor et al. (2024) are robust to 2SLS estimates with breakthrough patents as instruments. This is somewhat reassuring that the endogeneity concerns should not be substantial. Moreover, our exposure measures are based on patents spanning four decades and overlapping with our labor market data only for the last decade, which further mitigates the endogeneity bias. Nevertheless, we refrain from making strong causal interpretations of our results, instead presenting them as robust correlations observed in the data.

As a robustness check, we re-estimate the specification in Equation 5, replacing the IHS-transformed measure of occupational exposure to automation technologies with a measure capturing the change in these exposure scores over two sub-periods: 2000–1980 and 2020–2000, which are potentially more exogenous. Standard errors in all models are clustered at the level of industry-occupation cells.

As discussed in Section 3, we assume that innovation in each sector should have a negative effect on the overall wage bill, as automation driven by robot technology predominantly replaces workers in the unskilled sector. Although there is an indirect absorption effect in the skilled sector, multiple limiting mechanisms constrain this absorption. This implies that the overall change in the wage bill across the economy should be negative. A similar mechanism applies to automation in the skilled sector driven by AI technology. Therefore, we assume that the signs of the estimated coefficients are negative when these technologies are considered separately in Equation 5.

Secondly, drawing inspiration from Acemoglu and Restrepo (2020b), our focus lies in examining the shift in relative skill demand alongside our exposure to automation technologies, and we estimate the subsequent model:

$$\Delta \log \left(\frac{\omega_H}{\omega_L}\right)_{ij} = \beta_0 + \beta_1 Aut_{\mathcal{R}j}^{robots} + \beta_2 Aut_{\mathcal{R}j}^{AI} + \gamma_i + \varepsilon_{ij} \tag{6}$$

the term $(\omega_H/\omega_L)_{ij}$ captures the relative skill demand computed as the relative wage bill of college workers (H) to the wage bill of high school workers (L) within the industry-occupation cell. The long-run difference between 2012 and 2022 is conditioned on the relative exposure to automation by robot and AI technology. In all models, we control only for industry fixed effects (γ_i) due to constraints imposed by the effective number of observations.

Since we assume that automation by robot technology predominantly affects the skill-non-intensive sector, and automation by AI technology affects occupations in the skill-intensive sector, we can directly test the implications of automation in these sectors on skill demand. This contrasts with the findings of Autor et al. (2024), who show that automation in the skill-non-intensive sector increases skill demand in the economy, while automation in the skill-intensive sector decreases skill demand. Similar results were found in the industry-level model by Bloom et al. (2023).

All models are estimated using Correia (2016) multi-way fixed effects estimator.

5 Results and Discussion

This section provides a descriptive analysis of the occupational exposure to automation technologies across skill distribution and link these occupational exposures to the change in labor and skill demand in the UK economy across the last decade.

5.1 Descriptive analysis of occupational exposure to robot and AI technology across skill distribution

Figure 1 reveals a significant discrepancy in robot and AI exposure across education levels. The group of workers without secondary education (high school dropouts) shows the highest exposure to automation by robot technology, while simultaneously having the lowest exposure to automation by AI technology. In the middle group of workers with completed high school, automation exposures are more or less balanced, leaning slightly towards AI. A stark difference emerges among college graduates; they appear to be substantially more exposed to AI than the previous group of workers. However, our results document that they have minimal exposure to robot technology. This observation aligns closely with findings initially made by Webb (2019) among US workers.

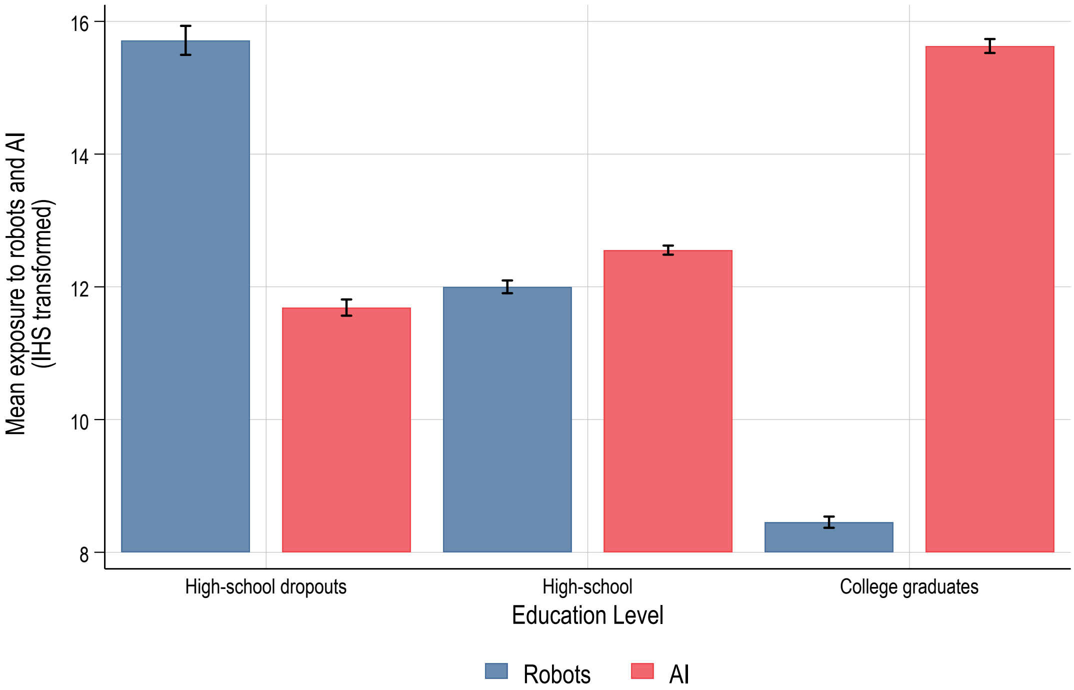


Fig. 1: Mean Cumulative Exposure to Automation Patents for Robot and AI Technology by Education Level

Note: The Figure presents the mean cumulative exposure to automation patents (Aut_t^τ) in the period 1980-2020 for robot and AI technology across the entire workforce of the Annual Population Survey (APS) in the year 2012, categorized by education level over the specified period. Error bars extending above and below each bar indicate the 95% confidence interval for the mean cumulative exposure in the 'robot' and 'AI' groups are computed using the t-distribution for each exposure and educational group.

Figure 2 depicts the mean exposure to robots and AI technology across six demographic groups defined by gender and educational attainment. We see that after we split the mean occupational exposure by gender, the previous results hold. In particular the mean exposure to robots decreases as educational attainment increases, while mean exposure to AI rises with higher levels of education. A new insight from this analysis is that, for men, exposure to both technologies is consistently higher than for women across all education levels. However, among women, we observed that AI exposure is similar between high school dropouts and high school graduates, and robot exposure is roughly equivalent for women with high school and college degrees. This pattern may indicate a stronger specialization of women in 'pink-collar' occupations, which are associated with the lowest calculated exposure to robots.

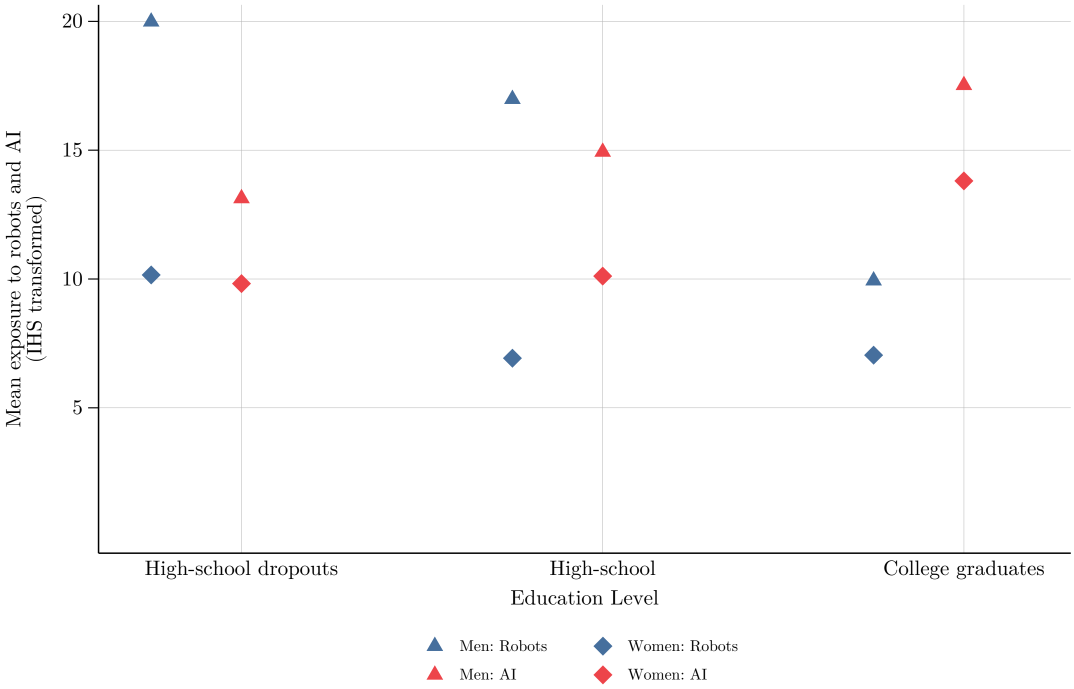


Fig. 2: Mean Cumulative Exposure to Automation Patents for Robot and AI Technology by Gender and Education Level

Note: The figure illustrates the mean cumulative exposure to automation patents (Aut_t^τ) for robot and AI technologies over the period 1980–2020. The analysis is based on the workforce represented in the 2012 Annual Population Survey (APS), categorized by gender and education level. Error bars represent the 95% confidence intervals and correspond to the size of the displayed triangles and diamonds.

Figure A4 in the Appendix depicts the distribution of occupations to automation exposures for different aggregate skill levels (Level 1 (low) to Level 4 (high)). The distributions across these skill groups exhibit a notable left-skewness, which indicates that the median occupational exposure is higher than the mean occupational exposure across all skill groups and both technologies. Moreover, these occupational exposures not only indicate that there is variation across different skill groups, but also across the robot and AI technology within the same skill group. Notably, workers with the lowest required skills (Level 1), engaged in occupations such as postal work or cleaning, and those requiring trained skills (Level 2), such as machine operators or drivers, demonstrate fat left tails. This observation implies that many occupations within these skill groups have below-average automation exposure scores.

Within occupations requiring specific training, particularly in trade and technical roles, exposure to automation by AI technology is markedly lower than exposure to robot technology. The distribution within this category is notably less skewed, indicating that observations are more centered around the mean exposure within this skill group. This trend is consistent for (Level 3) workers, typically associated with educational, technical, and trade occupations, who exhibit significantly less exposure scores to AI technology compared to robot technology.

In contrast, high-skilled roles, including managerial positions (Level 4), shows nearly identical distributions of exposure to both robot and AI technology. Notably, the cumulative density for these high-skilled workers is not at the bottom; rather, workers at the lowest skill level exhibit the lowest cumulative density in automation exposure. This discrepancy is possibly due to the more unstructured environments (planning, or experimenting) in which lower-skilled workers operate.

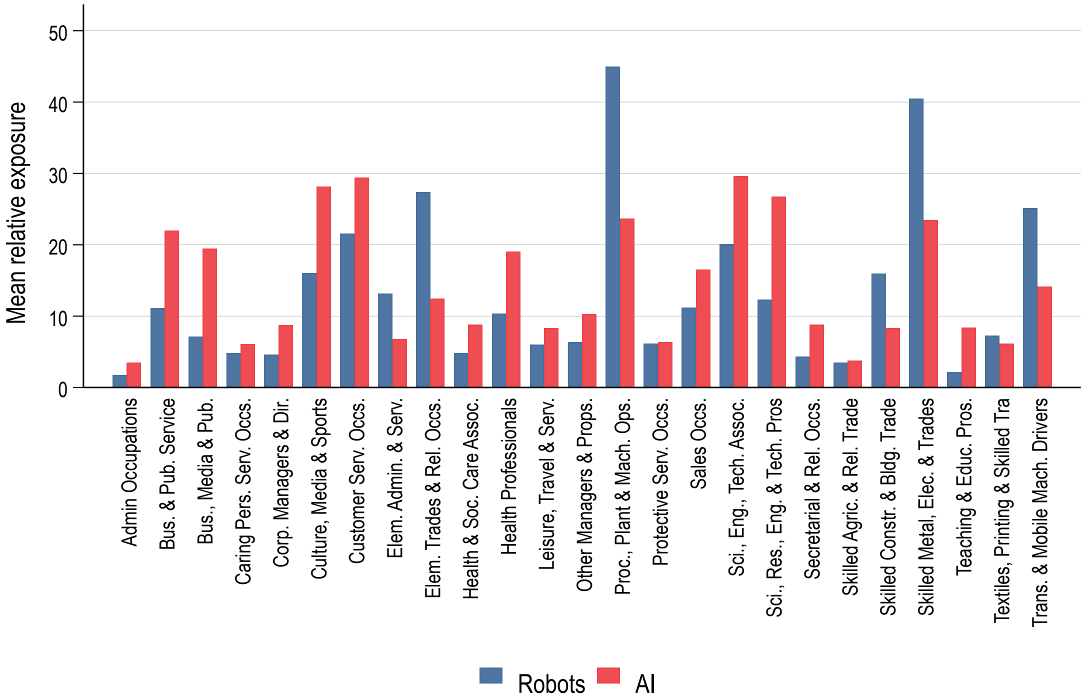


Fig. 3: Mean Relative Automation Exposures Across Two-Digit SOC 2010 Occupations to Robot and AI Technology

Note: The Figure displays the mean relative automation exposures ($Aut^{\tau}_{\mathcal{R}t}$) across two-digit SOC 2010 occupations to robot and AI technology across the 1980-2020 period. The unabbreviated forms of occupational titles can be found in the publication by Office for National Statistics (2010).

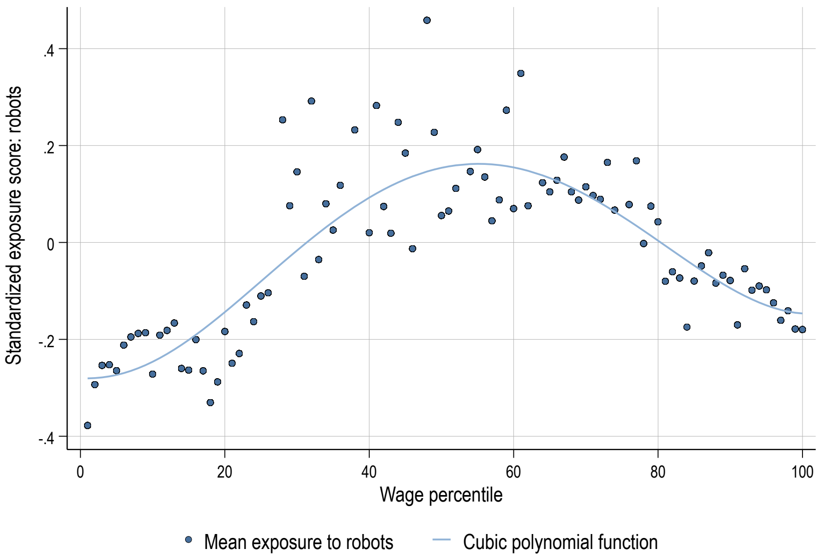
Next, we examine the automation exposures across twenty-five broad occupational groups in more detail. Figure 3 plots the mean relative exposure to robot and AI technology, revealing considerable variation across occupational groups. Here, we use the relative exposure, which normalizes the counts of automation patents to the size of patent families for robots and AI technology. This approach accounts for the differences in patent family sizes, as shown in Figure A1, enabling direct comparison of the exposure scores between the two technologies. Administrative occupations, caring and personal service occupations, health and social care occupations, secretarial and related occupations, teaching, and textiles skilled occupations show the lowest exposure to both technologies, all exhibiting higher exposure to AI automation than to robots. This is intuitive, as these occupations require personal contact, empathy, and other human-centric qualities that are currently challenging for robots or AI to imitate effectively.

On the opposite end of the spectrum, production, plants and machine operators, skilled metal, electrical and electronic trades, and transport and mobile machine drivers and operatives have significantly high exposures to our measure of being vulnerable to robot technology. This susceptibility to automation may be attributed to the prevalence of routine and repetitive tasks within these occupations. Robots excel at performing tasks that follow predictable patterns, and occupations involving production lines, machine operation, and routine tasks may be more easily automated by robots. The nature of these roles, often characterized by well-defined processes and a structured environment, makes them prone to automation, contributing to their higher exposure to robot technology.

Conversely, professionals in science, research, engineering, and technology, along with individuals in customer service, culture, media, sports, and various business, media, and public service roles, exhibit notably higher susceptibility to automation by AI compared to robot technology. This heightened our automation exposure scores to AI can be attributed to the cognitive complexity and non-routine nature of tasks inherent in these occupations, which AI can simulate cost-effectively. Many tasks, such as problem-solving, creativity, and intricate decision-making—areas where AI technology presently holds potential to match some of the human capabilities. Similarly, roles in customer service, creativity, and management heavily rely on interpersonal skills and nuanced understanding, making them less conducive to automation by robot technology but more exposed to AI technology.

5.2 Impact of automation on labor and skill demand

In this section, we turn our attention to change in labor demand proxied by changes of wage bills of industry-occupation cells over the last decade in the UK. We link these changes to exposures to automation by robot and AI technology. First, we would to see how our exposure measure is distributed across the earnings distribution. In Figure 4, we plot the standardized relative exposure ($Aut^{\tau}_{\mathcal{R}}$) to both robot and AI technology across the wage distribution. Notably, the exposure to AI technology exhibits a monotonically increasing trend as we move to the right across the earning distribution. In contrast, the average exposure to robot technology is lower at both ends of the distribution. On the left tail of earnings distribution, robots may not be cost-effective due to the unstructured environment, while on the right-hand side, tasks are of a non-routine nature, requiring high expertise. Workers most exposed to robot technology seem to be primarily in the middle part of the distribution. Intriguingly, AI is indeed replacing the upper part of the distribution, marking the first indication that AI is capable of reducing the relative demand for skills, as we will explore in greater detail later in this section.



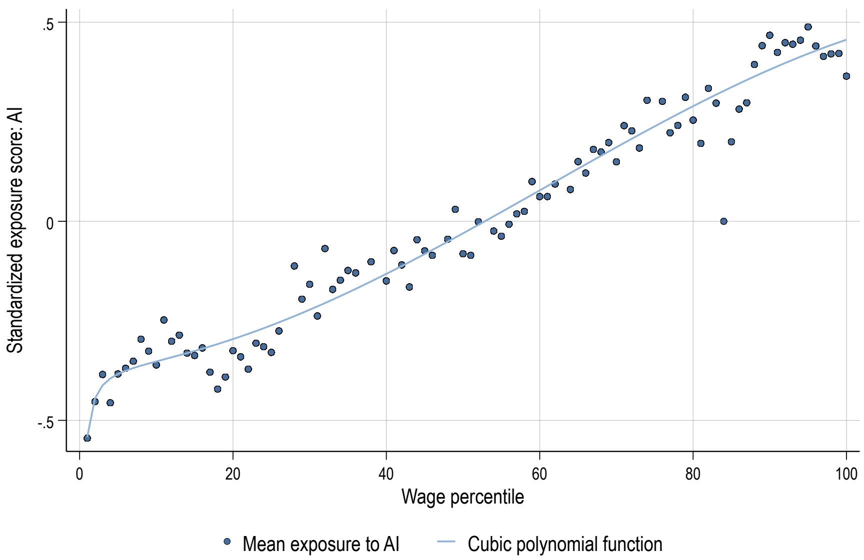


Fig. 4: Standardized Relative Exposures to Robot and AI Technology Across the Wage Distribution

Note: The Figure plots standardized relative exposures ($Aut^{\tau}_{\mathcal{R}}$) to robot and AI technology across the wage distribution. The upper panel displays the average of standardized occupation-level relative automation exposure scores for robot technology by occupational wage percentile rank, along with a smoothed value created using a cubic polynomial function, following (Webb, 2019). The lower panel exhibits the average of standardized occupation-level relative automation exposure scores for AI technology by occupational wage percentile rank, also with a smoothed value generated using a cubic polynomial function. Wage percentiles are measured as the percentile rank of an occupation's mean weekly real wage in the Annual Population Survey in 2012.

Our exposure score closely aligns with Webb (2019), who assessed robots and AI tasks (extracted verb-noun pairs) from patent titles. These were grouped into conceptual categories, resembling those used to describe occupational tasks. Webb (2019) calculated the relative patenting intensity of each task across both technology groups and correlated them as exposures by aggregating patenting intensities across O*NET tasks for US occupations. He observed a monotonically decreasing function of exposure to robots along the earnings distribution. In contrast, our results reveal a different trend. Despite Webb's AI exposure to automation decreases slightly in the top decile, he also observed a monotonically increasing function of earning, which is encouraging.

In a similar vein, Felten et al. (2019) constructed occupational exposure to AI but in a slightly different manner. They linked AI applications to workplace abilities using a crowd-sourced dataset from Amazon mTurk, creating a matrix linking 10 AI applications in which AI has made significant progress since 2010 to 52 O*NET occupational abilities. Ability-level exposure was then calculated by summing relatedness scores with equal weighting. To determine occupational exposure, they further weighted ability-level exposure using O*NET-derived prevalence and importance scores. Their AI occupational exposure is also a monotonously increasing function, consistent with our findings. For the comparison of a standardized of AI exposures scores in the US Occupational Employment Statistics by Webb (2019) and Felten et al. (2019), we refer to Figure 4 in Acemoglu, Autor, Hazell, and Restrepo (2022).

To empirically evaluate whether higher exposure to both robot and AI-driven automation leads to an overall decline in labor demand, we combine automation exposure data with information on two consecutive changes in the wage bill at the industry-occupation cell level in the UK economy over the past decade.

In Panel A, we estimate the relationship between changes in the wage bill and automation exposure for robotic technology, using inverse hyperbolic sine (IHS) transformation for the robot exposure variable. Panel B replicates this specification for AI technology exposure. For all specifications, except the baseline, we follow Autor et al. (2024) by including industry fixed effects, ensuring that the coefficients of interest capture within-industry occupational employment changes while accounting for overall shifts in industry employment.

We also control for broad occupational group fixed effects to account for unobserved characteristics, group-specific trends, and heterogeneity across groups of similar occupations. Additionally, we iteratively include controls for key labor market variables such as the shares of high-school-educated workers, college-educated workers, wage levels, and the proportion of foreign workers in the start-of-the period, as done in Webb (2019). This approach allows us to comprehensively isolate the effects of automation exposure on labor demand. However, as discussed in Section 3, these effects represent a combination of the direct negative impact on skill-non-intensive sectors and the positive absorption effects in skill-intensive sectors. To evaluate this, we test whether the negative direct effects on specific sectors outweigh the positive absorption effects in the opposite sectors as formulated in Proposition 1.

Table 1 presents estimates of Equation 5, where automation exposures are measured as the IHS-transformed count of automation patents for robot and AI technologies. The primary coefficient of interest is $\beta_1 Aut^{\tau}_{\mathcal{R}}$, representing the effect of automation exposure. We assume that the predominant direct effect of automation aligns with theoretical predictions.

The estimates in Panel A document that occupations more exposed to automation via robot technology experienced reductions in within-industry labor demand growth. For instance, in the fully saturated model presented in column (6), an increase in the automation measure for robot technology by 10 percent is associated with a decline in the wage bill growth by -0.27 percentage points ($\beta_1 Aut^{robots} = -2.69$, s.e.: 1.84) among workers within the same industry and broad occupational group over a five-year period in the last decade. However, this estimate is only weakly significant after including multiple controls, compared to the baseline estimates in column (1).

These findings are consistent with Proposition 1, which states that automation in sector U reduces the wage bill in that sector, with displaced workers moving into sector S. However, the reduction in the wage bill in sector U exceeds the increase in sector S, resulting in a net decline in the overall wage bill for the economy.

Panel B presents the estimates for AI technology and its associated changes in industry-occupation wage bills. The results show a similar pattern to those for robot technology. In the baseline model, industry-occupation cells more exposed to AI technology experienced a decline in the wage bill over the last decade. In the fully saturated model, the point estimate becomes smaller but remains statistically significant. Specifically, column (6) indicates that an increase in the automation measure for AI technology by 10 percent is associated with a decline in the wage bill growth by -0.43 percentage points ($\beta_1 Aut^{AI} = -4.26$, s.e.: 2.43) among workers within the same industry and broad occupational group over a five-year period in the last decade.

As with robot technology, these findings align with Proposition 1, which predicts that automation in sector S reduces the wage bill in that sector, with displaced workers moving into sector U. However, the reduction in the wage bill in sector S exceeds the increase in sector U, leading to a net decline in the overall wage bill for the economy.

Despite the differences in the magnitude of the effects between robot and AI exposures, the coefficients for the two technologies are not directly comparable because they are not standardized. This distinction underscores the need for caution in interpreting the relative impacts of these technologies.

It is also notable that the estimates for our control variables reveal interesting patterns. Industries with a higher share of college-educated workers experienced smaller reductions in wage bills over the five-year period compared to industries with a lower share of college-educated workers. This finding may indicate a declining skill premium in the UK economy, consistent with evidence from Stansbury et al. (2023).

	Panel A					
	Δ Log(Wage $\text{Bill}_{i,j,t}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Automation exposure (IHS) - robots_j	-2.83**	-1.05	-1.60+	-1.80*	-2.43+	-2.69+
	(1.25)	(1.18)	(1.00)	(1.00)	(1.84)	(1.84)
High school workers share				-0.29*	-0.83***	-0.73***
				(0.16)	(0.25)	(0.25)
College workers share				-0.49***	-1.87***	-1.81***
				(0.17)	(0.28)	(0.28)
Wages					0.18+	0.19+
					(0.14)	(0.14)
Wages squared					0.00***	0.00***
					(0.00)	(0.00)
Foreign workers share						0.38+
						(0.25)
FE Industry	No	Yes	Yes	Yes	Yes	Yes
FE Broad Occ. Group.	No	No	Yes	Yes	Yes	Yes
N	2228.00	2228.00	2228.00	2228.00	2228.00	2228.00
R^2	0.00	0.03	0.08	0.08	0.46	0.46
	Panel B					
Automation exposure (IHS) - AI_j	-7.62***	-5.39***	-2.51*	-2.30*	-3.92+	-4.26*
	(1.35)	(1.38)	(1.32)	(1.31)	(2.43)	(2.43)
High school workers share				-0.27*	-0.81***	-0.69***
				(0.16)	(0.25)	(0.26)
College workers share				-0.46***	-1.83***	-1.76***
				(0.17)	(0.28)	(0.28)
Wages					0.18+	0.19+
					(0.14)	(0.14)
Wages squared					0.00***	0.00***
					(0.00)	(0.00)
Foreign workers share						0.40+
						(0.26)
FE Industry	No	Yes	Yes	Yes	Yes	Yes
FE Broad Occ. Group.	No	No	Yes	Yes	Yes	Yes
N	2228.00	2228.00	2228.00	2228.00	2228.00	2228.00
R^2	0.00	0.03	0.08	0.08	0.46	0.46

Table 1: Relationship between exposure to automation by robot and AI technology and change in the wage bill.
Note: Wage bill changes are defined within consistent SOC 2010 and SIC 2007 occupation-industry cells from the Annual Population Survey (APS) for 2012-2017-2022. The dependent variable is the five-year stacked log change in the wage bill, scaled by 100 to express growth rates in percentage points per five years. The main independent variable is the IHS-transformed automation exposure (Aut_j^τ) calculated for 1980-2020. Observations are weighted by the start-of-period working hours of each occupation-industry cell. Standard errors are clustered at the industry level. $p^+ < 0.15,\ p^* < 0.10,\ p^{**} < 0.05,\ p^{***} < 0.01$.

As a robustness check, we present the results in Table A2, where we use an alternative measure of automation exposure. Instead of relying on IHS-transformed exposure scores in levels, we employ the log change in exposure between the periods 1980–2000 and 2000–2020. This approach offers a potentially more exogenous measure of automation exposure, as it captures the relative change in automation intensity over time rather than its absolute level. By focusing on changes, this measure is less likely to be influenced by the possible augmentation of these technologies, which could confound estimates based on exposure levels.

The results confirm that the negative effects of automation on wage bills remain robust across this specification. For both robot and AI technologies, the estimated effects are consistent with the theoretical predictions outlined in Proposition 1. Specifically, higher exposure to automation is associated with a significant reduction in the wage bill, further reinforcing the evidence that automation leads to net declines in labor demand within sectors most affected by these technologies.

Our previous results suggest that the trend of middle-class hollowing may have been reversed due to the emergence of AI technology in the UK during the decade studied. We observed that industries with a higher share of college-educated workers experienced larger declines in labor demand. If this trend continues, future advances in AI technology could potentially contribute to rebuilding the middle class, as argued by Autor (2024), by reducing the overall demand for skills.

Figure 5 depicts the reduced form relationship between the change in the log of the college wage bill relative to the high school wage bill and the mean exposure of industry-occupation cells to robots between 2012 and 2022. The data points represent different industry-occupation cells, with the size of each bubble corresponding to the wage bill size within that cell at the beginning of the period. The colors of the bubbles indicate the industry's sectors. The fitted line suggests a weak positive association between robot exposure and the change in relative skill demand. Figure 5 reveals that the manufacturing, utilities, and construction sectors exhibit the highest exposure to robots. This is indicated by the large red bubbles positioned towards the right end of the horizontal axis. In contrast, public services and arts show the low exposure to robot technology, with light blue bubbles clustering towards the lower end. The services sector has some sub-sectors with notable robot exposure, while agriculture and mining generally exhibit the lowest exposure, despite some exceptions.

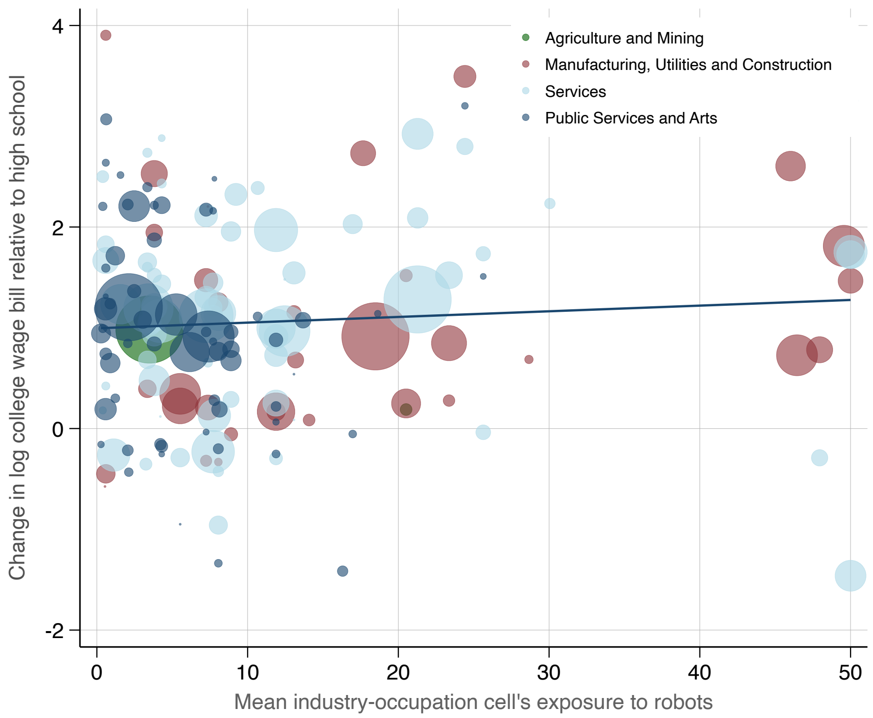


Fig. 5: Relationship Between Change in Relative Skill Demand and Mean Industry-Occupation Cell's Exposure to Robot Technology

Note: Weighted by hours worked in 2012 for each occupation-industry cell.

In Figure 6, we plot the same relationship but now for the mean exposure of industry-occupation cells to AI technology. A primary observation is that numerous observations belonging to the sectors of services, public services, and arts have now shifted to the right end of the horizontal axis, indicating that their exposure to AI technology is much higher compared to robot technology. Agriculture and mining industries remain at the very left-hand side, again exhibiting the lowest exposure to AI technology. The fitted line suggests a weaker and less steep but negative association between AI exposure and changes in relative skill demand.

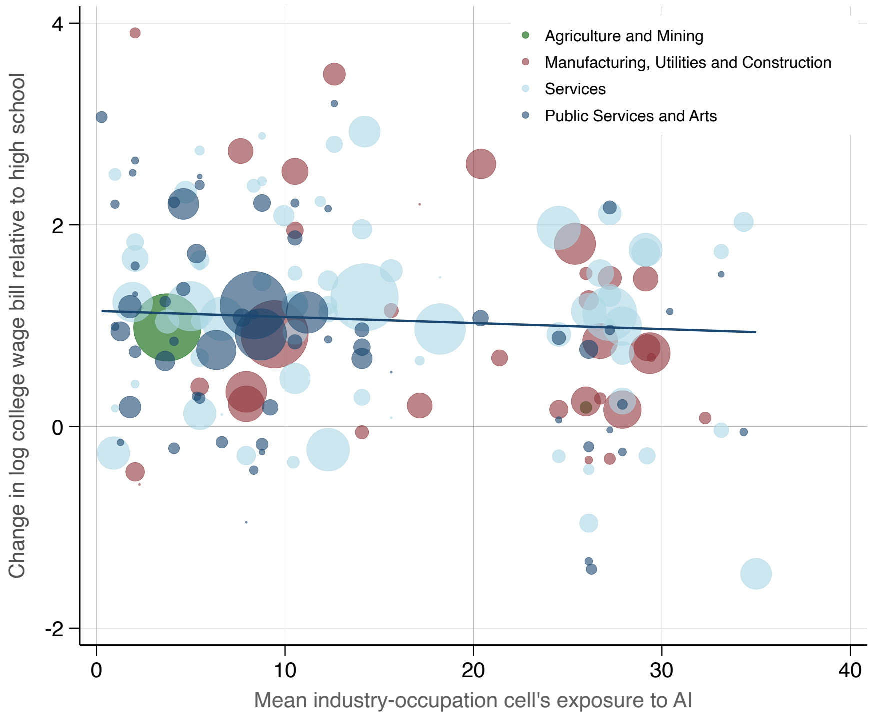


Fig. 6: Relationship Between Change in Relative Skill Demand and Mean Industry-Occupation Cell's Exposure to AI Technology

Note: Weighted by hours worked in 2012 for each occupation-industry cell.

In Table 2, we extend the reduced-form relationships depicted in Figures 5 and 6 by incorporating industry fixed effects. The first two columns estimate the relationship between changes in relative skill demand and relative exposure to robots and AI separately. These estimates are not statistically significant when analyzed in isolation. In the third column, both exposure measures are included in a single model.

	Δ log(Relative skill demand$_{i,j}$)		
	(1)	(2)	(3)
Automation exposure (IHS) - robots$_j$	0.11		0.35*
	(0.09)		(0.18)
Automation exposure (IHS) - AI$_j$		-0.00	-0.38*
		(0.10)	(0.20)
Constant	-0.14	1.24	1.14
	(1.08)	(1.09)	(0.88)
FE Industry	Yes	Yes	Yes
N	152	152	152
R^2	0.10	0.09	0.13

Table 2: Relationship between exposure to automation by robot and AI technology and change in the skill demand.
Note: Changes in skill demand are defined in consistent SOC 2010 and SIC 2007 occupation-industry cells in the Annual Population Survey (APS) 2012-2022 period. The independent variables are the IHS-transformed automation exposures (Aut_j^τ) calculated for 1980-2020. Observations are weighted by start-of-period working hours of an occupation-industry cell. The long-difference is a one-decade change, 2012-2022. Fixed effects are defined across 19 industries. Standard errors are clustered at the industry level. $p^* < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

The results reveal that exposure to robots has a positive and significant relationship with changes in skill demand. This finding suggests that higher exposure to robot automation technology is associated with an increase in the demand for college-educated workers. Specifically, our model predicts that a 10 percent increase in exposure to robot automation corresponds to a 0.03 percentage-point increase in skill demand growth ($\beta_1 Aut^{robots} = 0.35$, s.e.: 0.18) among workers in the same industry over the past decade. These results align with the predictions of Autor et al. (2024), particularly Corollary 2, under the assumption that robot automation primarily affects low-skilled workers, as documented empirically in Figure 1. Similarly, AI exposure is associated with skill demand growth, but in the opposite direction, suggesting that higher exposure to AI technology predominantly affects high-skilled workers. However, while these estimates are weakly significant, their economic significance remains limited.

As a robustness check, we present additional results in Table A3, where we use an alternative measure of automation exposure. Instead of relying on IHS-transformed exposure scores in levels, we employ the log change in exposure between the periods 1980–2000 and 2000–2020. However, using this alternative measure, we find no significant association between automation exposure and changes in skill demand growth.

6 Conclusions

In this paper, we explored the impact of industrial robots and AI on wage bill and the relative demand for skills in the UK over the last decade. To this end, we provided empirical insights into the evolving dynamics of the labor market and the role of AI in labor displacement. Building on the framework developed by Webb (2019) and Autor et al. (2024), we constructed UK specific occupational exposures to automation technologies, offering a direct measurement beyond the US-centric perspective.

We documented a distinct pattern of exposure, with the middle-income distribution primarily exposed to our measure of automation by robots, while the tails of the income distributions seem to be unaffected. When it comes to AI, we found that the exposure is a monotonically increasing function across income percentiles. We also documented exposure across educational levels, where low-skilled workers are mostly exposed to robot technology and high-skilled workers to AI technology.

We found consistent evidence that occupations more exposed to automation by robot and AI technology experienced negative within-industry growth in labor demand. Robot automation predominantly affects lower-skilled workers, leading to reductions in wage bill growth for occupations within sectors exposed to this technology, consistent with the extension of the Autor et al. (2024) model. Similarly, AI technology primarily impacts higher-skilled workers, resulting in declines in wage bills. Additionally, the finding that industries with a higher share of college-educated workers experienced smaller reductions in wage bills may indicate a declining skill premium in the UK economy, consistent with evidence from Stansbury et al. (2023).

Lastly, our analysis highlights the differing effects of robot and AI automation on skill demand. We found a subtle positive relationship between exposure to robots and changes in relative skill demand, with sectors such as manufacturing, utilities, and construction showing increased exposure to robot automation. Conversely, exposure to AI technology exhibited a weaker, negative relationship with changes in skill demand, with sectors such as services, public administration, and the arts being significantly more exposed to AI than robots. When estimating the conditional correlation of exposure to both robot and AI automation jointly, we found that robot automation is positively and significantly associated with an increase in demand for college-educated workers. Conversely, in this joint model, AI automation is weakly associated with a decline in skill demand growth, predominantly affecting high-skilled workers. While the economic significance of these findings is limited, they underscore the asymmetric impacts of automation technologies across skill groups. Robustness checks using alternative measures of automation exposure as a change over two time periods did not reveal significant associations, suggesting the results may depend on the specific measure of automation exposure.

Although the majority of our findings are statistically and economically significant, they highlight the nuanced impact of automation technologies on the labor market. These results urge policymakers to adopt cautious strategies to manage potential disruptions while harnessing the benefits of technological advances. Our findings also suggest that the trend of middle-class hollowing in the UK over the past decade may have been reversed. As argued by Autor (2024), future advances in AI technology, if properly managed, have the potential to rebuild the middle class by reducing skill polarization.

Disclosure statement

The opinions expressed are the authors' personal views and not necessarily those of the institution the authors are affiliated with. The usual disclaimers apply.

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Data availability statement

We are committed to ensuring transparency and replicability in our research. The data used in this paper, sourced from the Annual Population Survey (APS), are available through the UK Data Service for research purposes. Access to the APS dataset can be obtained by contacting the UK Data Service at https://ukdataservice.ac.uk/. The data used to obtain the corpus of patents are sourced from Google Patents Public Data, provided by IFI CLAIMS Patent Services and Google. Google Patents Public Data can be directly obtained from Google Cloud at https://console.cloud.google.com/marketplace/product/google_patents_public_datasets/google-patents-public-data?pli=1. Due to size limitations, the raw database is not shared. However, detailed information is provided in the methodology section, enabling the replication of queries and analyses performed on this dataset for research purposes. Additionally, the computed exposure scores used in this paper, aggregated at the level of unit groups in the SOC 2010 occupational classification, are accessible through the authors' GitHub repository at https://github.com/authors. All relevant cleaning and replication files necessary for reproducing the paper's findings are available upon request.

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Appendix A

SOC Code	Title of Occupation	Tasks
2121	Civil Engineers	Undertakes research and advises on soil mechanics, concrete technology, hydraulics, water and wastewater treatment processes, and other civil engineering matters; determines and specifies construction methods, materials, quality and safety standards and ensures that equipment operation and maintenance comply with design specifications; designs foundations and earthworks; designs structures such as roads, dams, bridges, railways, hydraulic systems, sewerage systems, industrial and other buildings, and plans the layout of tunnels, wells, and construction shafts; organizes and plans projects, arranges work schedules, carries out inspection work, and plans maintenance control; organizes and establishes control systems to monitor operational efficiency and performance of materials and systems.
8137	Sewing Machinists	Operates standard and specialized machines to sew, finish, and repair garments and other textile, fabric, fur, and skin products; examines fabrics of all types to identify imperfections and determine the best method of repair; performs hand sewing tasks in the making, trimming, and finishing of fur, sheepskin, leather, upholstery, mats, carpets, umbrellas, and other textile products; embroiders decorative designs on textiles with machine stitching; cleans and oils machines and reports or remedies any mechanical faults.

Table A1: Example of Occupational Tasks from UK SOC (2010) Classification published by (Office for National Statistics, 2010).

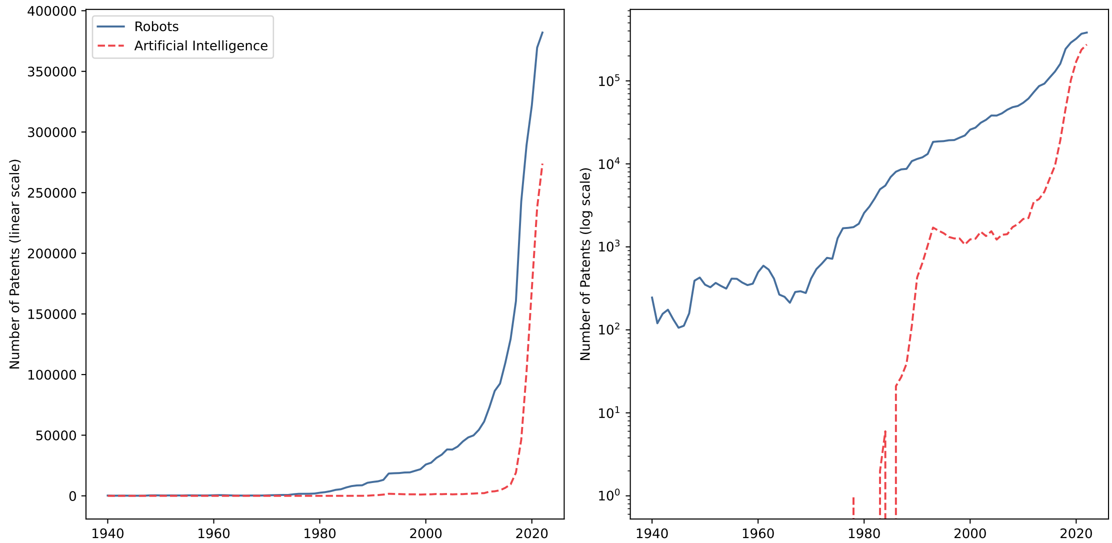

Fig. A1: Number of Patents Related to Robot and AI Technology. The left panel displays the data on a linear scale, while the right panel presents it on a logarithmic scale. Source: Google Patents Public Database.

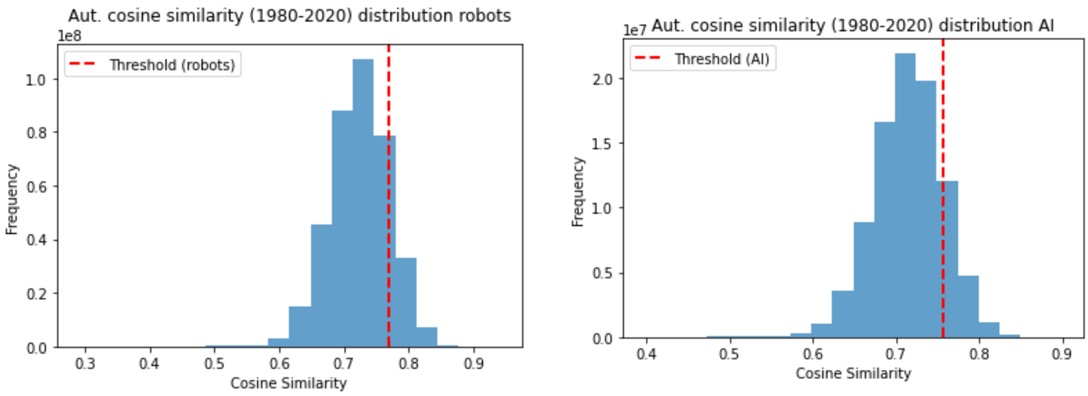

Fig. A2: Cosine Similarity Matrix Between Dense Vectors Representing Patents for Robot (Left Panel) and AI (Right Panel) Technology and the Description of Tasks

Note: The Figure plots distributions of the cosine similarity matrix ($X^{\tau}_{p,j}$) between dense vectors representing patents for robots (left panel) and AI (right panel) technology, and dense vectors representing the description of labor tasks across four-digit SOC 2010 occupations obtained with the BERT model by Devlin et al. (2018). The distribution is plotted across the entire period from 1980 to 2020. The dashed line represents the 85th percentile of the similarity distribution for each similarity matrix, above which we consider a patent as highly likely to automate labor tasks in the production process.

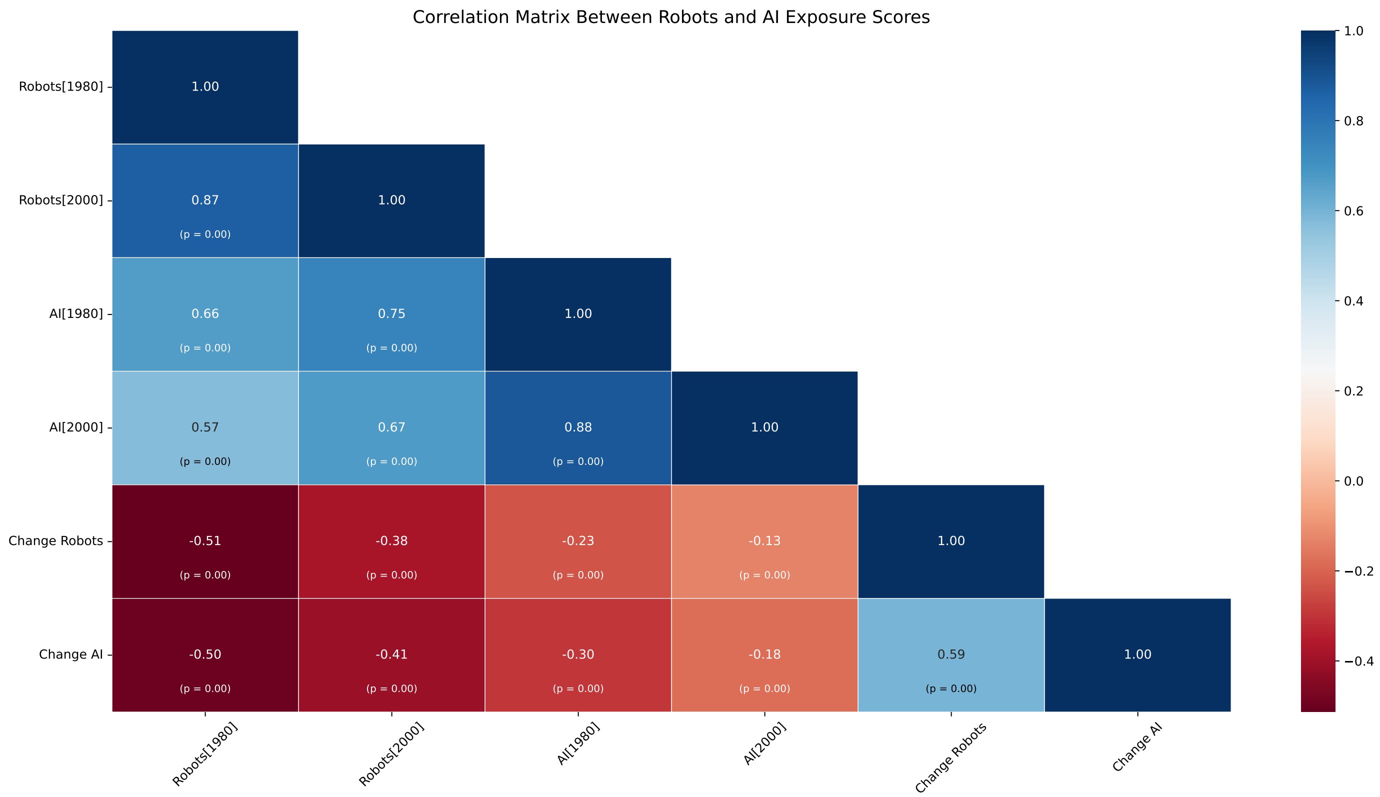

Fig. A3: Correlation Matrix Between Automation Patent Raw Counts and Their Relative Changes During the Periods 1980-2000 and 2000-2020

Note: The Figure displays the correlation matrix between automation patent raw counts (patents above 85th percentile of the cosine similarity matrix ($X^{\tau}_{p,j}$)) and their relative changes during the periods 1980-2000 and 2000-2020. Reported correlation coefficients and p-values, are computed using the Kendall method.

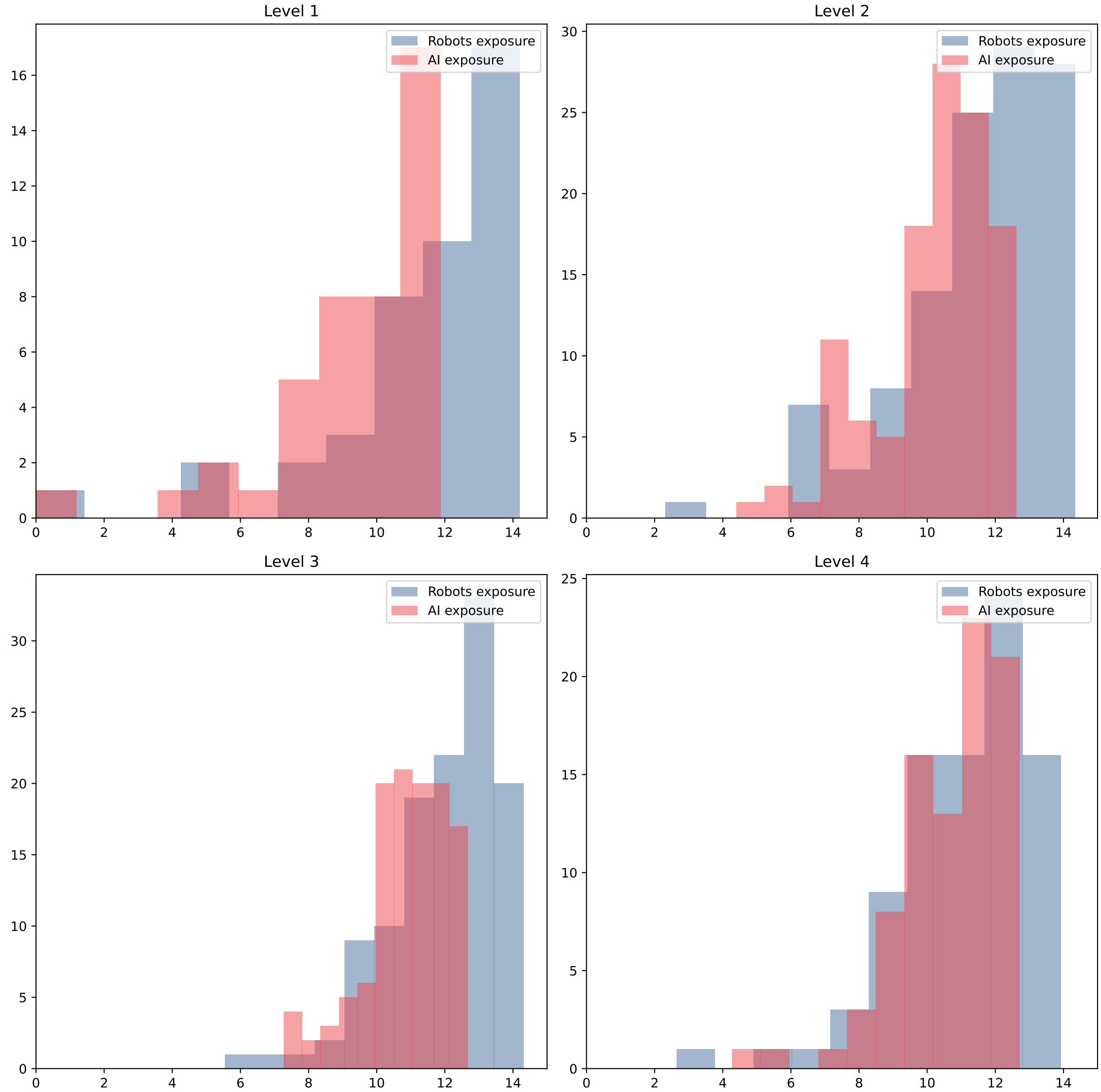

Fig. A4: Distributions of the SOC 2010 Occupations to Automation Exposures (Aut_t^τ) from 1980 to 2020 for Robot and AI Technology Across Four Skill Levels

Note: Automation measures are transformed using the inverse hyperbolic sine (IHS). Skill levels range from basic education (Level 1) to professional roles (Level 4). Level 1 involves general education and tasks such as postal work or cleaning. Level 2 includes roles like machine operation and driving, which require extended training. Level 3 encompasses post-compulsory education roles, technical and trade jobs. Educational qualifications in these occupations are not always mandatory, but work experience is crucial. Level 4 is reserved for high-level roles, demanding a degree or equivalent experience in professional or managerial positions (Office for National Statistics, 2010).

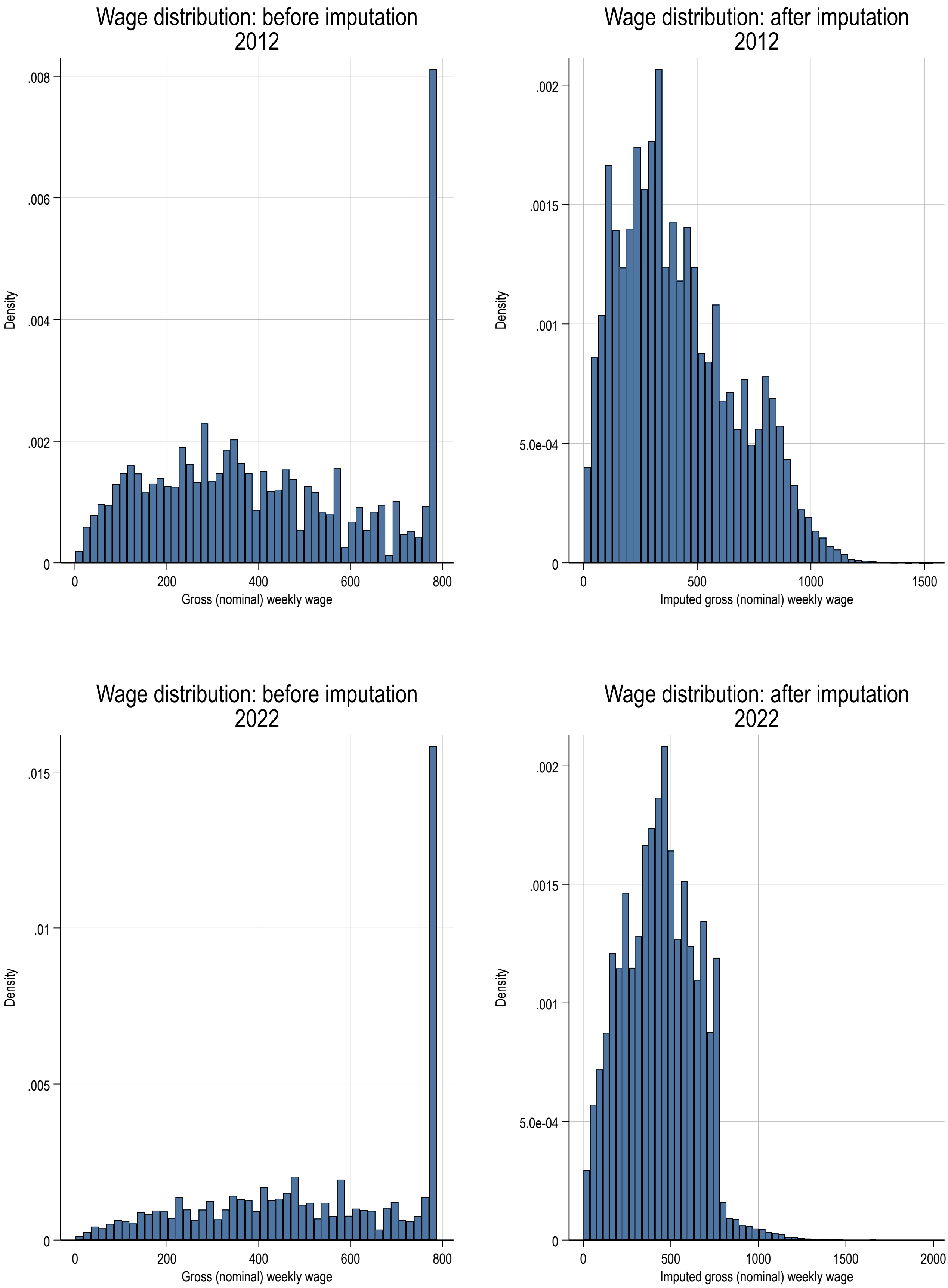

Fig. A5: Wage Distributions Before and After Imputation Using the Tobit Model Described in (Büttner & Rässler, 2008)

Note: The left panels illustrate the distribution of wages before imputation from the Annual Population Survey (APS), while the right panels depict wage distributions after imputation. The imputation method involves a single imputation by estimating parameters based on observable characteristics of workers, such as education level, working hours, gender, nationality, and age (first stage). For censored wages, a random value is drawn from a truncated normal distribution, considering that the true value is above the censoring threshold (second stage).

	Panel A					
	Δ Log(Wage $\text{Bill}_{\text{i,j,t}}$)					
	(1)	(2)	(3)	(4)	(5)	(6)
Change in automation exposure - robots_{j}	-0.10***	-0.15***	-0.01	0.00	-0.13*	-0.13*
	(0.04)	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)
High school workers share				-0.27*	-0.76***	-0.67***
				(0.16)	(0.25)	(0.26)
College workers share				-0.47***	-1.76***	-1.70***
				(0.17)	(0.29)	(0.29)
Wages					0.19	0.20
					(0.14)	(0.14)
Wages squared					0.00***	0.00***
					(0.00)	(0.00)
Foreign workers share						0.29
						(0.25)
FE Industry	No	Yes	Yes	Yes	Yes	Yes
FE Broad Occ. Group.	No	No	Yes	Yes	Yes	Yes
N	2228.00	2228.00	2228.00	2228.00	2228.00	2228.00
R^2	0.00	0.03	0.08	0.08	0.46	0.46

	Panel B					
Change in automation exposure - AI_{j}	-0.10	-0.27***	-0.07	-0.06	-0.38***	-0.37**
	(0.08)	(0.08)	(0.08)	(0.07)	(0.15)	(0.14)
High school workers share				-0.26+	-0.75***	-0.68***
				(0.16)	(0.25)	(0.26)
College workers share				-0.46***	-1.79***	-1.74***
				(0.17)	(0.29)	(0.28)
Wages					0.19	0.20+
					(0.14)	(0.14)
Wages squared					0.00***	0.00***
					(0.00)	(0.00)
Foreign workers share						0.27
						(0.24)
FE Industry	No	Yes	Yes	Yes	Yes	Yes
FE Broad Occ. Group.	No	No	Yes	Yes	Yes	Yes
N	2228.00	2228.00	2228.00	2228.00	2228.00	2228.00
R^2	0.00	0.03	0.08	0.08	0.46	0.46

Table A2: Relationship between exposure to automation by robot and AI technology and change in the wage bill.

Note: Wage bill changes are defined within consistent SOC 2010 and SIC 2007 occupation-industry cells from the Annual Population Survey (APS) for 2012-2017-2022. The dependent variable is the five-year stacked log change in the wage bill, scaled by 100 to express growth rates in percentage points per five years. The main independent variable is the log change in automation exposure (Aut_j^τ) calculated between 1980-2000 and 2000-2020 period. Observations are weighted by the start-of-period working hours of each occupation-industry cell. Standard errors are clustered at the industry level. $p^+ < 0.15$, $p^* < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

	Δ log(Relative skill demand$_{\mathrm{i,j}}$)		
	(1)	(2)	(3)
Change in automation exposure - robots$_{\mathrm{j}}$	-0.00		0.00
	(0.00)		(0.01)
Change in automation exposure - AI$_{\mathrm{j}}$		-0.01	-0.01
		(0.01)	(0.02)
Constant	1.62**	3.93	4.68
	(0.59)	(3.27)	(4.63)
Constant	-0.14	1.24	1.14
	(1.08)	(1.09)	(0.88)
FE Industry	Yes	Yes	Yes
N	152	152	152
R^2	0.09	0.10	0.10

Table A3: Relationship between exposure to automation by robot and AI technology and change in the skill demand.

Note: Changes in skill demand are defined in consistent SOC 2010 and SIC 2007 occupation-industry cells in the Annual Population Survey (APS) 2012-2022 period. The independent variables are the log changes in automation exposure (Aut_j^τ) calculated between 1980-2000 and 2000-2020 period. Observations are weighted by start-of-period working hours of an occupation-industry cell. The long-difference is a one-decade change, 2012-2022. Fixed effects are defined across 19 industries. Standard errors are clustered at the industry level. $p^* < 0.10$, $p^{**} < 0.05$, $p^{***} < 0.01$.

Appendix B

B.1 Environment

We consider and empirically test the same model as in Autor et al. (2024), an economy with two sectors $j \in \{U, S\}$, producing skill-non-intensive (Y_U) and skill-intensive (Y_S) goods or services. A representative household consumes Y_U and Y_S according to:

$$U(Y_U, Y_S) = Y_U^{\beta} Y_S^{1-\beta}, \quad \beta \in (0, 1),$$

where β represents the preference for skill-non-intensive goods. Exogenous changes in β shift demand between the two sectors.

Each sector j produces a unique final output by combining a unit measure of tasks $i \in [N_j - 1, N_j]$:

$$Y_j = \left(\int_{N_j - 1}^{N_j} y_j(i)^{\frac{\sigma-1}{\sigma}} \, di \right)^{\frac{\sigma}{\sigma-1}},$$

where $y_j(i)$ is the output of task i in sector j, and $\sigma > 1$ is the elasticity of substitution between tasks.

Each task i is produced by combining intermediates $q_j(i)$, capital $k_j(i)$, and a labor composite $n_j(i)$. The production function for task i is:

$$y_j(i) = \begin{cases} B_j q_j(i)^{\eta} k_j(i)^{1-\eta}, & \text{if } i \in [N_j - 1, I_j], \\ B_j q_j(i)^{\eta} [\gamma_j(i) n_j(i)]^{1-\eta}, & \text{if } i \in (I_j, N_j], \end{cases}$$

where $B_j = \psi_j^{\eta} (1-\eta)^{1-\eta}$ is a scaling factor for notational convenience, $\eta \in (0, 1)$ is the share of output paid to intermediates, $\gamma_j(i)$ is the productivity of the labor composite $n_j(i)$, and I_j is the threshold for automation. They assume $\gamma_j(i)$ is strictly increasing, implying that labor has a comparative advantage in tasks with higher indices. It implies a workers' higher comparative advantage and specialization in the production of tasks with an increasing index, as demonstrated by Acemoglu and Restrepo (2019). Additionally, Autor et al. (2024) show the existence of a unique static equilibrium in the task space N_{j-1}, N_j. This equilibrium is determined by a range of tasks, the capital stock and automation technology frontier I^*, and the automation threshold I, resulting in a unique employment level for low-skilled and high-skilled labor in each sector j. Task-specific intermediates $q_j(i)$ embody the technology used for production. Automation requires the production of corresponding intermediate products. Intermediates are supplied competitively and can be produced using ψ_j units of the final good.

Autor et al. (2024) model each task i is produced by low-skilled (L), high-skilled (H) labor, or capital. The total measures of high-skill and low-skill labor are $H > 0$ and $L > 0$, respectively. Labor is supplied inelastically across sectors. The labor composite $n_j(i)$ in each sector is a Cobb-Douglas combination of L and H:

$$n_j(i) = l_j(i)^{\alpha_j} h_j(i)^{1-\alpha_j},$$

where $0 < \alpha_S < \alpha_U < 1$. Sector S is skill-intensive ($\alpha_S < \alpha_U$), while sector U is skill-non-intensive. Equilibrium labor allocations satisfy (Autor et al., 2024):

$$L_U + L_S = L, \quad H_U + H_S = H.$$

Autor et al. (2024) show that sectoral wage index is defined as:

$$W_j = \alpha_j^{-\alpha_j} (1-\alpha_j)^{\alpha_j - 1} W_L^{\alpha_j} W_H^{1-\alpha_j},$$

where W_L and W_H are the economy-wide wages for low-skill and high-skill labor, respectively. Capital is sector-specific, with K_U and K_S taken as given, and capital rental rate R_j.

Both types of labor are used in each sector, but a crucial assumption is that H labor is used more intensively in the skill-intensive S sector, and L labor is used more intensively in the skill-non-intensive U sector ($0 < \alpha_S < \alpha_U < 1$).

Autor et al. (2024) show that the automation process is characterized as shifting the sectoral automation threshold I_j to the right, while the augmentation process involves introducing new labor-using tasks in a sector, leading to an increase in N_j. Since we lack an objective measure of augmentation exposures in occupations that would follow Autor et al. (2024), we will use only the measure of automation exposure scores to capture an exogenous change in automation at the level of occupations within sectors of the economy.

Consequently, we can only partially test their *Proposition 1: Employment effects of automation* (Autor et al., 2024):

Automation in sector U (an increase in I_U) increases the range of tasks produced by capital in sector U (skill-non-intensive sector), which reduces the employment of both high-skilled and low-skilled workers in that sector. These workers move into sector S (skill-intensive sector):

$$\frac{\partial L_U}{\partial I_U}, \frac{\partial H_U}{\partial I_U} < 0, \quad \frac{\partial L_S}{\partial I_U}, \frac{\partial H_S}{\partial I_U} > 0;$$
$$\frac{\partial L_U}{\partial I_S}, \frac{\partial H_U}{\partial I_S} > 0, \quad \frac{\partial L_S}{\partial I_S}, \frac{\partial H_S}{\partial I_S} < 0.$$

This proposition, a key testable implication of their conceptual framework, reveals the direction of labor flows in response to automation. All else equal, automation in a sector leads to the contraction of that sector by reducing employment of both types of workers. Three mechanisms jointly underlie the co-movement of low- and high-skill workers across sectors in response to automation. First, tasks are gross substitutes in each sector ($\sigma > 1$), so automation in a given sector implies a fall in that sector's labor share. Second, high- and low-skill labor are combined in Cobb-Douglas fashion in each sector, so the wagebill paid to each skill group by a sector is proportional to that sector's labor share. Finally, the share of aggregate expenditure devoted to each sector is fixed by the utility function. Hence, automation in a sector spurs a decline in the sector's labor share, yielding an inward shift in both high- and low-skill sectoral labor demand relative to the other sector (Autor et al., 2024).

Building on the previous sections, and with automation exposure scores computed for two distinct technologies, we can analyze the sector-wise impact of changes in the automation frontier, I_U and I_S. First, we analyze the impact of automation in the unskilled sector U on the wage bills in both sectors U and S. Autor et al. (2024) showed that the change in wage bill due to the automation in sector U is of the opposite sign compared to the change of wage bill in sector S, and vice versa. We show that it is not only of the opposite sign, but the magnitude of the direct effect (decline) in sector U is larger, than the associated absorption effect (increase) in sector S. This absorption is lower because the sector S has a limited capacity to absorb unskilled and skilled labor due to its reliance on high-skilled workers and other structural constraints. Therefore, we observe the decline in overall wage bill in the economy. In this part we aim to show the equilibrium conditions and assumptions for the Proposition 1 to hold:

Proposition 1. *Automation in sector U, through the adoption of robot technology—reduces the wage bill in that sector, with displaced workers moving into sector S. This results in the reduction of the wage bill in sector U and an increase of the wage bill in sector S, while the following inequality holds:*

$$\left|\frac{\partial \, Wage\ Bill_U}{\partial I_U} \Delta I_U\right| > \frac{\partial \, Wage\ Bill_S}{\partial I_U} \Delta I_U, \tag{B1}$$

leading to a net decline in the economy-wide wage bill:

$$\frac{\partial \, Wage\ Bill}{\partial I_U} \Delta I_U < 0. \tag{B2}$$

Similar conditions apply when automation occurs in sector S, through the adoption of AI technology. In this case, displaced workers move to sector U, but the overall wage bill still declines:

$$\frac{\partial \, Wage\ Bill}{\partial I_S} \Delta I_S < 0. \tag{B3}$$

The wage bills for low-skilled and high-skilled labor in each sector are defined as (Equations (A32) to (A35) in Autor et al. (2024)):

$$
\begin{aligned}
W_L L_U &= \alpha_U s_L^U P_U Y_U = \alpha_U s_L^U \beta Y, \\
W_L L_S &= \alpha_S s_L^S P_S Y_S = \alpha_S s_L^S (1-\beta) Y, \\
W_H H_U &= (1-\alpha_U) s_L^U P_U Y_U = (1-\alpha_U) s_L^U \beta Y, \\
W_H H_S &= (1-\alpha_S) s_L^S P_S Y_S = (1-\alpha_S) s_L^S (1-\beta) Y.
\end{aligned}
$$

where, W_L and W_H are the wages for low-skilled and high-skilled labor, respectively. α_j represents the share of low-skilled labor in sector j. s_L^j is the labor share in sector j. β is the expenditure share on the unskilled sector Y_U, with $0 < \beta < 1$. Y is total output (normalized to 1).

These equations express the total wage bills in each sector as a function of the labor shares, the expenditure shares, and the total output. The labor share in sector j is given by (Acemoglu & Restrepo, 2019):

$$
s_L^j = \left[1 + \left(\frac{1-\Gamma_j}{\Gamma_j} \right)^{1/\sigma} \left(\frac{K_j}{L_j} \right)^{\frac{\sigma-1}{\sigma}} \right]^{-1}. \tag{B4}
$$

where $\sigma > 1$ is the elasticity of substitution between tasks. Γ_j depends on the range of tasks performed by labor in sector j:

$$
\Gamma_j = \frac{\int_{I_j}^{N_j} \gamma_j(i)^{\sigma-1}\, di}{[I_j - N_j + 1]^{\sigma-1} + \int_{I_j}^{N_j} \gamma_j(i)^{\sigma-1}\, di}.
$$

K_j is the fixed capital stock in sector j. L_j is the total labor employed in sector j.

The labor share s_L^j represents the proportion of total income in sector j that goes to labor. It depends on the relative productivity of labor and capital in that sector, as well as the capital-labor ratio and the range of tasks performed by labor.

B.2 Automation in Sector U with Robot Technology

When automation occurs in sector U, the automation threshold I_U increases, which means that more tasks are being performed by capital rather than labor. This reduces the range of tasks $[I_U, N_U]$ performed by labor, leading to a decrease in Γ_U:

$$
\frac{\partial \Gamma_U}{\partial I_U} < 0.
$$

Since Γ_U decreases, the labor share s_L^U in sector U also decreases:

$$
\frac{\partial s_L^U}{\partial I_U} < 0.
$$

This means that automation in sector U leads to a reduction in the proportion of income going to labor in that sector.

The total wage bill in sector U is given by:

$$
\text{Wage Bill}_U = W_L L_U + W_H H_U = s_L^U \beta Y.
$$

The change in the wage bill due to automation in sector U can be calculated by differentiating with respect to I_U:

$$
\Delta \text{Wage Bill}_U = \frac{\partial \text{Wage Bill}_U}{\partial I_U} \Delta I_U = \left(\frac{\partial s_L^U}{\partial I_U} \beta Y \right) \Delta I_U.
$$

Since $\frac{\partial s_L^U}{\partial I_U} < 0$, the change in the wage bill is negative:

$$\Delta \text{Wage Bill}_U < 0.$$

This indicates that automation in sector U reduces the total wage bill in that sector.

***Absorption in Sector** S*

Displaced workers from sector U (both low-skilled and high-skilled) move to sector S, increasing the total labor supply L_S and H_S in sector S. The increase in L_S affects the capital-labor ratio $\frac{K_S}{L_S}$ in sector S:

$$\frac{\partial L_S}{\partial I_U} > 0 \implies \frac{\partial \left(\frac{K_S}{L_S}\right)}{\partial L_S} < 0 \implies \frac{\partial s_L^S}{\partial L_S} > 0.$$

Similarly, for high-skilled labor:

$$\frac{\partial H_S}{\partial I_U} > 0 \implies \frac{\partial s_L^S}{\partial H_S} > 0.$$

Thus, the influx of labor into sector S raises the proportion of income going to labor in that sector.

The change in wage bill in sector S due to the ∂I_U must be opposite as posit in Autor et al. (2024) Proposition 1. Similarly, the total wage bill in sector S is:

$$\text{Wage Bill}_S = W_L L_S + W_H H_S = s_L^S (1-\beta) Y.$$

The change in the wage bill in sector S due to the influx of workers from sector U is:

$$\Delta \text{Wage Bill}_S = \frac{\partial \text{Wage Bill}_S}{\partial I_U} \Delta I_U = \left(\frac{\partial s_L^S}{\partial L_S} \frac{\partial L_S}{\partial I_U} + \frac{\partial s_L^S}{\partial H_S} \frac{\partial H_S}{\partial I_U} \right) (1-\beta) Y \Delta I_U.$$

Since $\frac{\partial L_S}{\partial I_U} > 0$, $\frac{\partial H_S}{\partial I_U} > 0$, and $\frac{\partial s_L^S}{\partial L_S}, \frac{\partial s_L^S}{\partial H_S} > 0$, the change in the wage bill in sector S is positive:

$$\Delta \text{Wage Bill}_S > 0.$$

This reflects the fact that sector S is absorbing displaced workers, leading to an increase in its total wage bill.

Our goal is to compare the magnitude of the decrease in the wage bill in sector U with the increase in the wage bill in sector S. Specifically, we aim to show:

$$|\Delta \text{Wage Bill}_U| > \Delta \text{Wage Bill}_S.$$

Consider the ratio of the increase in sector S to the decrease in sector U:

$$\frac{\Delta \text{Wage Bill}_S}{|\Delta \text{Wage Bill}_U|} = \frac{\left(\frac{\partial s_L^S}{\partial L_S} \frac{\partial L_S}{\partial I_U} + \frac{\partial s_L^S}{\partial H_S} \frac{\partial H_S}{\partial I_U} \right) (1-\beta) Y}{\left| \frac{\partial s_L^U}{\partial I_U} \beta Y \right|}.$$

We use the fact that $\frac{\partial L_S}{\partial I_U} = -\frac{\partial L_U}{\partial I_U} > 0$ and $\frac{\partial H_S}{\partial I_U} = -\frac{\partial H_U}{\partial I_U} > 0$, since workers leaving sector U enter sector S. Both the numerator and the denominator in this ratio are positive quantities.

To establish that the decrease in the wage bill in sector U exceeds the increase in sector S, we require:

$$\left| \frac{\partial s_L^U}{\partial I_U} \beta \right| > \left(\frac{\partial s_L^S}{\partial L_S} \left(-\frac{\partial L_U}{\partial I_U} \right) + \frac{\partial s_L^S}{\partial H_S} \left(-\frac{\partial H_U}{\partial I_U} \right) \right) (1-\beta).$$

This inequality suggests that the proportional decrease in the labor share in sector U, weighted by the expenditure share β, is larger than the product of the proportional increase in the labor share in sector S, the number of displaced workers absorbed, and the expenditure share $(1-\beta)$.

Given that $\beta > (1-\beta)$ when $\beta > 0.5$, and considering typical parameter values in the model (such as higher σ and $\alpha_U > \alpha_S$), this condition is likely to hold.

Under reasonable parameter values as shown in Figure B6 the direct negative effect of automation in sector U (i.e., the decrease in the wage bill in U) is larger than the indirect positive effect in sector S (i.e., the increase in the wage bill in S). As a result, the total wage bill in the economy decreases due to automation in sector U. The reduction in income for workers in sector U is not fully compensated by the increase in income for workers in sector S.

Moreover, several additional factors inherent in the Autor et al. (2024)s' model defining the structure of sector S contribute to its limited capacity to absorb the displaced workers from sector U:

First, sector S has a lower labor intensity compared to sector U. Recall the assumption that the labor composite in each sector is given by:

$$n_j(i) = l_j(i)^{\alpha_j} h_j(i)^{1-\alpha_j},$$

where α_j represents the share of low-skilled labor in sector j. We have:

$$0 < \alpha_S < \alpha_U < 1.$$

This inequality implies that sector S relies less on low-skilled labor than sector U. Consequently, the demand for low-skilled labor in sector S is inherently limited, reducing its ability to absorb a large influx of displaced low-skilled workers from sector U.

Second, the capital stock in sector S is fixed. As displaced workers enter sector S, the total labor supply L_S and H_S increase, leading to a decrease in the capital-labor ratios:

$$\frac{K_S}{L_S}\downarrow, \quad \frac{K_S}{H_S}\downarrow \quad \text{as} \quad L_S\uparrow,\ H_S\uparrow.$$

A decreasing capital-labor ratio implies that there is less capital available per worker, which can reduce the marginal productivity of labor. This decrease in productivity limits the extent to which sector S can utilize additional labor effectively, thus constraining its absorption capacity.

Third, the production function in sector S exhibits diminishing marginal returns to labor, especially when the capital stock is fixed. As more workers are employed, the additional output produced by each new worker decreases. This is reflected in the marginal product of labor, which declines as L_S and H_S increase:

$$\text{MP}_{L_S} = \frac{\partial Y_S}{\partial L_S} = \text{function of}\left(\frac{K_S}{L_S}\right), \quad \text{MP}_{H_S} = \frac{\partial Y_S}{\partial H_S} = \text{function of}\left(\frac{K_S}{H_S}\right).$$

With decreasing capital-labor ratios, the marginal products MP_{L_S} and MP_{H_S} decline, reducing the incentive for sector S to hire additional workers beyond a certain point.

Fourth, elasticity of substitution between tasks, $\sigma > 1$, affects how easily sector S can substitute between capital-intensive and labor-intensive tasks. Although a higher σ indicates that tasks are more easily substitutable, in sector S, the lower labor intensity and the nature of tasks may limit this substitution.

Last, the parameter Γ_S, which depends on the range of tasks performed by labor, is affected by the influx of workers. However, since the range of tasks and the productivity parameter $\gamma_S(i)$ are technologically determined, there is a limit to how much additional labor can contribute to increased output.

As the labor supply L_S and H_S increase, the wage rates for workers in sector S may decrease due to the higher supply, further limiting the attractiveness of sector S for displaced workers (Acemoglu & Restrepo, 2022). Additionally, employers in sector S may prefer to hire high-skilled workers due to the sector's higher reliance on high-skilled labor $(1-\alpha_S)$, limiting opportunities for low-skilled workers.

The combination of lower labor intensity, fixed capital stock, diminishing marginal returns, and potential wage rate adjustments leads to a limited capacity for sector S to absorb a large number of displaced workers from sector U. This limitation reinforces the earlier conclusion that the direct negative effect of automation in sector U exceeds the indirect positive effect in sector S:

This outcome supports our earlier proposition that automation leads to a net reduction in the total wage bill and aggregate labor demand in the economy. It highlights the potential for the negative effects of automation in one sector to outweigh the positive effects in another sector, particularly when the absorbing sector has a lower capacity to integrate displaced workers effectively.

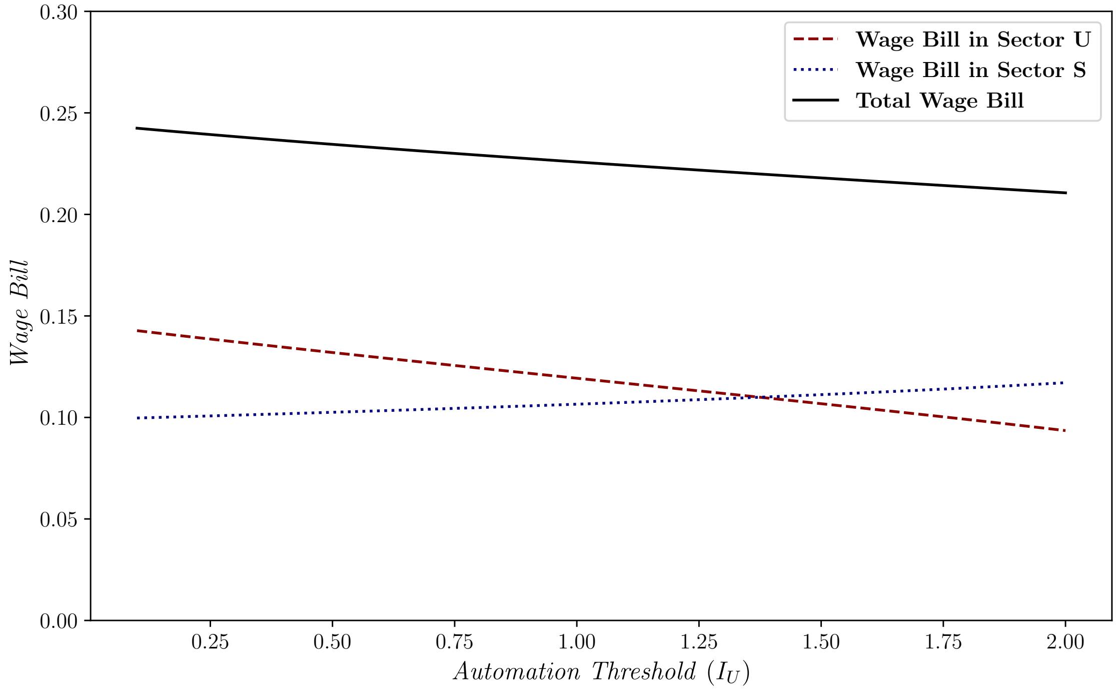

Fig. B6: Wage Bills and Change in Automation Threshold (I_U).
Parameters: $\beta = 0.5$, $\sigma = 2$, $\alpha_U = 0.5$, $\alpha_S = 0.3$, $\Gamma_U = 0.5$, $\Gamma_S = 0.9$, $\frac{K_U}{L_U} = 1.2$, $\frac{K_S}{L_S} = 1.5$, $Y = 1$

B.3 Automation in Sector S with AI Technology

A similar scenario applies when automation occurs in the skilled sector S, particularly through the adoption of AI technology. Displaced workers from sector S (both low-skilled and high-skilled) move to sector U:

$$\frac{\partial L_S}{\partial I_S}, \frac{\partial H_S}{\partial I_S} < 0, \quad \frac{\partial L_U}{\partial I_S}, \frac{\partial H_U}{\partial I_S} > 0.$$

However, the unskilled sector U has a limited capacity to absorb these displaced workers due to factors such as lower reliance on high-skilled labor, fixed capital stock, and diminishing returns to labor. This limitation arises because:

Sector U primarily employs low-skilled labor ($\alpha_U > \alpha_S$), so opportunities for high-skilled workers are limited. The fixed capital stock K_U leads to decreasing capital-labor ratios as L_U and H_U increase, reducing marginal productivity. The production function in sector U exhibits diminishing marginal returns to labor, limiting the effectiveness of employing additional workers. There is a mismatch between the skills of displaced high-skilled workers and the tasks available in sector U.