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Weisstanner, David; van Kersbergen, Kees

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Managing the Artificial Intelligence Revolution: Perceived Risks and Social Policy Preferences among Firm-Level Decision Makers

David Weisstanner
University of Lucerne
david.weisstanner@unilu.ch

Kees van Kersbergen
Aarhus University
kvk@ps.au.dk

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Abstract

This paper examines the political and policy implications of artificial intelligence (AI) from the perspective of managers in Danish firms. We investigate how managers perceive AI's impact on the workplace, their preferences for social and regulatory policies to address AI's societal effects, and how information about AI's economic consequences and regulation influences these preferences. Utilizing a novel firm-level survey in Denmark with experimental treatments, we find that firms perceiving AI-related risks are more likely to support AI regulation and social investment (education and upskilling). Firms with extensive AI experience are more likely to oppose AI regulation but, paradoxically, are more likely to express concern about AI. They also tend to prefer social investment over compensation policies. While information treatments partly increased firms' expression of concern about AI, they did not significantly alter their policy preferences. Overall, our findings indicate that subjective AI risk and AI experience significantly influence managers' policy preferences, leading to a general preference for social investment over compensation, with firms expressing concern supporting regulation and those with extensive AI experience opposing it.

Keywords: artificial intelligence (AI), AI regulation, social policy preferences, managers, survey

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Introduction

The rapid advancement of artificial intelligence (AI) has ushered in a wave of transformative changes that have profound implications for workplaces, society, and the policy landscape.

This study builds on prior research (Acemoglu & Restrepo 2019, 2020b, 2020a; Arntz et al. 2016; Bessen 2019; Eurofound 2021; Kraus et al. 2021) to address three new questions: (1) How do managers perceive AI's impact on the workplace? (2) What are their preferences for social and regulatory policies to address AI's societal effects? (3) How does information on AI's economic consequences and regulation influence these preferences?

We aim to contribute to the literature on the political and social policy consequences of technological change, particularly AI. While this growing body of research largely focuses on *employee* responses to technological risks (e.g. Borwein, Bonikowski, et al. 2024; Borwein, Magistro, et al. 2024; Busemeyer & Tober 2023; Finseraas & Nyhus 2024; Gallego et al. 2022; Haslberger et al. 2024; Heinrich & Witko 2024; Jeffrey & Matakos 2024; Knotz et al. 2024; Magistro, Loewen, et al. 2024; Magistro, Borwein, et al. 2024), our study shifts the focus to *managers*, not only as key decision-makers in AI adoption but also as critical actors in policy implementation. Even though managers do not directly create AI-related policies, they determine how these policies are put into practice within firms. They decide how to integrate AI, whether to retrain or replace employees, and how to comply with, or strategically respond to, new regulations. In this sense, managers function as intermediaries between policy and outcomes, making their perspectives essential for understanding the political and policy implications of AI adoption.

We answer our three questions with data from a novel firm-level manager survey, which contains a representative sample of all Danish firms. Rather than examining how managers in Denmark perceive and assess AI's impact on their own business operations (see Brock & von

Wangenheim 2019; Cao et al. 2021; Füller et al. 2022; Kolbjørnsrud et al. 2017; Leyer & Schneider 2021; Tuisku et al. 2023), we explore how they estimate the social and economic ramifications of AI for their workforce and society (see Lane et al. 2023). In the survey, we capture the attitudes of managers toward AI regulation, compensation policies, and social investment initiatives. We included treatments on economic effects and on current and future regulation to gauge the extent to which such information influences managers' preferences.

We find that firms expressing concern about AI are more likely to support AI regulation and to prefer social investment (education and upskilling) over compensation (unemployment benefits) policies. Those with higher AI knowledge are more likely to oppose AI regulation and to prefer social investment over compensation policies but, paradoxically, are significantly more likely to express concern about AI. This suggests that greater familiarity with AI heightens awareness of its potential risks but also leads to a preference for self-regulation. Firms using advanced AI technologies are also more likely to oppose AI regulation but do not differ in their support for social investment or compensation policies. While information treatments increased firms' expression of concern about AI, they did not significantly alter their policy preferences. Overall, our findings indicate that concern about AI risks and AI experience significantly influence managers' policy preferences, leading to a general preference for social investment over compensation, with firms expressing concern supporting regulation and those with extensive AI experience opposing it.

This paper begins with a review of the literature on AI adoption, managerial decision-making and policy preferences. We then outline our conceptual risk-based framework and the hypotheses, followed by a discussion of case selection, survey design, and methodology, including experimental treatments. Next, we present the empirical findings, analyzing the factors shaping managers' preferences for AI regulation, compensation, and social

investment. In the discussion, we relate the findings to our hypotheses, documenting support and disproof. We conclude with a summary of key insights.

Artificial Intelligence: Beyond Digitalization

AI is often used alongside terms like automation, robotization, and platformization (Busemeyer et al. 2022), but it stands apart with distinct features, applications, and implications. Following Zolas et al. (2020: 7), we can define AI as a broad set of technologies that stimulate human capabilities – such as decision-making, recognition, and communication – through processes like learning, reasoning, and self-correction. These technologies include tools such as machine learning, natural language processing, robotics, speech recognition, data interpretation, autonomous operation in vehicles, and automated decision-making systems, which enable machines to perform complex tasks independently, enhancing efficiency and adaptability across various business functions (Zolas et al. 2020: 7, 50).

AI adoption varies across different firm sizes, sectors, and regions. Zolas et al. (2020: 34) report that AI adoption in the US is 6.6% on average, though it exceeds 60% in large firms with over 10,000 employees. This disparity may impact inequality, competition, and the rise of ‘superstar’ firms (Autor et al. 2020; Lashkari et al. 2022). Firms that successfully employ AI may gain a competitive advantage, widening the gap between leading and lagging firms (Tambe et al. 2020). In Europe, 42% of firms adopt at least one AI technology, driven by factors such as supportive policies and a conducive business environment (European Commission 2020). Factors promoting AI adoption include productivity gains, the availability of large volumes of data, digital infrastructure, skilled personnel, and competitive environments. Barriers include high costs, skills shortages, privacy concerns,

and regulatory uncertainties (Cuéllar et al. 2022; Ernst et al. 2019; Nicoletti et al. 2020). Successful AI adoption also demands organizational cultural shifts, innovation, and adaptability (Brock & von Wangenheim 2019; Cao et al. 2021), which can be challenging for small and medium-sized enterprises (Ghobakhloo 2018: 930).

AI's transformative power challenges established theoretical frameworks, questioning long-standing assumptions about the direction, speed, and bias of technological change (Agrawal et al. 2019; Furman & Seamans 2019; Marwala & Hurwitz 2017). Technological change has traditionally been seen as an evolutionary process driven by knowledge and capital accumulation (Dosi & Nelson 2010). AI disrupts this view with sudden breakthroughs such as deep learning that drastically alter the course of technological change. Moreover, AI's direction is influenced by diverse factors beyond economics, including ethics, societal acceptance, regulations, and public sentiment (Dwivedi et al. 2021). AI's exponential advancement also challenges policy-making processes, which traditionally evolve more slowly and gradually (van Kersbergen & Vis 2022; Qureshi & Woo 2022).

The impact of AI on policy preferences

The advent of AI and its societal effects have sparked growing interest in how technological change shapes voter policy preferences (Borwein, Bonikowski, et al. 2024; Borwein, Magistro, et al. 2024; Busemeyer & Tober 2023; Finseraas & Nyhus 2024; Gallego et al. 2021, 2022; Gallego & Kurer 2022; Gingrich 2019; Haslberger et al. 2024; Heinrich & Witko 2024; Jeffrey & Matakos 2024; Knotz et al. 2024; Kurer 2020; Kurer & Häusermann 2022; Magistro, Loewen, et al. 2024; Magistro, Borwein, et al. 2024; Weisstanner 2023). While the research on automation and digitalization provides useful insights, AI introduces distinct challenges. Unlike previous waves of technological change, which primarily displaced routine and low-skill jobs, AI has the potential to affect a much broader range of

occupations, including high-skilled and decision-making roles. Analyzing survey data from 25 countries, Knotz et al. (2024) indeed find that higher-educated employees perceive higher risks of being replaced by AI and related technologies, in particular those working in heavily AI-exposed sectors like finance and IT. However, Haslberger et al. (2024) find that exposure to generative AI (ChatGPT) does not increase the perceived risk of job replacement, although AI exposure still increases support for government interventions.

AI also raises unique regulatory concerns, such as algorithmic transparency and ethical AI deployment. Ehret (2022), for instance, shows that people prefer to ban those AI applications that increase unemployment risk, although perceptions of transparency, privacy, or discrimination moderate the effect. Borwein, Magistro et al. (2024) show a gender gap in risk perception: women perceive AI at their workplace as less fair than men. In contrast to the vast existing literature on automation, the literature on AI perceptions and policy preferences is only starting to emerge. While we can draw on the insights of the research on automation and digitalization, we acknowledge that AI may lead to different policy reactions due to these unique characteristics.

In addition, the existing literature primarily focuses on employees and overlooks employers, especially firm managers, whose views on AI's impact are critical. A few studies have explored employers' preferences on social policy and regulation (Culpepper 2010; Mares 2003; Martin & Swank 2012), with Trampusch (2023) focusing on data governance. However, we are aware only of one empirical study of employers' preferences towards AI. Tallberg et al. (2023) explored employers' policy ideas regarding the European Union (EU) AI Act, finding widespread support for EU regulation, although business actors were less concerned and less supportive of regulation than other non-state actors. While this literature provides a foundation for understanding firms' policy preferences, more research is required to understand how AI impacts influences decision-making, regulation, and firm-level strategy in

unprecedented ways. Our study builds on this by examining the AI policy preferences of a representative sample of Danish firm managers, addressing gaps in the literature regarding employers' views on AI regulation and its implications.

A risk-based approach to AI

Like much of the comparative political economy literature reviewed in the previous section, we use a risk-based approach highlighting the potential winners and losers of AI adoption and its societal impact. This framework considers the risks and benefits of AI technology for firms and employees. Technological change has traditionally been biased towards different sectors, groups, or production factors, particularly in the labor market with skill and routine-based biases (Busemeyer 2022). In the context of AI, this bias takes on new dimensions, affecting a wide range of jobs across sectors, from routine to non-routine and from low-skilled to high-skilled roles (Hatzius et al. 2023; WEF 2021).

At the employee level, the traditional literature on automation has defined 'winners' as high-skilled employees in non-routine occupations (e.g., Gallego et al. 2021) and 'losers' as workers in jobs vulnerable to routine-based automation. However, AI operates differently from past waves of technological change (Autor 2024; Knotz et al. 2024). Unlike traditional automation, which primarily replaces workers performing routine tasks, AI often complements skilled labour and enhances decision-making rather than directly substituting jobs.

While some employees in AI-intensive firms may face displacement risks, we argue that a significant but often overlooked risk is faced by employees in firms that do not – or only very slowly – adopt AI technologies. Firms that fail to integrate AI may struggle to remain competitive as AI adoption spreads across sectors. Employees in these firms face a different kind of vulnerability: not immediate job loss due to automation, but outdated skills and

diminishing employment opportunities in firms unable to keep pace with technological change.

In addition, AI-intensive firms often provide retraining and upskilling opportunities, particularly in Denmark, where well-developed labour market training systems (e.g., Arbejdsmarkedssuddannelser, see Pedersen et al. 2012) help workers move into more AI-intensive jobs. In contrast, workers in firms that do not adopt AI may miss out on these opportunities, making them less adaptable to labour market shifts. This suggests that, unlike traditional automation risks, AI-related economic risks are not merely about exposure but also about exclusion: being left behind in firms that fail to adopt AI.

Therefore, we define as ‘losers’ those employees in firms that lag behind in AI adoption, not because AI replaces their jobs directly, but because non-adoption may lead to declining competitiveness, limited retraining opportunities, and eventual economic marginalization.

At the firm level, the implication of this framework is that the main ‘winners’ are firms already experienced with AI and using it extensively, gaining advantages in efficiency, productivity, and innovation. These early adopters differ from those typically seen as ‘winners’ of technological change that mainly benefited from automating routine tasks. In contrast, ‘losers’ are firms with limited or no AI adoption, which may struggle to keep pace with their AI-adopting competitors. We therefore hypothesize that firms with extensive AI experience focus on the competitive advantages AI provides, such as increased efficiency, productivity, and profitability. They perceive fewer risks from automation and are less concerned about the impact of AI on the firm and broader society.

H1: Firms with extensive AI experience are less likely to perceive AI-related risks than firms with limited AI experience.

Following the literature on technological change, we expect a close correspondence between (subjective) risk perceptions and policy preferences (Kurer & Häusermann 2022; Gallego et al. 2022; Weisstanner 2023). Specifically, we examine preferences for three types of ‘AI-embedding policies’ (see Bürgisser 2023): (1) regulation, (2) compensation, and (3) social investment.

- *Regulation* includes guidelines for ethical AI practices, data protection, and safety, such as ensuring algorithmic transparency.
- *Compensation* policies support workers affected by AI automation, such as unemployment benefits.
- *Social investment* focuses on education and retraining programs to improve AI-related skills and increase chances of re-employability.

We hypothesize that firms perceiving low risks related to the impact of AI on their firm or broader society (presumably, AI-intensive firms; the ‘winners’) are more likely to oppose regulation and compensation policies, which could increase costs and slow adoption.

Instead, and assuming that social investment policies aimed at workforce upskilling play a crucial role in preparing employees for AI-driven transformations, these firms may prefer social investment policies that enhance AI skills. In contrast, firms perceiving high AI-related risks (presumably, those firms not using AI, the ‘losers’) may support regulatory and compensatory policies to limit their competitors’ AI advantages, while showing less interest in social investment.

H2: Firms perceiving low AI-related risks are less supportive of AI regulation and unemployment benefits but more supportive of social investment policies than firms perceiving high AI-related risks.

The role of information on AI on managers' perceptions and policy preferences

The association between firm profiles and AI-related policy preferences could be influenced by unobserved confounding factors rather than risk perceptions or AI technology itself. To better understand AI's causal impact, we conducted a survey experiment incorporating two types of information treatments. First, managers' perceptions and policy preferences may change in response to information about positive or negative economic effects of AI (see Di Tella and Rodrik 2020 for similar arguments in the effects of trade shocks). We theorize that firms with *positive* information about AI's economic impact will create optimism even among less AI-experienced firms and reduce demand for protectionist policies like regulation and unemployment benefits. Conversely, information about AI's *negative* economic impact may lead firms to become more cautious and favor protective measures.

H3a: When firms are informed about AI's positive economic impact, they are less likely to demand protectionist policies (AI regulation and unemployment benefits).

H3b: When firms are informed about AI's negative economic impact, they are more likely to demand protectionist policies.

Second, managers may update their policy preferences in line with information about the state of AI regulation. Cuéllar et al. (2022) conducted an online experiment with US managers, showing that information about AI regulation increased the importance of ethical and safety concerns while decreasing their intent to adopt AI, likely due to concerns about compliance costs, regulatory burdens, or potential penalties. We therefore posit that firms learning about existing or forthcoming AI regulation may perceive higher AI-related risks and support regulation, also seeing it as a means to level the playing field or protect themselves from competitive disadvantages by AI-experienced firms.

H4a: Firms with extensive AI experience become more opposed to AI regulation when informed about the state of AI regulation.

H4b: Firms with limited AI experience become more supportive of AI regulation when informed about the state of AI regulation.

Data and Methods

Case selection

Denmark provides a strong case for studying firm-level decision-makers' perceptions of AI for several reasons. First, Denmark is a frontrunner in digitalization, consistently ranking at the top in Europe for AI adoption, digital infrastructure, and workforce skills (European Commission 2024). Second, our study focuses on an understudied yet highly relevant group: managers. As discussed, while much of the literature centers on workers' concerns about automation, understanding managers' views provides new insights, as they are key decision-makers in AI adoption. Our analysis therefore complements existing studies, particularly those focused on employees. Finally, we assure comparability of Denmark's case with other countries (e.g., the US) by using similar methodological approaches as in other studies. In this way, our findings are comparable to key research in the field. While Denmark's specific regulatory environment may limit full generalizability, the country's advanced digital development and our firm-level focus offer insights that are relevant for broader debates.

Survey design

To test our hypotheses, we conducted an original firm-level manager survey based on a representative sample of all Danish firms, conducted online between June and October 2023. The survey captures a wide range of perspectives on AI adoption, impacts, policy

preferences, and managerial perceptions of risk and opportunity. The governmental authority on Danish statistics, Statistics Denmark (Danmarks Statistik, DST), sent the online survey to 10,083 randomly selected firms with a minimum of five employees, excluding agriculture, small retail, and public sector firms. The sample was stratified by company size and industry group, with a quota ensuring two-thirds of the respondents were from firms with over 50 employees. Questions were directed to managing directors or senior managers with knowledge of the firm's IT strategy, although DST did not disclose to us who completed the survey. While we do not have direct factual AI knowledge measures to verify respondent expertise, we rely on self-reported AI knowledge, which distinguishes between those who say they know 'nothing', 'a little', or 'a lot' about AI. This provides an indirect assessment of familiarity with AI but does not serve as a formal validation of respondents' knowledge status. Given that the survey was explicitly sent to firms with instructions for it to be completed by senior managers, we assume that the responses largely reflect managerial perspectives. Moreover, respondents were repeatedly reminded to answer all questions from the 'perspective of the firm'. The survey was answered by 2,326 firms (response rate: 23.1 percent). After accounting for missing values on our main variables, our final sample size was 2,284 firms. While the response rate is relatively low, we do not believe this affects the generalizability of our findings. Our sample remains large, and DST applied weighting corrections for firm size, ensuring representativeness across different types of firms. We have no indication that firms with particular AI-related views or experiences were systematically more or less likely to respond.

Operationalization

Our primary outcome variables focus on managers' preferences regarding AI-embedding policies: regulation, compensation, and social investment. To measure attitudes toward *regulation*, we used the following item: '*From the perspective of the firm, is AI sufficiently*

regulated at the moment?'. Responses were recorded on a 5-point scale ranging from 'strongly disagree' to 'strongly agree'. For compensation, we asked: 'Finally, from the perspective of the firm, does the government spend the right amount of money for the following tasks? ...Unemployment benefits'. Response options were 'too much money', 'about the right amount', and 'too little money'. Social investment preferences were measured similarly, asking respondents whether they believed the government spends too much or too little on 'education and retraining for the unemployed'.

To measure firms' *perceived AI-related risks*, we combined nine items with a high scale reliability (Cronbach's $\alpha=0.75$). The first five items asked if firms were concerned about any of the following social effects of AI: 'Layoffs or redundancies', 'Transparency and supervision of AI algorithms (e.g. to counter-act bias and discrimination)', 'Occupational health and safety (e.g. accidents, stress)', 'Privacy and data protection issues', 'Work-life balance issues (e.g. no limits to working hours, no right to disconnect)'. Four additional items asked firms whether they had concerns related to their AI experience, such as: 'cost of adoption', 'lack of infrastructure in the firm (e.g. lack of skills, lack of suppliers, lack of IT infrastructure etc.)', 'legal issues, e.g. uncertainty about AI regulation', 'reputational risks'. Each item is measured as 1='concerned' and 0='unconcerned'. We combined these nine items into a simple additive index, rescaled to a range from 0 to 1. We also show some additional results with a binary operationalization of AI risks (0=no concern, 1=concern about one or more of the nine areas).

We operationalized firms' *AI experience* with items on AI usage and AI knowledge. We measured firms' *AI usage* by asking them: 'To the best of your knowledge, are any of the following AI technologies used in the firm?' Respondents were then presented with a list of 11 AI technologies (adapted from Zolas et al. 2020: 50, and listed in Online Appendix A1, Table A1's first column) and asked to indicate whether they used any of these technologies

(yes/no). An info button was available for respondents to hover to receive definitions for each technology (see Table A1's second column). Exploratory factor analyses revealed that three items – machine learning, machine vision, and natural language processing – loaded strongly on an independent factor, which we consider as firms experienced with advanced AI technologies. Consequently, we created two dummy variables measuring firms' AI usage: one indicating if firms use any of the three advanced AI technologies (machine learning, machine vision or natural language processing) and another indicating if firms used any of the remaining eight, more traditional technologies. As an additional indicator for firms' AI experience, we measured managers' *AI knowledge* using the question: '*How much would you say you personally know about artificial intelligence (AI)?*' Responses were coded into three separate categories: 1 ('*nothing*'), 2 ('*a little*'), and 3 ('*a lot*').

For the experimental component of the survey, we randomly assigned managers to one of five equal-sized groups. Four groups received an information treatment in the form of a short vignette, either about the positive or negative economic effects of AI (treatment groups 1 and 2) or about existing or expected future regulation (treatment groups 3 and 4). The fifth group served as the control group and received no vignette. Table 1 provides the text of the four information treatments. The first two treatments referred to prominent recent studies: one highlighting a positive impact of AI on individual earnings in AI-related jobs (Alekseeva et al. 2021), and the other showing a negative impact of AI on employment in non-AI jobs (Acemoglu et al. 2022). These treatments were designed to closely replicate and make our study comparable to previous survey experiments that provided information on the positive/negative impact of trade shocks (Di Tella & Rodrik 2020).

Table 1: Information treatment vignettes

<p>Treatment group 1 (positive economic effects):</p> <p>‘A line of recent research has shown that there is a wage premium of 11% for job postings that require AI skills compared to similar jobs within the same firm. Managerial occupations have the highest wage premium for AI skills. Firms demanding AI skills more intensively also offer higher salaries in non-AI jobs.’ (Alekseeva et al. 2021)</p>
<p>Treatment group 2 (negative economic effects):</p> <p>‘A line of recent research has shown that establishments that are more prone to adopt AI solutions search less for workers with skills previously sought in posted vacancies. An increase in the use of AI technologies therefore would reduce employment possibilities for such workers. Furthermore, AI exposure is associated with lower hiring of non-AI workers and overall hiring.’ (Acemoglu et al. 2022)</p>
<p>Treatment group 3 (information on existing regulation):</p> <p>‘In Denmark, there is no regulation specifically on the use of artificial intelligence, but companies must adhere to the general rules for its activities found in EU law, Danish legislation, and collective agreements. This includes rules on e.g. commercial contracts, liability, product liability, data protection, privacy, health and safety, managerial prerogatives, equality and non-discrimination.’</p>
<p>Treatment group 4 (information on expected future regulation):</p> <p>‘In Denmark today, there is no regulation specifically on the use of artificial intelligence. It is expected that rules aiming to regulate the use of artificial intelligence will soon be adopted by the EU. These are expected to establish new obligations for providers as well as users of AI technologies. Obligations include documentation and record keeping, and requirements of transparency, information, and human oversight. Certain uses of artificial intelligence will be prohibited entirely.’</p>

The last two information treatments in Table 1 were designed to replicate the approach used by Cuéllar et al. (2022), which similarly employed a firm-level survey structure. The third treatment informed respondents about the current lack of specific AI regulation in Denmark, noting that companies are still subject to general rules at both the EU and national level. The fourth treatment provided a brief description of the upcoming EU AI regulation (EU AI Act), which was still being developed at the time of the survey’s design in early 2023.

Statistical methods

We present three types of statistical analysis. First, we estimate OLS regression models on the determinants of subjective risk (AI-related concerns), focusing on the role of AI experience. Second, we analyze the determinants of AI regulation preferences by estimating

multinomial logistic regression models distinguishing between four outcomes: (1) support (respondents who ‘disagree’ or ‘strongly disagree’ with the statement that AI is sufficiently regulated at the moment), (2) oppose (‘agree’ or ‘strongly agree’), (3) neutral (‘neither agree nor disagree’), and (4) don’t know. We use the multinomial logistic regression models due to the high share of answers in the ‘neutral’ and ‘don’t know’ categories.

Third, to compare firms’ preferences for AI regulation with their preferences for compensation and investment, we estimate binary logistic regression models of support for AI regulation, compensation, or investment compared to opposing, neutral, or uncertain stances. Here we use the simpler logistic regression models to reduce complexity and because our main interest is in comparing support for these different policy areas rather than explaining neutral or undecided answers.

All models control for *firm size*, measured on a 5-point scale from 1 (‘5-10 full-time equivalent employees’ [FTE]) to 5 (‘more than 100 FTE’), which we recoded onto a scale from 0 and 1, and industry fixed effects (12 categories, see Appendix A4 for descriptive findings by industry). We included survey weights and estimated robust standard errors.

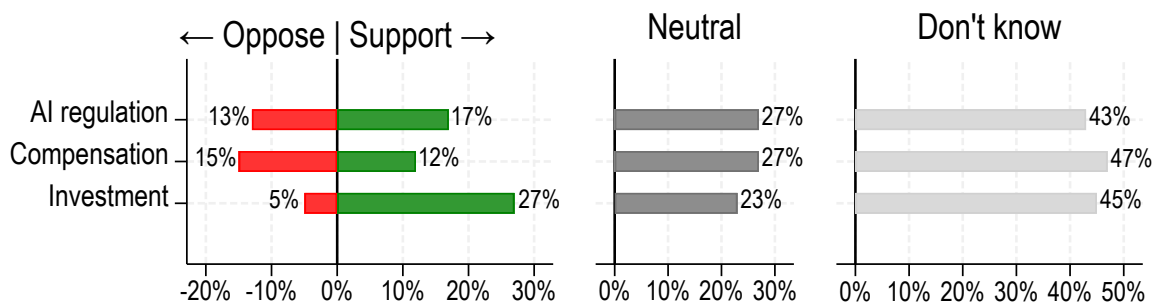
Findings

In this section, we first present descriptive statistics on firms’ preferences for AI regulation, compensation (unemployment benefits), and social investment (education and upskilling). Next, we identify which firms perceive significant AI-related risks and explore the key determinants of such concerns. Lastly, we explore the factors influencing support, opposition, or neutrality towards these policies, first focusing on preferences for regulation and then comparing these with preferences for social compensation and social investment.

Policy preferences: Descriptives

Figure 1 visualizes the distribution of preferences for AI regulation, compensation, and social investment. Firms' views on AI regulation are fairly balanced, with 17% in support (indicating AI is under-regulated) and 13% in opposition. While our survey did not explicitly force respondents to choose between social investment and compensation, managers show a clear preference for the former over the latter. In all three policy areas, there is a high share of uncertain responses based on the 'don't know' and neutral answer categories. Although this behavior might be influenced by firms' hesitancy to express political opinions, we also show below (Figure 3) that choosing the 'don't know' option is systematically associated to low AI knowledge and low AI risk perceptions.

Figure 1: Share of firms supporting or opposing AI regulation, compensation and social investment



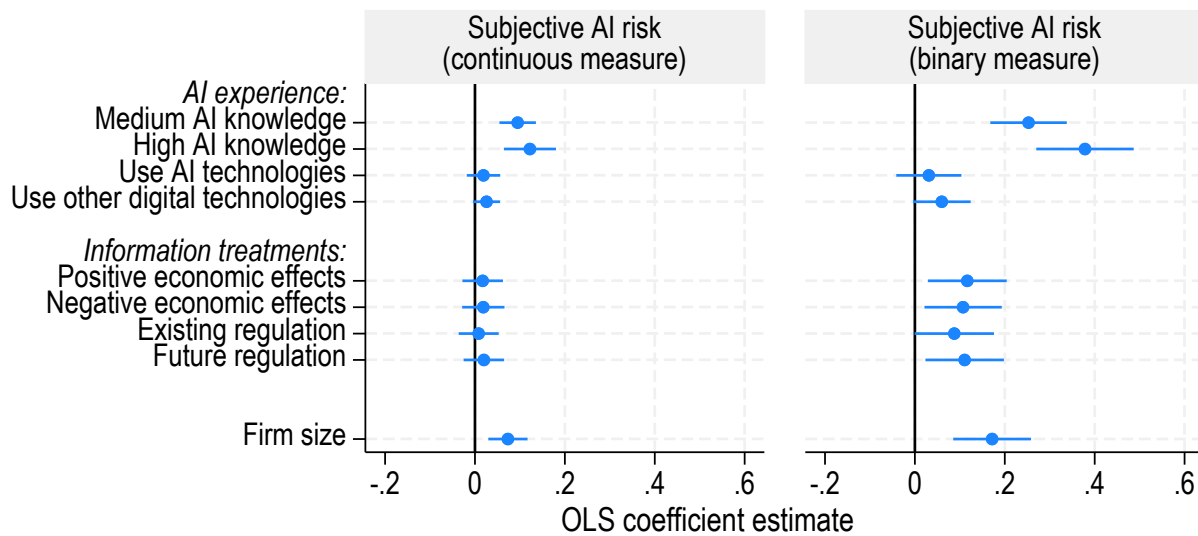
Notes: N=2,284. For coding details and summary statistics see Online Appendix Table A2.

Determinants of AI risk

Do firms with AI experience express fewer concerns about AI? Contrary to this expectation, Figure 2 shows that firms with medium and high AI knowledge are significantly more likely to express AI concerns than firms with low AI knowledge. This holds both for the continuous operationalization of AI risk (where firms could select between 0 and 9 AI concerns, recoded to a scale from 0 to 1) and a binary operationalization of AI risk (expressing *some* AI concern, relative to firms that express *no* concern) on the left- and right-hand panel of Figure 2, respectively. Firms that use advanced AI technologies (machine learning, machine vision, or natural language processing) and other AI-related digital technologies also tend to perceive higher AI-related risks than firms not using such technologies, although the coefficients are not statistically significant. Firm size also has a significant positive association with AI risk. These results strongly contradict our first hypothesis that firms with extensive AI experience are less likely to perceive AI-related risks than firms with limited AI experience.

Notably, in addition to AI experience and firm size, we find some indication that our four information treatments increase AI risk perceptions. While the effects of the information treatments are not statistically significant for the continuous AI risk measure, we find positive and statistically significant effects at the 1% level (positive economic effects treatment), 5% (negative economic effects, future regulation) and at the 10% level ($p=0.052$, existing regulation) on expressing *some* concern about AI compared to the control group receiving no information treatment. This suggests that priming firms about AI – no matter the precise message of the information – may increase the likelihood of perceiving AI-related risks.

Figure 2: Firms' concern about AI



Notes: OLS estimates (N=2,284) with 95% confidence intervals, industry fixed effects (not shown) and robust standard errors. Full regression output: Online Appendix Table A3.1.

Determinants of policy preferences

Figure 3 presents the results of our multinomial logistic regression models of AI regulation preferences. The coefficients are average marginal effects (AMEs) that can be interpreted as marginal effects on the predicted probabilities for each of the four outcomes (support, oppose, neutral, don't know) given a change in the explanatory variables.

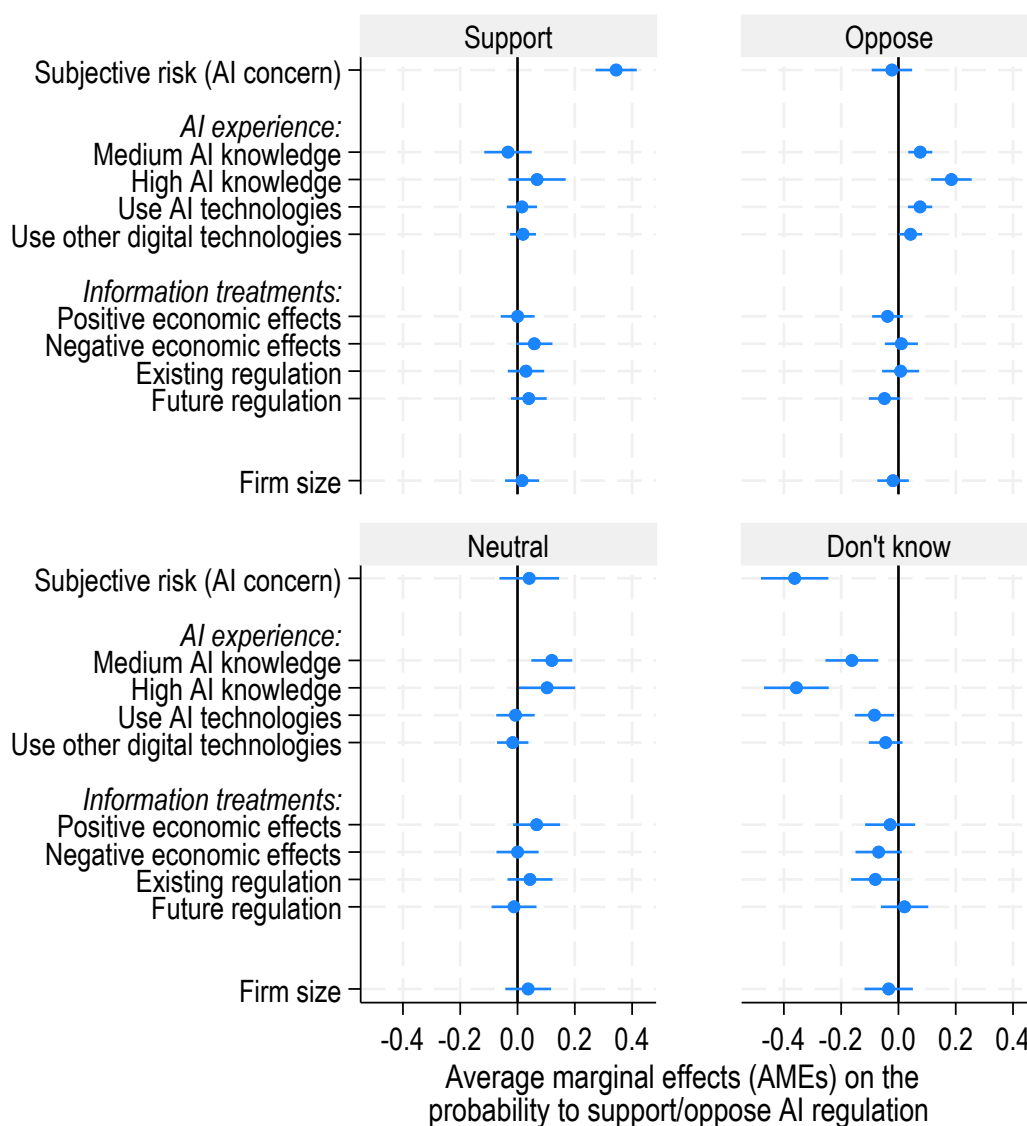
Our analysis highlights three factors that drive firms' preferences for AI regulation:

subjective risk (concern about AI), AI experience (knowledge and usage), and firm size.

First, firms that perceived higher *AI-related risks*, i.e. concerns about the societal implications or barriers of adopting AI, are significantly more likely to support AI regulation compared to firms expressing fewer AI-related concerns, and they are also substantially less likely to select the 'don't know' option. The effect sizes are substantial: moving from no AI concern to

being concerned about all nine AI-related risk areas is associated with a 34 percentage point (pp.) increase in support for AI regulation, while an increase in AI concern from one standard deviation below the mean to one standard deviation above the mean is associated with an increase in AI regulation support from 8.5 to 25.7 percent.

Figure 3: Firms' preferences of AI regulation



Notes: Based on multinomial logistic regression model (N=2,284) with 95% confidence intervals, industry fixed effects (not shown) and robust standard errors. Full regression output: Online Appendix Table A3.2.

Second, firms that reported *knowing* ‘a lot’ about AI are 18 pp. more likely to oppose AI regulation, 10pp. more likely to be neutral, and 36 pp. less likely to choose ‘don’t know’ compared to firms that indicated knowing ‘nothing’ about AI. Third, firms *using* advanced AI technologies such as machine learning, machine vision, and natural language processing are 8 pp. more likely to oppose AI regulation and 8 pp. less likely to choose ‘don’t know’.

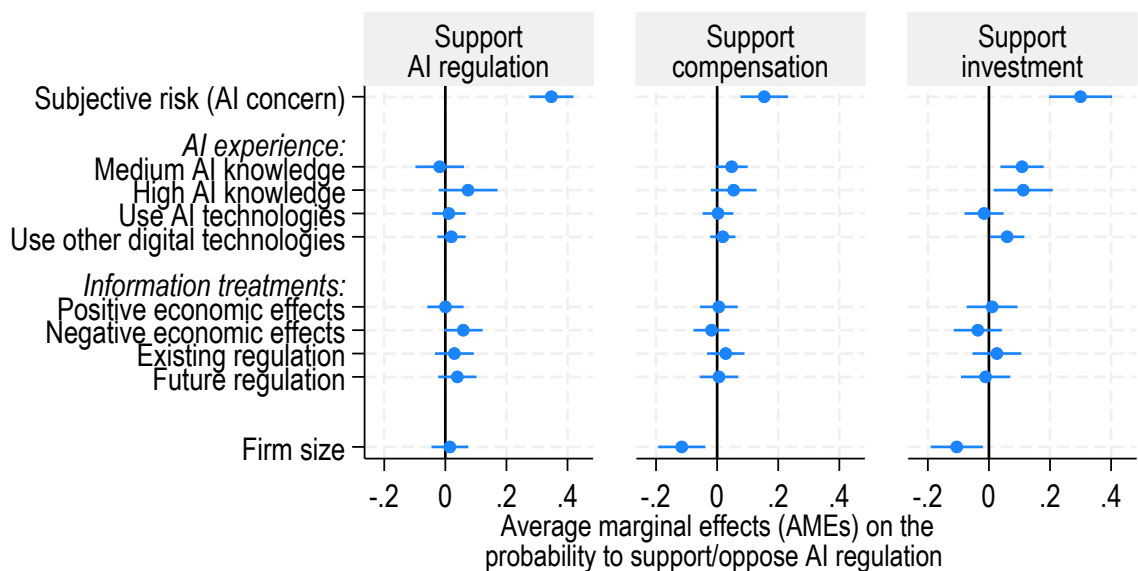
All remaining explanatory variables are not statistically significant. This includes the four information treatments, none of which is robustly associated with firms’ preferences for AI regulation. Firm size also has no statistically significant association with AI regulation preferences. Overall, the explanatory power of the model is quite high, with a pseudo R^2 of 0.11, especially considering the high share of ‘don’t know’ and neutral answers.

In Figure 4, we compare preferences for AI regulation with their support for social investment and compensation policies. For simplicity, we estimate binary logistic regression models of support for AI regulation, compensation, or investment compared to opposing, neutral, or uncertain stances.

We find that AI-related *subjective risk* is not only associated with higher support for AI regulation, but also with higher support for compensation (unemployment benefits) and social investment (education and upskilling). The effect size for social investment is far larger than for compensation. Firms strongly concerned about AI (the maximum value of 1 of our risk measure) are 30 pp. more likely to support social investment than unconcerned firms (minimum value of 0), while this effect is only 15 pp. for compensation, although both effect sizes are not as large as for AI regulation (35 pp.). We also find that medium and high AI *knowledge* is significantly associated with support for social investment, increasing support by about 11 pp., while the effects on AI regulation and compensation are not statistically significant. By contrast, *usage* has no significant effect on policy preferences. Finally, larger

firm size is significantly associated with reduced support for compensation and investment. Firms with 100 or more FTE are more than 10 pp. less likely to support either compensation or investment, compared to firms with less than 10 FTE. However, firm size is not associated with AI regulation preferences. The information treatments have no statistically significant associations with investment and compensation preferences.

Figure 4: Preferences for AI regulation, compensation and investment compared



Notes: Based on logistic regression models (N=2,284), with 95% confidence intervals, industry fixed effects (not shown) and robust standard errors. Full regression output: Online Appendix Table A3.3.

Discussion

In this section, we interpret the empirical findings presented above in light of the hypotheses proposed in our risk-based framework. We aim to assess the extent to which the evidence supports or contradicts our initial theoretical expectations regarding the political and policy implications of AI experience among firms.

H1: Firms with extensive AI experience are less likely to perceive AI-related risks than firms with limited AI experience.

Our findings do not support this hypothesis. In fact, the results suggest the opposite: Firms with medium and high AI knowledge are more likely to express concern about AI's potential societal impacts compared to firms with low AI knowledge. Usage has no effect. However, despite their higher AI concern, firms with high AI knowledge as well as firms using advanced AI technologies are more likely to oppose AI regulation. We take this to indicate that firms deeply engaged with AI perceive regulation as a potential hindrance to their operations and innovation, even though they are aware about the potential societal issues of AI. Firms with higher AI knowledge are also more likely to support social investment policies, while there is no significant association with preferences for compensation policies.

H2: Firms perceiving low AI-related risks are less supportive of AI regulation and unemployment benefits but more supportive of social investment policies than firms perceiving high AI-related risks.

Our findings provide strong support for this hypothesis. The results indicate that AI-concerned firms are more supportive of AI regulation than unconcerned firms. AI-concerned firms support both social investment and compensation, but the estimated coefficient is almost double for social investment than for compensation. The fact that managers prioritize

social investment over compensation seems to align with Denmark's emphasis on retraining and labour market adaptability. Denmark has a well-developed labour market training system, which provides structured, goal-oriented retraining programs for firms' employees. This system likely fosters trust among managers that upskilling is an effective response to AI-driven labour market shifts. In addition, Denmark's existing generous compensation system probably reduces the perceived urgency for more generous unemployment benefits, reinforcing the preference for social investment. While these factors suggest that our findings are influenced by Denmark's institutional setting, they highlight how well-developed social investment structures may shape managerial policy preferences in other advanced welfare states.

H3a: When firms with extensive AI experience are informed about AI's positive economic impact, they are less likely to demand protectionist policies (AI regulation and unemployment benefits).

H3b: When firms with limited AI experience are informed about AI's negative economic impact, they are more likely to demand protectionist policies.

Our evidence does not support these hypotheses. While the information treatments increased the likelihood of firms expressing *some* concern about AI, they did not significantly alter firms' policy preferences for AI regulation or unemployment benefits, regardless of their level of AI experience. These results seem to indicate that managers' policy preferences are relatively stable and not easily altered by short-term informational interventions.

H4a: Firms with extensive AI experience become more opposed to AI regulation when informed about the state of AI regulation.

H4b: Firms with limited AI experience become more supportive of AI regulation when informed about the state of AI regulation.

Our findings do not support these hypotheses. Information about existing and forthcoming AI regulations increased firms' expression of *some* concern about AI but did not significantly affect their support for AI regulation. There were also no significant changes in support for AI regulation among firms, regardless of their AI experience, after receiving regulatory information treatments. These results suggest that information about the regulatory environment does not alter firms' stances on AI regulation, irrespective of their engagement with AI.

Conclusion

In this paper, we examined the transformative implications of AI for firms, focusing on how managers perceive AI's impact on the workplace and their resulting policy preferences. We addressed three key questions: How do managers perceive AI's impact on the workplace? What are their preferences for social and regulatory policies to address AI's societal effects? And how does information on AI's economic consequences and regulation influence these preferences?

We conducted a novel firm-level survey of Danish managers, a group often overlooked in studies on technological change and policy preferences. Our goal was to provide new insights into AI's real-world impact on firms and broader policy implications.

Our findings are partly in line with the existing literature on technological change and policy preferences, but also highlight some paradoxical findings. We show that AI-concerned firms are strongly more supportive of AI regulation than unconcerned firms, and AI-concerned

firms support both social investment and compensation. This broadly aligns with the literature highlighting objective and subjective technological risks as a central driver of policy preferences (Borwein, Bonikowski, et al. 2024; Borwein, Magistro, et al. 2024; Magistro, Loewen, et al. 2024; Magistro, Borwein, et al. 2024; Busemeyer & Tober 2023; Finseraas & Nyhus 2024; Gallego et al. 2022; Gallego & Kurer 2022; Haslberger et al. 2024; Heinrich & Witko 2024; Jeffrey & Matakos 2024; Knotz et al. 2024; Kurer & Häusermann 2022; Weisstanner 2023).

Our findings also show that firms with extensive AI experience – characterized by high AI knowledge and using advanced AI technologies – are more likely to oppose AI regulation. Firms deeply engaged with AI apparently see regulation as a potential hindrance to their operations and innovation, preferring self-regulation over government interference. By contrast, firms with higher AI knowledge are more supportive of social investment policies. We believe that this means that theoretical understanding of AI's potential impacts, rather than practical usage, drives support for social investment.

We also have several noteworthy and paradoxical findings that seem to challenge expectations and highlight areas for further research. First, we note the paradox (= a *seeming* contradiction) that extensive AI experience seems to go together with increased AI concern but also with opposition to AI regulation. Our results challenge the notion that firms with extensive AI experience are less concerned about AI's societal impacts. On the contrary, firms with higher AI knowledge are significantly more likely to express concern about AI, compared to firms with low AI knowledge, while AI usage does not have an impact. We think that greater theoretical understanding of AI increases awareness of potential risks, contradicting our expectation that extensive AI experience reduces concern. We think that this is explained by the fact that firms with high AI knowledge believe they know the

potential risks and are well equipped to manage them internally. They do not want government-imposed regulation. Such regulation is seen as a constraint on innovation, increases costs, and reduces competitive advantage. In short, they are convinced that for them self-regulation is better than government interference.

Second, a noteworthy finding concerns our concept of AI experience. AI knowledge and AI usage do not have a similar impact on firms' levels of concern about AI. While higher AI *knowledge* is associated with increased concern, AI *usage* is not. Apparently, theoretical and practical experience have a differential impact on risk assessment.

Third, the impact of our information treatments on policy preferences was limited. While they increased the probability of firms expressing some concern about AI, they did not alter policy preferences as we expected. We think this means that managers' preferences are entrenched and therefore relatively stable. However, we cannot exclude the possibility that managers simply did not fully grasp the information treatment. It is possible that the informational vignettes were overlooked, misunderstood, or deemed irrelevant by some managers. In other words, the treatments may have failed to influence policy preferences either because they had no real effect or because they were not adequately processed by the respondents.

Overall, our study contributes to the literature by demonstrating that AI experience, particularly AI knowledge, significantly influences managerial policy preferences and concerns about AI's societal impacts. We highlight a paradox where firms with extensive AI experience are more aware of potential AI risks yet oppose regulation. They seem to prefer self-regulation over government intervention. Additionally, the differential impacts of AI knowledge and AI usage on concerns indicate that these are distinct dimensions of AI experience. The strong preference for social investment over compensation highlights that

managers prefer to respond to the ongoing AI revolution not by compensating losers, but by preparing their workforce for it and turning them (and hence their firms) into winners. This suggests that policymakers should prioritize AI-specific retraining programs and workforce upskilling. In addition, because firms with high AI experience tend to resist regulation while AI-concerned firms support it, policymakers must balance innovation incentives with regulatory safeguards. Finally, given that in firms that are slow to adopt AI employees' skills may be outdated, policies should support lagging firms in integrating AI-related technologies and training.

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Managing the Artificial Intelligence Revolution:

Perceived Risks and Social Policy Preferences

among Firm-Level Decision Makers

Online Appendix

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A1. Artificial Intelligence Technologies

Table A1: Artificial Intelligence Technologies

AI Technology	Description
Augmented reality	Technology that provides a view of a real-world environment with computer-generated overlays.
Automated guided vehicles (AGV) or AGV systems	A computer-controlled transport vehicle that operates without a human driver. AGVs can navigate facilities (e.g., warehouses) with the use of software and sensors.
Automated storage and retrieval systems	Technology that locates, retrieves, and replaces items from predetermined storage locations.
Machine learning	Computer algorithms that use data to improve their predictive performance without being reprogrammed.
Machine vision	Technology used to provide image-based inspection, recognition, or analysis.
Natural language processing	Technology that allows a computer to process text or human speech.
Radio-frequency identification (RFID) system	A system of tags and readers used for identification and tracking. Tags store information and transmit them using radio waves.
Robotics	Reprogrammable machines capable of automatically carrying out a complex set of actions.
Touchscreens/kiosks for customer interface	A computer with a touchscreen that allows a customer to receive information or perform tasks related to the business such as registering for a service or purchasing items (e.g., self-checkout, self-check-in, touchscreen ordering).
Voice recognition software	Software that converts speech to text or executes simple commands based on a limited vocabulary or executes more complex commands when combined with natural language processing.
Automated decision-making systems for staff management	Algorithms that automatically makes staff-related decisions based on data input, such as performance-related decisions and recruitment assistance (e.g., ranking applicants, issuing warnings, requesting speed improvements, requesting check-in with manager, sanctioning unwanted behavior).

Source: Adapted from Zolas et al. (2020: 50).

A2. Summary statistics (final sample)

Variable	Obs	Mean	Std. Dev.	Min	Max
AI regulation preferences (categorical)					
Disagree or strongly disagree	2284	.133	.339	0	1
Neither nor	2284	.285	.452	0	1
Don't know	2284	.393	.488	0	1
Agree or strongly agree	2284	.189	.392	0	1
AI regulation preferences (dummy)					
(Strongly) disagree/neutral/don't know	2284	.811	.392	0	1
Agree/strongly agree	2284	.189	.392	0	1
Compensation preferences (dummy)					
(Strongly) disagree/neutral/don't know	2284	.901	.299	0	1
Agree/strongly agree	2284	.099	.299	0	1
Social investment preferences (dummy)					
(Strongly) disagree/neutral/don't know	2284	.747	.435	0	1
Agree/strongly agree	2284	.253	.435	0	1
Concerned about AI (continuous)					
Concerned about AI (dummy)	2284	.252	.243	0	1
	2284	.665	.472	0	1
AI knowledge					
Nothing	2284	.114	.318	0	1
Medium AI knowledge	2284	.69	.463	0	1
High AI knowledge	2284	.197	.398	0	1
Use AI technologies					
Use other digital technologies	2284	.315	.465	0	1
	2284	.49	.5	0	1
Experimental information treatments					
Treatment 1: Positive economic effects	2284	.193	.395	0	1
Treatment 2: Negative economic effects	2284	.206	.404	0	1
Treatment 3: Existing regulation	2284	.204	.403	0	1
Treatment 4: Future regulation	2284	.19	.392	0	1
Control group	2284	.207	.405	0	1
Firm size					
	2284	.548	.309	0	1
Industry (12 categories)					
B/D/E Mining/electricity/water	2284	.018	.134	0	1
C Manufacturing	2284	.172	.377	0	1
F Construction	2284	.106	.308	0	1
G Wholesale/retail trade	2284	.132	.339	0	1
H Transportation	2284	.075	.264	0	1
I Hotels/restaurants	2284	.044	.206	0	1
J Information/communication	2284	.081	.273	0	1
K Finance and insurance	2284	.034	.182	0	1
L Real estate	2284	.043	.204	0	1
M Knowledge-based services	2284	.113	.317	0	1
N Other services (e.g. travel/cleaning)	2284	.077	.267	0	1
O/P/Q/R/S Public sector/arts/other	2284	.103	.304	0	1

A3. Regression models – full output

Table A3.1: OLS regression model of firms' concerns about AI (see Figure 2)

	(1) AI risk (continuous)	(2) AI risk (dummy)
AI knowledge: a little (<i>ref: nothing</i>)	0.095*** (0.021)	0.253*** (0.043)
AI knowledge: a lot (<i>ref: nothing</i>)	0.122*** (0.030)	0.378*** (0.055)
Use of AI technologies	0.019 (0.019)	0.031 (0.037)
Use of other digital technologies	0.026+ (0.015)	0.060+ (0.033)
Treatment 1: Positive economic effects	0.017 (0.023)	0.117** (0.045)
Treatment 2: Negative economic effects	0.019 (0.024)	0.107* (0.044)
Treatment 3: Existing regulation	0.008 (0.023)	0.088+ (0.045)
Treatment 4: Future regulation	0.020 (0.023)	0.111* (0.045)
Firm size	0.073*** (0.022)	0.172*** (0.044)
C Manufacturing (<i>ref: B/D/E Mining/electricity/water</i>)	-0.055 (0.050)	-0.118 (0.106)
F Construction (<i>ref: B/D/E Mining/electricity/water</i>)	-0.048 (0.056)	-0.215+ (0.111)
G Wholesale/retail trade (<i>ref: B/D/E Mining/electricity/water</i>)	0.008 (0.054)	-0.045 (0.108)
H Transportation (<i>ref: B/D/E Mining/electricity/water</i>)	0.002 (0.056)	-0.095 (0.114)
I Hotels/restaurants (<i>ref: B/D/E Mining/electricity/water</i>)	-0.095+ (0.053)	-0.184 (0.118)
J Information/communication (<i>ref: B/D/E Mining/electricity/water</i>)	-0.046 (0.052)	-0.027 (0.111)
K Finance and insurance (<i>ref: B/D/E Mining/electricity/water</i>)	0.058 (0.062)	0.019 (0.123)
L Real estate (<i>ref: B/D/E Mining/electricity/water</i>)	-0.038 (0.057)	-0.120 (0.119)
M Knowledge-based services (<i>ref: B/D/E Mining/electricity/water</i>)	0.001 (0.051)	-0.058 (0.106)
N Other services (<i>ref: B/D/E Mining/electricity/water</i>)	-0.036 (0.054)	-0.185+ (0.110)
O/P/Q/R/S Public sector / other (<i>ref: B/D/E Mining/electricity/water</i>)	-0.011 (0.052)	-0.076 (0.107)
Observations	2,284	2,284
Prob > F	0.000	0.000
R2	0.074	0.126

Notes: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses.

Table A3.2: Multinomial logistic regression models of firms' preferences of AI regulation
(see Figure 3)

	(1) Oppose	(2) Neutral	(3) Don't know	(4) Support
Concerns about AI (continuous)	-0.023 (0.036)	0.041 (0.053)	-0.362*** (0.060)	0.344*** (0.037)
AI knowledge: a little (ref: nothing)	0.076*** (0.021)	0.120** (0.036)	-0.163*** (0.047)	-0.033 (0.042)
AI knowledge: a lot (ref: nothing)	0.185*** (0.036)	0.103* (0.050)	-0.356*** (0.058)	0.068 (0.051)
Use of AI technologies	0.075*** (0.021)	-0.007 (0.034)	-0.084* (0.035)	0.015 (0.027)
Use of other digital technologies	0.042* (0.021)	-0.017 (0.028)	-0.045 (0.030)	0.019 (0.023)
Treatment 1: Positive economic effects	-0.038 (0.027)	0.067 (0.042)	-0.029 (0.045)	0.000 (0.030)
Treatment 2: Negative economic effects	0.010 (0.029)	0.000 (0.038)	-0.069+ (0.041)	0.059+ (0.032)
Treatment 3: Existing regulation	0.008 (0.033)	0.044 (0.040)	-0.081+ (0.043)	0.030 (0.032)
Treatment 4: Future regulation	-0.049+ (0.028)	-0.012 (0.040)	0.021 (0.042)	0.039 (0.032)
Firm size	-0.019 (0.028)	0.037 (0.041)	-0.034 (0.043)	0.016 (0.030)
C Manufacturing (ref: B/D/E Mining/electricity/water)	0.031 (0.070)	-0.030 (0.104)	0.137 (0.095)	-0.138+ (0.076)
F Construction (ref: B/D/E Mining/electricity/water)	-0.061 (0.070)	0.014 (0.110)	0.165 (0.101)	-0.119 (0.082)
G Wholesale/retail trade (ref: B/D/E Mining/electricity/water)	-0.039 (0.066)	0.003 (0.107)	0.174+ (0.097)	-0.139+ (0.077)
H Transportation (ref: B/D/E Mining/electricity/water)	0.034 (0.079)	-0.030 (0.110)	0.146 (0.102)	-0.150+ (0.079)
I Hotels/restaurants (ref: B/D/E Mining/electricity/water)	0.139 (0.086)	-0.097 (0.111)	0.050 (0.103)	-0.092 (0.092)
J Information/communication (ref: B/D/E Mining/electricity/water)	-0.008 (0.071)	-0.009 (0.111)	-0.003 (0.103)	0.020 (0.083)
K Finance and insurance (ref: B/D/E Mining/electricity/water)	0.036 (0.082)	0.022 (0.124)	0.069 (0.119)	-0.127 (0.086)
L Real estate (ref: B/D/E Mining/electricity/water)	-0.011 (0.076)	-0.056 (0.113)	0.114 (0.106)	-0.046 (0.089)
M Knowledge-based services (ref: B/D/E Mining/electricity/water)	-0.002 (0.069)	-0.003 (0.105)	0.019 (0.095)	-0.014 (0.079)
N Other services (ref: B/D/E Mining/electricity/water)	0.015 (0.074)	-0.081 (0.106)	0.093 (0.098)	-0.026 (0.082)
O/P/Q/R/S Public sector / other (ref: B/D/E Mining/electricity/water)	-0.014 (0.070)	-0.089 (0.104)	0.165+ (0.097)	-0.062 (0.079)
Observations		2,284		
Prob > chi2		0.000		
Pseudo R2		0.114		

Notes: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, + $p < 0.1$. Robust standard errors in parentheses. Coefficients are average marginal effects (AMEs).

Table A3.3: Logistic regression models of firms' preferences of AI regulation, compensation and investment (see Figure 4)

	(1) AI regulation	(2) Compensation	(3) Investment
Concerns about AI (continuous)	0.347*** (0.037)	0.154*** (0.040)	0.300*** (0.053)
AI knowledge: a little (<i>ref: nothing</i>)	-0.019 (0.041)	0.048+ (0.027)	0.108** (0.036)
AI knowledge: a lot (<i>ref: nothing</i>)	0.075 (0.049)	0.054 (0.038)	0.112* (0.049)
Use of AI technologies	0.012 (0.028)	0.003 (0.026)	-0.016 (0.033)
Use of other digital technologies	0.020 (0.024)	0.019 (0.021)	0.059* (0.029)
Treatment 1: Positive economic effects	0.000 (0.030)	0.006 (0.031)	0.011 (0.043)
Treatment 2: Negative economic effects	0.059+ (0.032)	-0.018 (0.030)	-0.036 (0.040)
Treatment 3: Existing regulation	0.030 (0.033)	0.028 (0.031)	0.026 (0.041)
Treatment 4: Future regulation	0.039 (0.032)	0.006 (0.032)	-0.011 (0.041)
Firm size	0.015 (0.031)	-0.116** (0.039)	-0.105* (0.044)
C Manufacturing (<i>ref: B/D/E Mining/electricity/water</i>)	-0.138+ (0.076)	0.113 (0.075)	0.021 (0.103)
F Construction (<i>ref: B/D/E Mining/electricity/water</i>)	-0.124 (0.081)	0.056 (0.077)	-0.007 (0.106)
G Wholesale/retail trade (<i>ref: B/D/E Mining/electricity/water</i>)	-0.139+ (0.077)	0.040 (0.073)	0.007 (0.105)
H Transportation (<i>ref: B/D/E Mining/electricity/water</i>)	-0.149+ (0.079)	0.009 (0.073)	-0.070 (0.104)
I Hotels/restaurants (<i>ref: B/D/E Mining/electricity/water</i>)	-0.081 (0.093)	0.114 (0.084)	0.054 (0.115)
J Information/communication (<i>ref: B/D/E Mining/electricity/water</i>)	0.016 (0.083)	-0.015 (0.069)	-0.026 (0.107)
K Finance and insurance (<i>ref: B/D/E Mining/electricity/water</i>)	-0.129 (0.086)	-0.035 (0.074)	-0.114 (0.112)
L Real estate (<i>ref: B/D/E Mining/electricity/water</i>)	-0.045 (0.089)	-0.000 (0.076)	0.013 (0.114)
M Knowledge-based services (<i>ref: B/D/E Mining/electricity/water</i>)	-0.015 (0.079)	-0.022 (0.068)	-0.085 (0.100)
N Other services (<i>ref: B/D/E Mining/electricity/water</i>)	-0.024 (0.082)	0.034 (0.074)	0.003 (0.106)
O/P/Q/R/S Public sector / other (<i>ref: B/D/E Mining/electricity/water</i>)	-0.061 (0.079)	0.026 (0.071)	-0.006 (0.103)
Observations	2,284	2,284	2,284
Prob > chi2	0.000	0.001	0.000
Pseudo R2	0.130	0.061	0.051

Notes: *** p<0.001, ** p<0.01, * p<0.05, + p<0.1. Robust standard errors in parentheses. Coefficients are average marginal effects (AMEs).

A4. Sectoral differences in AI risk and regulation preferences

Figure A4.1: Average subjective AI risk (continuous measure, 0-1 scale) and support for AI regulation (dummy), by industry

