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A tale of two genders: How women and men differ in their social policy responses to automation risk

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A tale of two genders: How women and men differ in their social policy responses to automation risk

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Abstract

A growing literature in political science has established that the risk of automation shapes welfare preferences. Despite women and men's divergent risk experience with automation, we know little about how these differences impact social policy preferences. I address this research gap and argue that in order to understand this gender difference, we need to conceptually distinguish between three types of risk related to technological change that play a role in determining social policy preferences: the risk of unemployment, the risk of occupational downgrading and the risk of status loss. Genders differ particularly in the first two: while males are at greater risk of becoming unemployed with increasing technological change, females are more likely to transition to low-skill occupations. These risks are not addressed by the same social policies. Analysing individual cross-sectional data from 2018 (Welfarepriorities), I show that in line with an insurance-based argument of self-interest, genders want to see their (expected) risk addressed and increasingly diverge in their preferences with rising automation exposure. Women are more likely to support education and childcare that prevent them from occupational downgrading. Men, in contrast, prefer policies supporting them in case of job loss, namely unemployment benefits and reintegration services for unemployed. Moreover, I find that with increasing risk exposure women are not less welfare chauvinist than men. Both genders show higher support for restricting social benefits to only nationals with rising exposure to automation. The findings have far reaching implications for our understanding of the welfare impact of automation and show the complexity of possible policy responses.

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Table of contents

List of Figures

List of Tables

1 Introduction

The risk of being automated is one of the main risks in the contemporary labour market. Yet, it is only in the past few years that the topic has reached political debates, with sometimes alarmist forecasts of mass unemployment for an increasing number of occupations (Frey and Osborne 2017). While the majority of political science literature has focused on the electoral consequences of this new risk (Frey and Osborne 2017; Anelli et al. 2019; Kurer 2020), some recent contributions have analysed the welfare implications of automation (Thewissen and Rueda 2019; Martinelli and Chrisp 2020; Kurer and Häusermann 2021). These papers' results suggest that general demand for redistribution and particularly traditional passive insurance against the risk of job loss are stronger among individuals in occupations with higher level of routineness, which translates into higher susceptibility to automation.

The studies on the welfare implications of technological change have so far assumed a uniform experience of risk among respondents. However, literature in labour economics and my recent master thesis show that men and women differ in their risk experience when exposed to automation (Deming 2017; Dwyer 2013; Cortes and Pan 2019; Müller 2021): On the one hand, women seem to be more flexible in adapting to this new labour market situation by shifting towards occupations that are at lower risk of automation. Men, in contrast, are more likely to become unemployed. On the other hand, females experience occupational downgrading to low-skill and -wage jobs to a higher extent than men. These different experiences with automation suggest that women and men might diverge in their welfare preferences with increasing risk of automation as unemployment and occupational downgrading require divergent policy responses. Despite women constituting around half of the workforce and electorate in the 21st century, we know surprisingly little about gender differences in social policy preferences in general, and in relation to automation particularly. This paper aims to fill this gap by analysing the following question: *How do males' and females' different experiences with automation shape their relative social policy preferences?* A clearer understanding of the welfare priorities of men *and* women in the experience of automation risk can inform policymakers on possible reforms and will enable a more nuanced and complete picture of how automation affects the welfare states in Europe.

To examine how genders at risk differ in their social policy preferences, I rely on a recently published dataset by Häusermann et al. (2020b) conducted in the context of the ERC-project "welfarepriorities" in 2018, covering all four welfare regimes in the Western European context. The dataset provides detailed questions on social policy preferences and priorities as well as questions related to automation risk. The analysis is of descriptive nature and contains country fixed effect regressions to analyse if genders differ in their social policy preferences with increasing exposure to automation.

In this paper, I argue that in order to understand these gender differences in the context of technological change, we need to more carefully distinguish between three conceptions of risk, namely the risk of status loss, the risk of unemployment and the risk of occupational downgrading. Genders diverge most notably in the latter two, with men being at higher risk of unemployment and women of occupational downgrading. A differentiation between these risks is crucial since they require distinct policy responses. In line with self-interest considerations, I empirically find that with rising risk of automation women and men diverge in what risks they want to see addressed by the government. Women are more likely than men to prioritize expenses in education and childcare which prevent them from occupational downgrading. Men, in contrast, prefer unemployment benefits and reintegration services for the unemployed which counter the negative externalities of job loss. In addition, I find that women's support for old-age pensions increases more strongly with higher risk than for men, while genders do not differ in their preference for restricting benefits only to nationals.

The analysis contributes to literature in political science in four ways. Firstly, to my knowledge, I am the first one to examine gender differences in social policy preferences with increasing risk of automation. Secondly, I show the importance of differentiating between three divergent types of risk to understand the gendered response in social policy preferences to automation. Thirdly, I provide evidence that the widely claimed gender difference of social investment versus consumption policies is more complex than often assumed. Fourthly, I demonstrate that in contrast to what literature on automation might suggest, women are not less welfare chauvinist than men with increasing exposure to technological change.

The paper proceeds as follows: In the first part, I outline the existing literature and the theoretical framework of the analysis. In the second part, I present the data and empirical strategy. The third part shows the results, followed by a discussion of the findings in part four. The paper finishes with concluding remarks. Additional analyses can be found in the Appendix.

2 Literature review and theory

The following section outlines the existing literature and formulates the theory that guides the analysis. I aim to show that there are two key questions on genders in the context of automation and welfare preferences: do females experience automation somehow differently than men? And do these divergent experiences with automation lead to different social policy preferences? The section first outlines the general literature on risk and their welfare implications, before I turn to the gender difference in it.

2.1 (Automation) risk and social policy preferences

To derive expectations about welfare implications of automation, I draw on theoretical accounts of rational choice that view individuals' economic self-interest as an important determinant of social policy preferences (Iversen and Soskice 2001; Rehm 2009; Garritzsmann et al., forthcoming). Häusermann et al. (2020a) highlight that workers in general react self-centered when it comes to social policies in the sense that the more likely they are to experience the risk, the more strongly they support generosity in social schemes that address that risk. I thereby consider economic channels as a key mechanism linking automation to changing policy preferences but do not exclude the existence of non-economic psychological channels.

Risk as a determinant of social policy has become a standard element in research on welfare preferences over the past decade (Rehm 2009; Rehm et al. 2012; Schwander and Häusermann 2013; Rueda and Stegmueller 2019). The logic of this literature is in line with Häusermann et al. (2020a) and follows an insurance-based argument: To secure themselves against uncertain economic future, individuals will favour social protection when they are exposed to an increased risk (Moene and Wallerstein 2001; Iversen and Soskice 2001; Rehm 2009). At the same time, these individuals at risk often seem to feel threatened by immigrants (in the labour market) and express the preference for an exclusive and chauvinistic welfare state for nationals (Reeskens and Van Oorschot 2012; Kros and Coenders 2019). The individual risk has been conceptualized in different ways: inter alia in form of specific skills (Iversen and Soskice 2001), occupational unemployment rates (Rehm 2009), expected future income (Rueda and Stegmueller 2019), risk of unemployment due to economic recessions (Margalit 2019), offshoreability (Colantone and Stanig 2018) or atypical employment (Schwander and Häusermann 2013).

The risk of automation, meaning the risk of being substituted by machines, has only recently entered the analyses of political scientists. Pioneered by Autor et al. (2003), routineness in a worker's tasks is thereby the defining feature of susceptibility to automation. The higher the routineness in contrast to cognitive work in an occupation's task structure, the more likely this job will be substituted by machines and robots (Autor et al. 2003; Acemoglu and Autor 2011). These jobs at high risk of automation can be located in the (lower) middle of education and income distribution and include many so-called "blue-collar" jobs, such as machine operators, but also a large part of "white-collar" work in administration or accounting, such as office clerks or legal secretaries (Cortes and Pan 2019).

Literature on automation has stressed two specific risks related to automation: the risk of status loss and the economic risk. The first approach links technological change to social status, arguing that exposure to automation can lead to perceived status decline. These studies mostly examine the voting implications of automation and find that this status loss increases political mistrust and support for right-wing parties (Frey et al. 2017; Anelli et al. 2019; Kurer 2020). With regard to economic risks, political science literature has argued that the material implications of automation leads to a higher demand for protection and redistribution among workers at high risk. Thewissen and Rueda (2019), for example, highlight that workers at higher exposure to automation become more supportive of redistribution. In a similar vein, Sacchi et al. (2020) present evidence that being at risk of automation strengthens support for general minimum income scheme. Some studies have also analysed if automation risk increases demand for universal basic income, a form of social policy that is often brought forward as a possible solution to the negative economic effects of automation. Yet, the evidence is rather scant (Dermont and Weisstanner 2020; Im 2020; Martinelli and Chrisp 2020).

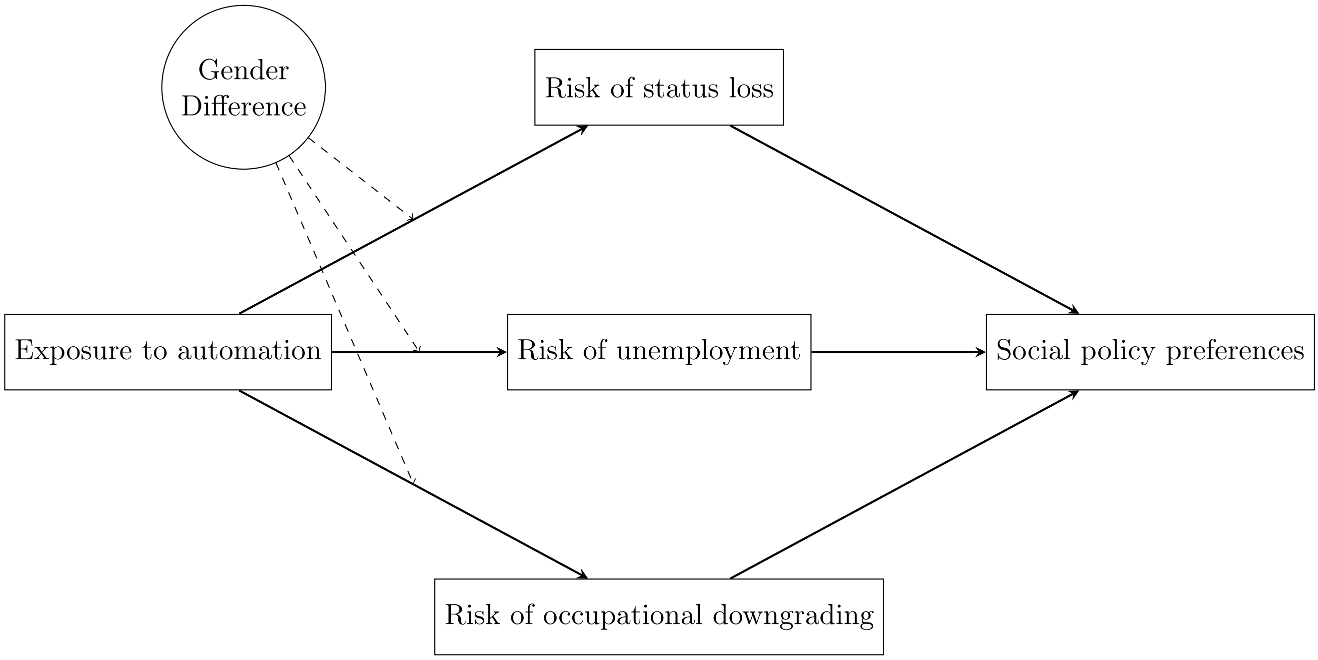
While these studies have mostly focused on traditional redistributive preferences and passive transfers, a recent paper by Kurer and Häusermann (2021) underlines the importance of looking beyond classic redistribution preferences and studying the implications of automation for support of so-called social investment policies (Im 2020, for similar argument). Social investment policies can be defined as welfare "that aims at creating, preserving, or mobilizing human skills and capabilities" (Garritzmann et al. 2017; Garritzsmann et al., forthcoming, p4). These policies mostly conceptualized in the form of education, childcare provisions or reintegration services provide individuals with additional skills, facilitate their use and help to safeguard them in life-course transition periods (Garritzmann et al. 2017) allowing workers to stay in the labour market rather than substituting income loss and unemployment. These more long-term approaches may be particularly important in the context of automation since the risk of ones job being automated - in contrast to job loss due to delocalization for example - can be reduced by training for and eventually selecting into a less substitutable occupation (Kurer and Häusermann 2021). Yet, analyzing the relationship between the subjective risk of automation and a wide range of social preferences, Kurer and Häusermann (2021) reveal that individuals at-risk first and foremost demand traditional passive insurance against the risk of job loss - while not showing any sign of support for investment policies.

2.2 The gender difference

These studies have so far (implicitly) assumed a mostly uniform experience with automation. Yet, literature in labour economics and my master thesis show that female workers differ in their experience with automation when compared to male workers. This divergent experience makes it necessary to differentiate between two types of economic risks resulting in the following distinction: the risk of unemployment, the risk of occupational downgrading and the risk of status loss (Black and Spitz-Oener 2010; Cerina et al. 2017; Cortes et al. 2017; Cortes and Pan 2019; Jerbashian 2019; Müller 2021). Respondents with different risk experiences are likely to demand a divergent set of social policies to address their risk. The argument is graphically presented in Figure 1.

With regard to the first risk of job loss, women seem to be less affected than men when exposed to automation. Black and Spitz-Oener (2010), for example, analyze how the task input of men and women has changed since the 1980s in the US and the European labour market. They find that rather than resulting in high unemployment or staying in routine occupations at risk, women adapt well to the new labour market realities by shifting to jobs less at risk of automation, compared to men (Autor and Wasserman 2013; Cerina et al. 2017; Jerbashian 2019; Cortes et al. 2018; Cortes and Pan 2019, for similar results). A recent master thesis by Müller (2021) confirms these findings at the aggregate level by tracing individual occupational transitions: women are slightly less likely than men to become unemployed but seem to have an advantage in flexibly adapting to these new labour market risks by shifting towards occupations at lower risk and into retirement. Table 1 presents some initial descriptive statistics and suggests that women at risk are aware of their labour flexibility. Around 25 percent of women at risk do not expect to work in the same job until they retire - in contrast to only 18 percent of men. There are many reasons for this advantageous labour flexibility that women possess. Müller (2021) descriptively analyses three possible reasons and shows that women's advantages in general, social and cognitive skills play a role in finding a good way out of automation risk. These skill advantages make women more flexible to change occupation, and brings them closer to the interpersonal skills and education level required for occupations that are

Figure (1) Model of the gendered political response to the experience with automation



less at risk of being automated.

This higher flexibility of women does not necessarily mean that they experience lower risk than men. Several studies have shown that women might not become unemployed but are more likely than men to shift towards low-skill and -wage occupations, hence experience occupational downgrading - the second type of risk. Cerina et al. (2017), for example, shows for the US labour market that women are not only more likely to increasingly fill high-skill but also low-skill jobs - which is often referred to as "job polarization" (Dwyer 2013, for similar results). Müller (2021) confirms this finding by highlighting that especially women with children that are highly exposed to automation are less likely to find a "good way out of" risk exposure and transition more into low-wage jobs, such as cleaning, care work or sales assistance. Table 1 seems to confirm this descriptively: the share of women with children compared to men is clearly higher in low-skill occupations than in any other occupation group. While not losing all advantages of being in the labour market, occupational downgrading includes at least three individual risks: financial loss (Manning 2003), more atypical employment (Schwander and Häusermann 2013) and being underemployed by skill (Müller 2021). Literature suggests that this higher likelihood of occupational downgrading is closely related to women's household or caring responsibilities (Estévez-Abe 2005; Iversen et al. 2005; Schwander and

Table (1) Descriptive statistics

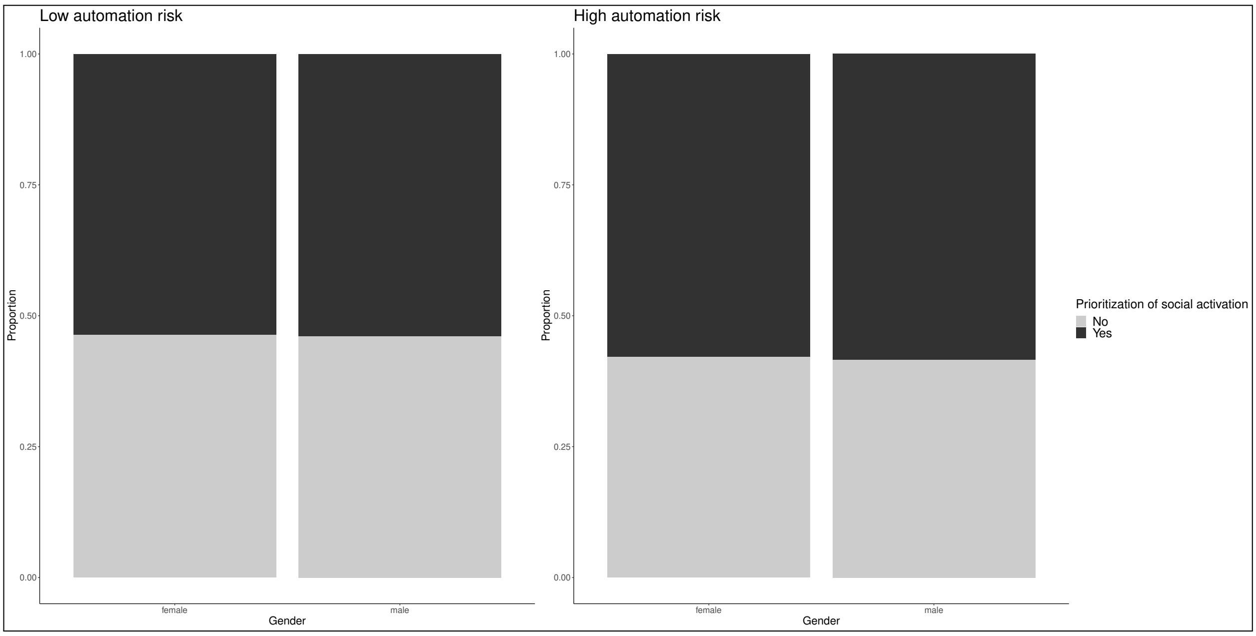
Automation risk	Gender	RTI	Share of (workers with)... Workforce	Subject. unstable prospects	Children	Low social status	Perceiving migrants as threat
R	Male	0.9	11.6	17.7	62.1	56.3	0.6
R	Female	1.7	9.1	25.1	66.5	63.7	0.6
NR - High skill	Male	-0.7	27.4	12.6	61.9	36.7	0.5
NR - High skill	Female	-0.6	26.6	12.0	58.2	41.3	0.4
NR - Low skill	Male	-0.3	11.2	21.9	52.5	59.6	0.5
NR - Low skill	Female	0.1	14.2	21.6	63.3	67.1	0.6

Own calculations. Data: Welfarepriorities, 2020. R = Routine (At high risk of automation), NR = Nonroutine (At lower risk of automation). RTI = Routine Task Index. Low social status = lower than the mean social status.

Häusermann 2013). Women still take on the larger share of childbearing and family work and are more likely to choose less demanding jobs in case they allow for more time flexibility than other occupations (Kjeldstad and Nymoen 2012; Van Bavel et al. 2018; Castagnetti et al. 2018). In addition, women are, on average, less geographically mobile. This reduces the extent to which they can take advantage of opportunities in different job markets (Sorenson and Dahl 2016; Gingrich and Kuo, forthcoming).

With regard to the third type of risk related to automation, status loss, several studies have argued that women's overall labour market status has risen at the same time as mass automation has increased (since the 1980s) - which makes status-decline arguments less applicable to females exposed to automation (Hochschild 2016; Inglehart and Norris 2017; Gidron and Hall 2017; Roos and Stevens 2018; Gingrich and Kuo, forthcoming): while for males being automated is always accompanied by a perception of a decreased social status, this is not necessarily the case for women (Enders and Uscinski 2019; Gingrich and Kuo, forthcoming). Yet, few studies actually test the gender difference in social status empirically and no published paper examines the argument in the context of automation in a rigorous manner. In her recent master thesis, Müller (2021) sheds doubt on this hypothesis and presents some descriptive analysis that the social status of women has not risen for all females equally. While for most women - and in contrast to men - their subjective social recognition has indeed increased over time, this is not the case for females highly exposed to automation. Women at high risk have experienced stagnation and even a slight decrease in subjective status in the last decade rather than an increase. Table 1 similarly suggests that women do not necessarily report a higher social status than men, quite the contrary. The share of women at high risk perceiving a low social status is around 8 percent higher than that of men. It seems

Figure (2) Proportion to prioritize social activation measures over consumption policies by gender and automation risk



Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

hence less clear that females experience less of a status loss with automation than some literature might suggest.

What do these different risk experiences of men and women mean for their relative social policy preferences? It is often argued - but rarely tested empirically - that women belong to the main supporters of social activation policies as they would benefit most from social investment as labourers and care-givers (Häusermann 2010; Jenson 2010; Morel and Palier 2011). Yet, the different risk experiences with automation by gender suggest that the relationship might be more complex than that. Figure 2 additionally sheds doubt by showing that genders do not seem to substantially differ in their share to support social activation over consumption policies - neither among respondents at low nor at high automation risk (Garritzmann and Schwander 2021, for similar findings).[2]

Following an insurance based logic of self-interest, workers can be expected to react in a self-centered manner when it comes to social policies in the sense that the more likely they are to incur the specific risk, the more they support an increase in social schemes that address precisely that risk. For men, with a higher risk of unemployment compared to women, it is hence the most relevant interest to counter the negative consequences of job loss and support measures that allow

[2]Interesting to note is that the share of respondents being in favour of social activation policies seems to decline with increasing risk exposure.

them to find their way into the labour market again which comes in form of unemployment benefits and reintegration services for the unemployed. While the former replaces their income, the latter helps workers to adapt their skills to the need in demand and re-enter the job market (Garritzmann and Schwander 2021). In contrast, women are likely to prioritize policies that help them prevent occupational downgrading. Two social activation policies are important here, namely education and childcare. Education has been shown to be generally one of the most important factors for workers of finding a "good way out of routine work" and shift towards high-skill instead of low-skill occupations (Müller 2021). Childcare - as outlined above - is especially important for women as the absence of it makes them more likely to sacrifice job opportunities in favour of more flexible working hours since they still bear the brunt of child and care work. Access to childcare hence makes women more likely to realize high-skill job opportunities and makes it less likely for them to downgrade. In addition, women can be expected to be more supportive of old-age pension benefits as they are more likely to transition into (early) retirement from jobs highly exposed to automation (Müller 2021). In sum, I expect men - in relative terms with increasing risk of automation - to express stronger support for unemployment benefits and reintegration measures for unemployed as a result of their higher probability to experience job loss. Women, in contrast, experience more occupational downgrading and transitioning into retirement and can hence be expected to be more in favour of expanding childcare provisions, education and old-age pensions.

All of these policies, yet, might not help in case of status loss. Social decline is often related to apportionment of blame to a specific group, in many cases migrants. Workers experiencing a subjective decrease in their social appreciation might hence be more likely to support limiting the "to whom" of policies to only nationals. I have outlined above that men and women might not differ in their social status as much as often suggested (see also Table 1). On the one hand, men's subjective social appreciation may decline more with increasing exposure to automation risk as they start from a higher level of status and their jobs are not as highly regarded anymore (Gidron and Hall 2017; Kurer 2020). On the other hand, women at high risk show a generally lower social status than men and their status level has stagnated in an environment of an overall increase in social recognition for women (Müller 2021). This social comparison to other women might make females at high risk particularly sensitive to their stagnation. Taken together, with increasing exposure to automation, I do not expect women to be less welfare chauvinist than men but to show an increase in support for a restriction of social policies to only nationals with rising risk exposure equally to men. This leads me to the following hypotheses:

H1 Social policy positions general: With higher risk of automation, the support for rising expenditures on social policies generally increases.

H2 Gender difference in consumption and social activation policies: With increasing exposure to automation, women are more supportive of childcare, education and old-age pensions, relative to similar men who favour unemployment benefits and retraining programs.

H3 Gender difference in welfare chauvinism: With increasing exposure to automation, genders do not differ in their support for restricting welfare provisions only to nationals.

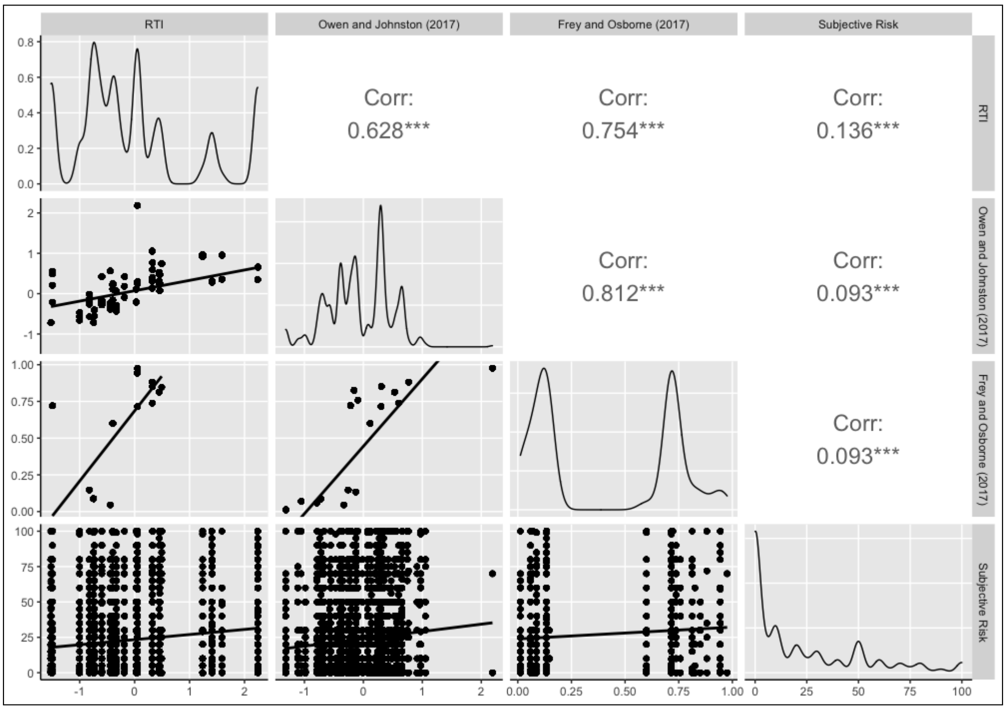
3 Data and methodological approach

To analyse the hypotheses, the dataset needs to fulfill two criteria. First, detailed information about a respondent's occupation is required to be able to calculate a respondent's risk of automation. Second, the dataset needs to contain detailed questions on individual social policy preferences to differentiate between traditional passive insurance against the risk of job loss and more long-term social activation approaches related to human capital investment and (re-)activation of labour supply. The original dataset Häusermann et al. (2020b) conducted in the context of the ERC-project "welfarepriorities" does fulfill both of these criteria and is hence ideally suited for this analysis. The dataset is available on request and contains eight Western European countries with each 1500 respondents. The countries represent the main welfare regimes in Western Europe: Denmark and Sweden for the social democratic regime, Germany and the Netherlands for the conservative type, Ireland and the United Kingdom for the liberal regime, and Italy and Spain representing the Southern welfare states. The total sample counts 12'501 completed interviews that were conducted in 2018. Additionally, I use datasets provided by Goos et al. (2014), Frey and Osborne (2017), and Owen and Johnston (2017) that entail measures of automation risk. The dataset only includes respondents older than 18 years. I additionally restrict the dataset to respondents currently in paid employment.

The main independent variable is the risk of being automated, measured as occupation-specific values of routine task intensity (RTI) supplied by Goos et al. (2014)'s study that assigned RTI values to occupations categorized at the International Classification of Occupations (ISCO) system at the two-digit level. RTI values are considered to be country invariant (Thewissen and Rueda 2019). An individual's automation risk reflects her occupation's vulnerability to automation. Across the sample, RTI ranges from -1.52 (managers of small enterprises) to 2.24 (office clerks). Increasing values of RTI indicate higher risk of automation. Although there are a few other indices used in the automation literature, most studies seem to use the RTI to measure an occupation's vulnerability to automation (Owen and Johnston 2017; Thewissen and Rueda 2019; Im 2020, e.g.).[3] To check robustness, I include two additional objective measures of automation provided by Frey and Osborne (2017) and Owen and Johnston (2017). Frey and Osborne (2017)'s measure of automation risk takes

[3]The RTI captures the idea that occupations that require high levels of routine work but include few abstract or manual tasks face a greater risk of automation and is based on 2-digit ISCO categories across 16 countries between 1993 and 2010. The authors do not include the occupation categories of legislators and senior officials (11), teaching professionals (23), teaching associate professionals (33), skilled agricultural and fishery workers (61), agricultural, fishery and related labourers (92) and armed forces (01). Instead of assigning values of similar occupations to these categories, I follow well-established literature (Gingrich and Kuo, forthcoming, e.g.) and drop those categories.

Figure (3) Correlation of different indices of automation risk



RTI = Routine Task Intensity measure by Goos et al. (2014). Subjective risk = Subjective risk of automation within the next 10 years.

into account that advances in machine learning increasingly allow for the replacement of non-routine tasks. Owen and Johnston (2017)'s measure of automation risk is closely aligned to the RTI provided by Goos et al. (2014) but at the three-digit level. The disadvantage of these two indices is that their values are based on the US labour market. Accordingly, I use the two as robustness checks but not in the main analysis. While one could argue that I should also incorporate a subjective measure of automation, I refrain from doing so as a result of its low correlation with the objective measures of automation risk, as illustrated in Figure 3. Objective and subjective automation risk hence seem to measure slightly different phenomena that should be analysed distinctively.

The main dependent variable are two types of items on social policy preferences. A first one captures general stands on social policies, asking "to what extent do you agree with the following policy reform proposals?" The policy proposals include increase of old age pension benefits, availability of good-quality childcare services, expand good-quality university education for students from lower-income families, increase unemployment benefits, expand services that help reintegrate the long-term unemployed and social assistance benefits only for nationals - with a range from 1 (disagree strongly) to 4 (agree strongly). All items have been dichotomized into a support/oppose dummy variable for the sake of simplicity. A second set of variables provides insight into social policy priorities, reflecting the relative importance respondents attribute to different strategies of welfare state expansion. The variables asks respondents to allocate 100 points to six items. The six policy fields are old age pensions, childcare, tertiary education, unemployment benefits, labour market reintegration services and services for the social and labour market integration of immigrants. Each variable reaches from 0 to 100 possible points an individual allocates to a policy area. This variable captures arguably most closely what parties would offer their voters, namely a prioritization of social policy areas. I additionally group the policy areas into social activation (childcare, education, reintegration services) versus consumption policies (unemployment benefits, pension). The resulting index ranges from 0-3, where 3 captures the social activation enthusiasts (more points to all three social activation policies than the mean point value), and 0 the consumption enthusiasts (below the mean for all three social investment policies and hence above the mean for passive consumption policy areas).

The third main variable for the analysis is gender, measured as follows: "Please indicate your sex", with the options of female and male. The value of 1 thereby captures respondents identifying as females, 0 as males. Additional variables in the analysis include the level of education, income, age, country, left-right positioning and union membership as covariates, which might all additionally influence social policy preferences (Kurer and Häusermann 2021). These variables are all included in the dataset.

The empirical purpose of this paper is descriptive, that is, to analyse whether and how women and men differ in their social policy preferences with increasing exposure to automation. I use a pooled fixed effects model (country dummies) with clustered and robust standard errors to control for potential country-related confounders (Allison 2009), which may include the rate of automation adoption (Acemoglu and Restrepo 2020), labour market institutions (Fernández-Macías and Hurley 2017) and social policy regimes. For the dependent variables of social policy positions (binary variables), I run binomial logistic regressions of these preferences on automation risk, with an interaction term of gender. For welfare priorities (numeric variable), I calculate linear regressions. The regressions are weighted by dataset specific weights to make the sample more representative by age, gender, educational attainment and partisanship (Häusermann et al. 2020a). To test the robustness of the results, I run the same analysis as linear and multinomial logistic regressions, use different measures of automation risk and exclude and/or add additional covariates.

4 Results

This chapter presents the results of the analysis and their robustness with regard to how increasing risk of automation impacts social policy preferences differently by gender. The discussion of the results in Section 4.1 is structured according to the hypotheses. I show that in line with formulated expectations, with higher exposure to automation, the social policy priorities of women and men increasingly diverge. While men are more in favour of unemployment benefits and reintegration measures for unemployed, women assign higher priority to childcare and education policies. Moreover, women's support for old-age pensions does more strongly increase with higher risk of automation than men's. Yet, with increasing risk, genders do not differ in their preferences to restrict social benefits to nationals. These findings are in line with recent contributions on gendered social policy preferences (Garritzmann and Schwander 2021) and add to a broad range of literature that has assumed women to generally favour social activation and to be more generous than men towards the integration of migrants into the labour market. Section 4.2 provides evidence that the results are robust to different specifications of the regressions.

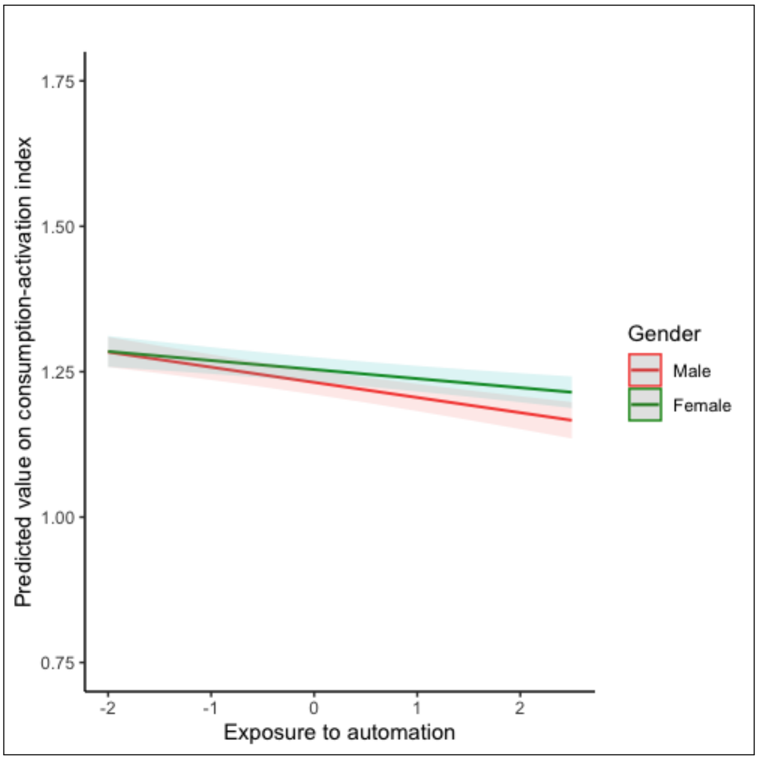
4.1 Gendered social policy preferences with increasing automation risk

Figures 4 to 6 present the predicted probabilities (Figures 5) respectively the linear prediction of prioritization (Figure 4, 6) of the weighted country-fixed regressions of social policy preferences on automation risk, with an interaction of gender. Figure 5 shows general preferences, and Figures 4 and 6 highlight social policy priorities (see more in detail in Section 3)[4]. The corresponding regression tables are in the Appendix. Since the regressions are run with country-fixed effects to account for country-specific differences, the level of support varies across context. For the sake of compactness and since I am most interested in the gender differences which stay identical in fixed-effects across countries, I only present the results graphically for one example country - which is Germany here. The results for the other countries can be found in the Appendix. The y-axis presents a constant delta in each figure to make the differences comparable across policies.

Let us first have a look at the general effect automation risk has on the level of social policy expenditures. Figure 5 reveals that with increasing automation risk, the support for higher social benefits does not necessarily increase. The only policy area where we can observe a noticeable rise in support is welfare chauvinism. With increasing risk to be affected by automation, respondents

[4]As a reminder, respondents receive a total of 100 points that they can allocate across these six different policy areas according to their preferences.

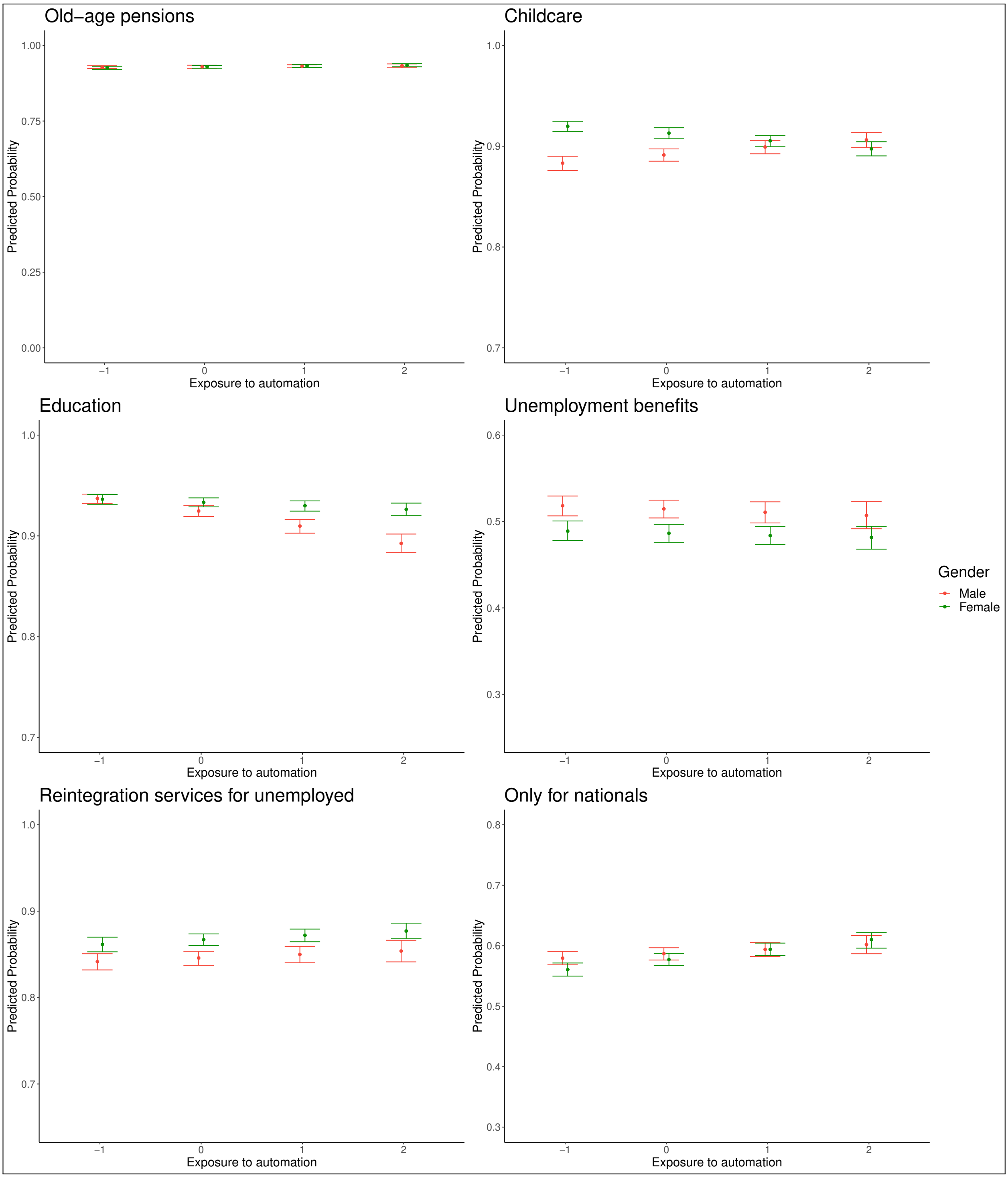
Figure (4) Activation-consumption priorities with increasing exposure to automation by gender



Linear regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Higher values on the y-axis mean higher prioritization of social investment.

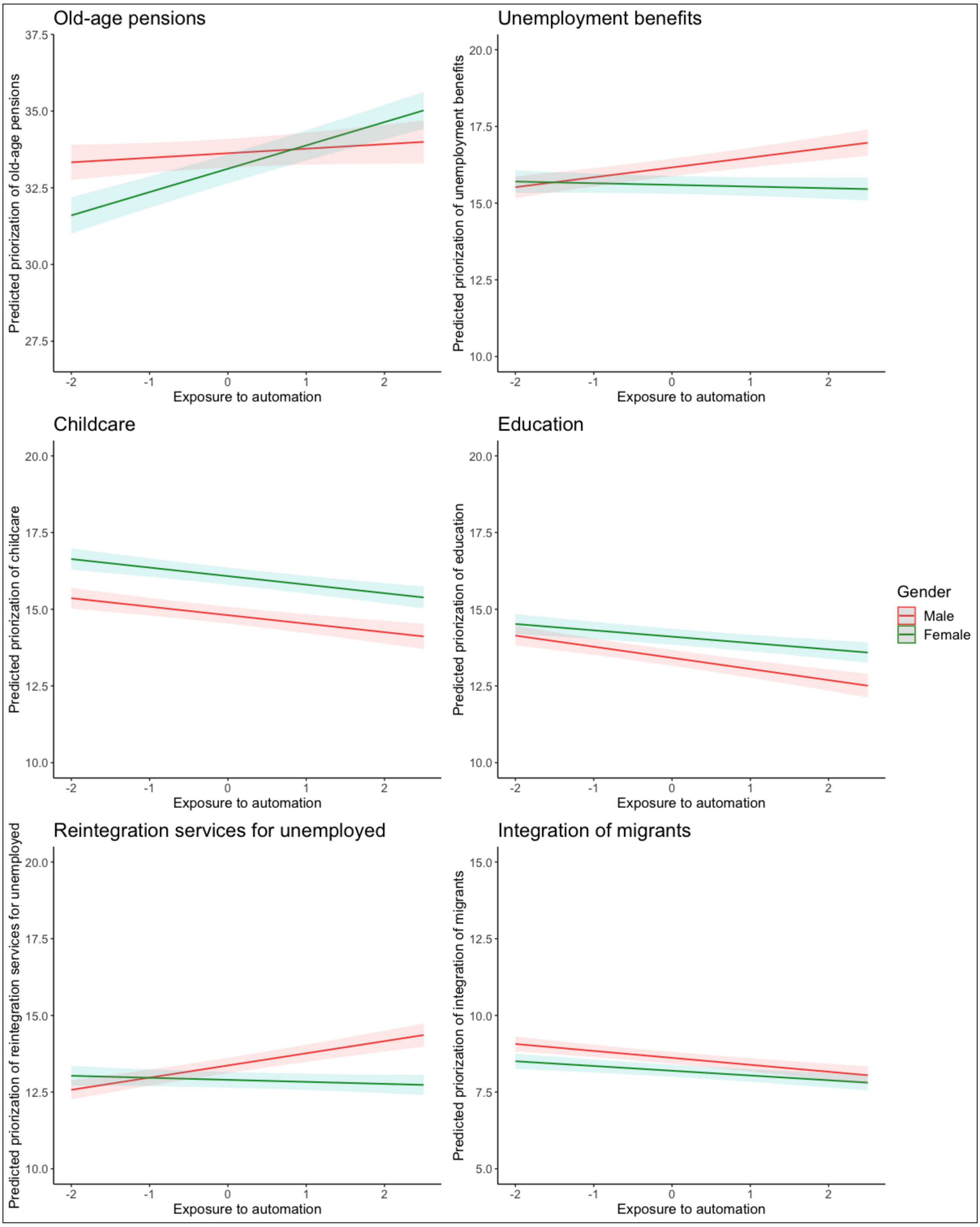
are more in favour of restricting the social expenditures to nationals. Hypothesis 1, suggesting that with higher exposure to automation, the support for expenditures on social policies increases, can hence not be confirmed. The absence of a significant increase in the support for social expenditures is surprising and somehow counter-intuitive as one would expect a higher support for insurance against automation risk. Of note is that with the additional two measures of automation risk (Frey and Osborne 2017; Owen and Johnston 2017), the level of support for a rise in benefits does significantly increase with higher exposure to technological change (see Figures 21 and 22 in the Appendix). The difference in results is difficult to explain ad-hoc. One possible explanation is that the classic RTI is less precise than the other two measures that catch additional elements. Alternatively and considering that the additional two measures are based on the US labour market which can be situated in the group of liberal welfare states and labour markets, another possible reason is that there are differences across welfare regimes that do not appear when eliminating country differences, an issue that could be addressed in future research.

Figure (5) Social policy positions with increasing exposure to automation by gender



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (6) Social policy priorities of respondents with increasing exposure to automation by gender



Linear regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

More important for this research paper is the question of whether genders differ in their social policy preferences and priorities with increasing exposure to automation. A broad range of literature (Häusermann 2010; Morel and Palier 2011) has suggested that women are more in favour of social activation policies than men. Yet, in line with formulated expectations, Figure 4 sheds doubt on this argument. Presenting the linear prediction of genders to prioritize social activation over consumption policies, the overlapping confidence intervals in the figure reveal that there is no clear gender difference with increasing automation. With rising automation risk, women are not stronger supporter of activation policies than men. The gender differences seem to be more complex than that. Let us hence have a look at the results for individual social policies.

Figure 5 and 6 present the results of how increasing automation affects individual social policies differently by gender. Most importantly, we do see clear gender differences with increasing risk exposure for unemployment benefits, childcare, education and reintegration services for unemployed and old-age pensions, particularly in terms of priorities. With regard to unemployment benefits, the results show that males are more in favour of expanding them, compared to females. The gender difference becomes stronger with higher risk of automation. This discrepancy is already apparent in general social policy positions but becomes more clear when respondents have to prioritize between different social policy areas. While men increasingly prioritize unemployment benefits, women's support marginally decreases.

The results are slightly more complicated for old-age pensions. In terms of general positions towards increasing benefits, both women and men show a high level of more than 90 percent support (see Figure 5). More diverging are the preferences when respondents have to prioritize. Figure 6 highlights that females' support more strongly increases with rising risk exposure than males'. While women's assigned priority is below men's at low risk, females' support increases significantly more strongly than males'.

Turning to what is portrayed in literature as social activation policies, gender differences do appear with increasing automation risk but not always as previous literature (Häusermann 2010; Morel and Palier 2011) would expect. In terms of childcare, the prioritization is gendered but the general positions of women and men converge with rising risk. This may seem surprising at first glance. Yet, Figure 6 reveals that this convergence is mostly due to men that do sympathize with childcare in general but as it comes to prioritizing policies, do not show the same level of support as they are less restricted in "finding a good way out" of routine occupations by the absence of adequate childcare possibilities. For both genders, childcare seems to lose priority with increasing risk of automation. However, women assign a higher priority to childcare than men. The difference between genders is statistically significant. In the Appendix, I also present the analysis when restricting the dataset to respondents with children. The results stay similar (see Section 4.2).

A clear gender difference with women showing higher support for expanding benefits is also prevalent for education. In both - general positions and prioritization - females show higher support for a rise in expenditures on education compared to men. The positions and assigned priority increasingly diverge with rising automation risk.

The contrary is the case of reintegration services for the unemployed. Figure 6 highlights that at higher level of risk exposure, genders increasingly differ in their prioritization of reintegration measures. While men increasingly prioritize reintegration possibilities, women's support decreases slightly. The gender difference is statistically significant. Interesting to note is that the results look slightly different for general social policy positions. Figure 5 shows that women across automation risk are even clearer supporters of the general idea of reintegration services. Yet, it does not seem to be their first concern in case they have to prioritize between different policies as Figure 6 highlights.

In line with expectations formulated earlier and in contrast to a wide range of literature, females are hence not generally more in favour of social activation policies. Rather, females and males express preferences that match their self-interest resulting from different (expected) experiences with automation: With increasing risk of technological change, females are more in favour of childcare, education and old-age pensions. Males, in contrast, prefer unemployment benefits and reintegration measures for unemployed (for pensions and reintegration only when prioritization). Hypothesis 2 suggests that with increasing exposure to automation, women prioritize childcare, education and pensions, relative to unemployment benefits and retraining programs than similar men. This hypothesis can hence be confirmed - except for pensions where the results seem slightly more complicated. Robustness checks with additional measures of automation risk reveal that the gender differences are generally even more pronounced when using alternative risk indices which suggests that the clarity and significance of the divergences are rather at the lower level here.[5]

After having discussed the question of how genders differ in their preference of "what" social policy areas should be expanded, I now turn to the issue of "whom" should be eligible to receive the benefits (Hypothesis 3). Figures 5 and 6 present the corresponding results graphically. The items on the position and priorities are asked slightly differently (welfare only for nationals versus labour market integration of migrants - which is not the exact opposite of each other) which makes them not

[5] An additional analysis on the gender differences in social policy trade-off decisions with increasing automation risk can be found in the Appendix.

directly comparable. Nevertheless, the results should give a good indication of whom respondents feel should receive state benefits. Firstly, it is to note that with increasing risk of automation, the generosity of respondents towards migrants receiving social benefits decreases. Both genders become more restrictive in who should profit from risk insurance - which are not migrants. More importantly in the context of this paper and in line with formulated expectations, with increasing risk of automation women do not appear to be less welfare chauvinist than men. Among genders highly exposed to automation, there is no difference in their preferences of whom to restrict risk insurance to. The results hence confirm Hypothesis 3, suggesting that with increasing exposure to automation, women are as likely as men to support welfare chauvinism. In contrast, respondents at low risk seem to differ slightly: While women are generally less supportive of the idea of restricting social benefits only to nationals, they prioritize the integration of migrants into the labour market less than men. This "turnaround" of females' preferences might result from the fact that women are still less integrated into labour market and in line with their self-interest prioritize to restrict the beneficiaries to the smallest group possible in order to "catch up" and profit from integration measures to the largest part possible - while in terms of their general position towards migrants are slightly less restrictive. A more rigorous analysis of this effect might be subject to future research.

4.2 Robustness of the results

Section 7.6 in the Appendix of this research paper provides several robustness checks to examine the sensitivity of the effect of automation risk on social policy preferences by gender to a number of different specifications and additional explanatory variables suggested in the literature. In a first step, I run the models with different sets of covariates: with no covariates, only socioeconomic control variables and with additional covariates in form of political positions of the respondents in cultural (migration) and economic terms (reduce income inequality) and expected job stability.[6] In a second step, I test if the results are dependent of a particular specification of automation risk. I therefore re-run the analysis with different indices provided by Frey and Osborne (2017) and Owen and Johnston (2017). In a third step, I estimate linear models for the impact of automation risk on social policy positions. Additionally, I use the original ordered version of the variable instead of a binary "support/oppose" to examine if the results hold also with a more fine graded dependent variable. I further use different R packages to calculate the clustered robust standard errors to examine the results' sensitivity to small calculation changes. Lastly, I analyse if the results diverge

[6]There is unfortunately no variable in the dataset asking about a respondent's relationship to religion that might additionally influence social policy preferences.

for the group of respondents that arguably most directly profit from social investment policies, namely workers with children.

The results of the robustness checks confirm that the results generally hold in their direction and significance: With increasing exposure to automation, genders diverge in their social policy preferences. While women prioritize education, childcare and pensions, men prefer unemployment benefits and reintegration services for unemployed. With increasing automation risk, there is no gender difference in the preference of restricting social benefits only to nationals. The results are - as already in the main analysis - stronger when focusing on prioritization of policies rather than general positions. Most divergent are the results when using different indices of automation risk. With both additional measures of risk, the predicted probabilities of workers to generally support to increase expenditures for any kind of social policy rise more sharply than with the classic RTI. Additionally, in the analysis with the index by Frey and Osborne (2017) genders do not seem to differ in their preference for unemployment benefits, while including the measurement by Owen and Johnston (2017) shows converging results for childcare preferences. These differences suggest that future studies should chose carefully and conceptually reasoned when using one of these three indices. It is of note that the robustness checks for the presented results are by no means exhaustive. In case of more time and line space, it might be important to examine possible cohort effects in the results and to include additional elements such as skill specificity, labour market outsiderness or offshoring in the analysis that could additionally impact an individual's social policy preferences.

5 Discussion

My results provide several new theoretical and empirical insights for political science literature on automation and its political implications. Firstly, this analysis has underlined the importance of differentiating between genders when analysing the welfare impact of automation risk. So far, we know surprisingly little about how genders differ in their social policy preferences generally and in the automation context specifically. Yet, the results show that while the welfare priorities might be more aligned for respondents at low risk, they increasingly diverge with rising risk - which brings us to a second insight.

Secondly, the results show how important it is to conceptually differentiate between two types of economic risks related to technological change: the risk of unemployment and the risk of occupational downgrading. These risks are often merged in the literature on automation (Im 2020, e.g.). The differentiation, yet, is crucial because of two reasons. First of all, genders differ in their risk experience, with men mostly experiencing the first one, while women are more likely to transition into low-skill jobs (Müller 2021). Moreover, these risk experiences cannot necessarily be countered by the same social policies. The analysis shows that women want to see their risk of occupational downgrading addressed with higher expenditures on education and childcare while men prioritize unemployment benefits and reintegration services for unemployed that shield them from the most negative consequences of job loss. These findings add to a broad range of literature that has suggested that women are generally be core supporters of social activation policies (Häusermann 2010; Jenson 2010; Morel and Palier 2011; Schwander and Häusermann 2013). The results, however, show that in the context of automation, the gender differences are less along the lines of social investment versus passive consumption policies but rather in accordance with women's and men's insurance based self-interest of what social policies address their experienced risk with automation best. These findings correspond to the results of a recent contribution by Garritzmann and Schwander (2021) who similarly conclude that in a more general context, women are not necessarily core-supporters of all social activation policies but only if they help to advance their interests.

With regard to the third risk, status loss, the analysis provides an additional new insight. The analysis highlights that with increasing risk of automation women become as welfare chauvinist as men. Both genders are hence similarly supportive of welfare benefits only for nationals if they are at high risk of automation. This might seem surprising in view of literature on welfare states (Fossati and Häusermann 2014) and social status (Gidron and Hall 2017; Kurer 2020) which suggests that women should be more generous towards benefits also for migrants because of firstly their increasing social status and secondly their tendency to have more universalistic values than men which resonates with less advantaging nationals. How can we then explain that in the context of automation, women are not less welfare chauvinist than men? Müller (2021) descriptively analyses status perceptions by gender over time and shows that the societal recognition increased heterogeneously for women across occupational groups. While a majority of women might indeed experience an increase in social status, this is not the case for women highly exposed to automation. These women at risk perceive their social recognition as stagnating, even slightly declining. Especially, in an environment of an overall increase of social status for women, this may make them particularly welfare-chauvinist. An additional explanatory element might be that women are still "catching up" with men to obtain similar protection status (Garritzmann and Schwander 2021). Consequently, a logical reaction might be to restrict social benefits to a smaller group to profit as much as possible. The underlying mechanisms for the absence of a gender difference in welfare chauvinism with increasing automation risk would need to be examined more carefully in future research.

Lastly, and on a more general note, the results underline previous findings by Kurer and Häusermann (2021) showing that workers affected by automation do not show higher support for social activation policies as such and even slightly prefer passive consumption policies. Despite what is often presented as effective counter measure to this new risk, the workers most affected by automation do not prioritize social investment. These preferences make it difficult for governments to find sufficient political support for an adequate response to automation - but underlines the importance to analyse social policy preferences in greater detail for workers exposed to automation.

Of note is that these new insights might not only be relevant knowledge for governments but might also impact individual vote choice. A broad range of studies has highlighted that social policy preferences impact voters' party choice (Rueda 2005; Schwander and Häusermann 2013; Fossati and Häusermann 2014). Yet, the different policy preferences by women and men with increasing automation risk correspond to different party programs. A recent study by Enggist and Pinggera (2021) examining parties welfare priorities in the Western European context suggests that while right-wing and radical left parties have a clear stand in favour of consumption policies, the contrary is the case for liberals, greens and conservatives. Social democrats seem to position themselves somewhere in between. A first mediation analysis (in the Appendix) suggests that these social policy preferences have an impact on vote choice and might also explain parts of the gender gap in voting for right-wing populist parties when highly exposed to automation. Yet, how exactly and in what way welfare preferences affect the relationship with party choice is subject to future research.

6 Conclusion

This research paper has analysed the gender difference in social policy preferences in a context of automation risk. Given that genders have different experiences with automation (Müller 2021), it stands to reason that females and males might differ in their preferences of what risks should be countered by state support. Analysing recent original data (Häusermann et al. 2020b) of eight Western European countries covering the four main welfare state types, I show that in line with a rational choice argument of self-interest, women are more supportive of increasing education and childcare than men - which help females in addressing their higher risk of occupational downgrading. In contrast, men are more supportive of unemployment benefits and reintegration services for unemployed which counters the negative consequences of their higher probability to lose their job when exposed to technological change. In addition, I present evidence that women and men do not differ in their degree of welfare chauvinism with increasing exposure to automation.

These findings importantly contribute to literature on welfare preferences and automation in two ways. It firstly shows that future research needs to disentangle not only the difference between the risk of status loss and economic implications but additionally differentiate between the risk of unemployment and occupational downgrading in order to capture the risk experiences of men *and* women. Secondly, the results contribute empirically to the literature by highlighting that as a result of a gendered experience with automation, women and men increasingly differ in their social policy preferences with rising exposure to automation. Yet, in contrast to previous literature, these gender differences are not simply along the lines of social activation versus consumption policies but are in agreement with women's and men's self-interest of what social policy addresses their experienced risk with automation best.

To be clear, this research paper does only provide partial and preliminary insight into gender differences in social policy preferences in the context of automation risk. Additionally to the possible future avenues of research that I outlined in the discussion, further research will be needed to answer questions brought up by the above analysis. I have, for example, not made a distinction between full- and part-time workers or different household dynamics to prevent disproportionate loss of observation. Since women still bear the majority of the family work, it might, however, be a worthwhile avenue to analyse the impact of women's role in the household and different levels of family responsibilities on their social policy preferences in a more nuanced way. Additional research should further explore if there is an age component in the results. Previous research suggests that younger cohorts of women might be more in favour of social activation policies such as education and childcare than females at a higher age (Dassonneville 2021). More systematic research on this possible age difference might reveal important additional insight. Moreover, I have used the classic measure of RTI to conceptualize automation risk - with the measures of Frey and Osborne (2017) and Owen and Johnston (2017), both focusing on the US labour market, as robustness checks. While the wast majority of the results and gender differences stay the same, the additional results suggest a stronger increase in the support to expand social expenses generally with rising risk compared to the RTI. A more nuanced analysis of the implications of different automation risk indices and possible differences between welfare regime specific results might add important insight.

What we can already conclude from the results is that finding adequate responses to increasing automation is highly complex. While scholars have generally proposed social activation policies (Kurer and Häusermann 2021) as a possible solution, the results of this paper demonstrate that the differing risk experiences men and women have with automation lead to different social policy preferences. While women request more education, old-age pensions and childcare services than men, males express stronger support for unemployment and reintegration services. Yet, in the age of ongoing welfare retrenchment and trade-offs, governments cannot increase expenditures in all of these policy areas. This research paper shows the underlying complexity of these trade-off decisions as not all workers at risk share the same experience and policy preferences. At the same time, several papers have shown that negative economic experiences with automation can lead to general dissatisfaction with and alienation from politics (Frey et al. 2017; Kurer 2020; Müller 2021). These consequences remind us - despite its complexity - to think more creatively and courageously about possible policy responses and to identify different responses to the experiences men and women have with technological change.

7 Appendix

7.1 Main variables

Table (2) Operationalization of main variables

Concept	Operationalization	Original variable
Risk of automation	RTI: 2.23 (maximum) -1.52 (minimum) Automation risk by Frey and Osborne (2017): 0 (minimum) 100 (maximum) Automation risk by Owen and Johnston (2017): -2.12 (minimum) 2.49 (maximum)	rti, frey, rti2, isco2d, isco3d, autom
Social policy positions	The government should increase... pension benefits childcare services university education for low-income families unemployment benefits reintegration into labour market social assistance for nationals	pos.e.pen, pos.e.cc, pos.e.educ pos.e.ub, pos.e.almp, pos.e.socass
Social policy priorities	Allocation of a total of 100 points to... pension benefits childcare services university education unemployment benefits reintegration into labour market social assistance for nationals	prio.f.e.pen, prio.f.e.cc, prio.f.e.educ, prio.f.e.ub, prio.f.e.almp, prio.f.e.migr
Social policy trade-offs	Lower pensions but increase... unemployment benefits services for migrants reintegration for young unemployed childcare	to3, to5, to6, to7
Gender	1 Female 0 Male	sex

Party family	Party most likely to support in elections next week: Conservatives Right-wing populists Greens Liberals Social democrats Radical left	party
Support for right-wing populist party	Party most likely to support in elections next week: 1 Right-wing populists 0 Other party	party
Age	18 (minimum) 108 (maximum)	age
Education	Highest level of education: 0 Less than primary education - 7 Master's and doctoral level	educ
Income	1 (minimum category) 10 (maximum category)	income
Left-right positioning in politics	0 Left 10 Right	lrscale
Union membership	1 Yes, currently 2 Yes, previously 3 No	lrscale
Country	Denmark, Sweden Germany, Netherlands Ireland, United Kingdom Italy, Spain	country

7.2 Regression tables of analysis

The following two tables present the regression results previously shown in form of figures. Table 3 shows how general social policy positions change for women and men with increasing automation risk. Table 4 highlights the corresponding results for social policy priorities. These results have been presented in the main analysis as figures since the interaction coefficient is more intuitive to interpret graphically than in form of a regression coefficient.

Table (3) Average effects of automation on social policy positions by gender

	Old-age pension	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
RTI	0.026	−0.014	0.030**	0.032	−0.194***	0.082***
	(0.016)	(0.011)	(0.011)	(0.018)	(0.017)	(0.015)
Female	−0.005	−0.112***	−0.040**	0.172***	0.131***	0.244***
	(0.021)	(0.015)	(0.015)	(0.025)	(0.024)	(0.021)
Age	0.010***	0.000	0.001	0.013***	0.012***	−0.002**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Education	−0.066***	−0.101***	−0.118***	0.037***	−0.078***	−0.005
	(0.006)	(0.005)	(0.005)	(0.008)	(0.007)	(0.006)
Income	−0.025***	−0.126***	−0.040***	−0.008	−0.020***	−0.007
	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.004)
Left-Right Position	−0.035***	−0.162***	0.182***	−0.074***	−0.181***	−0.094***
	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)	(0.004)
RTI*Female	0.019	0.005	0.038**	0.013	0.142***	−0.173***
	(0.020)	(0.014)	(0.014)	(0.024)	(0.022)	(0.019)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Num obs.	89504	89504	89504	89504	89504	89504

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.
Own calculations. Weighted and logistic country fixed-effect models with clustered and heteroskedasticity robust standard errors. Covariates are age, education, income, left-right position, union membership. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

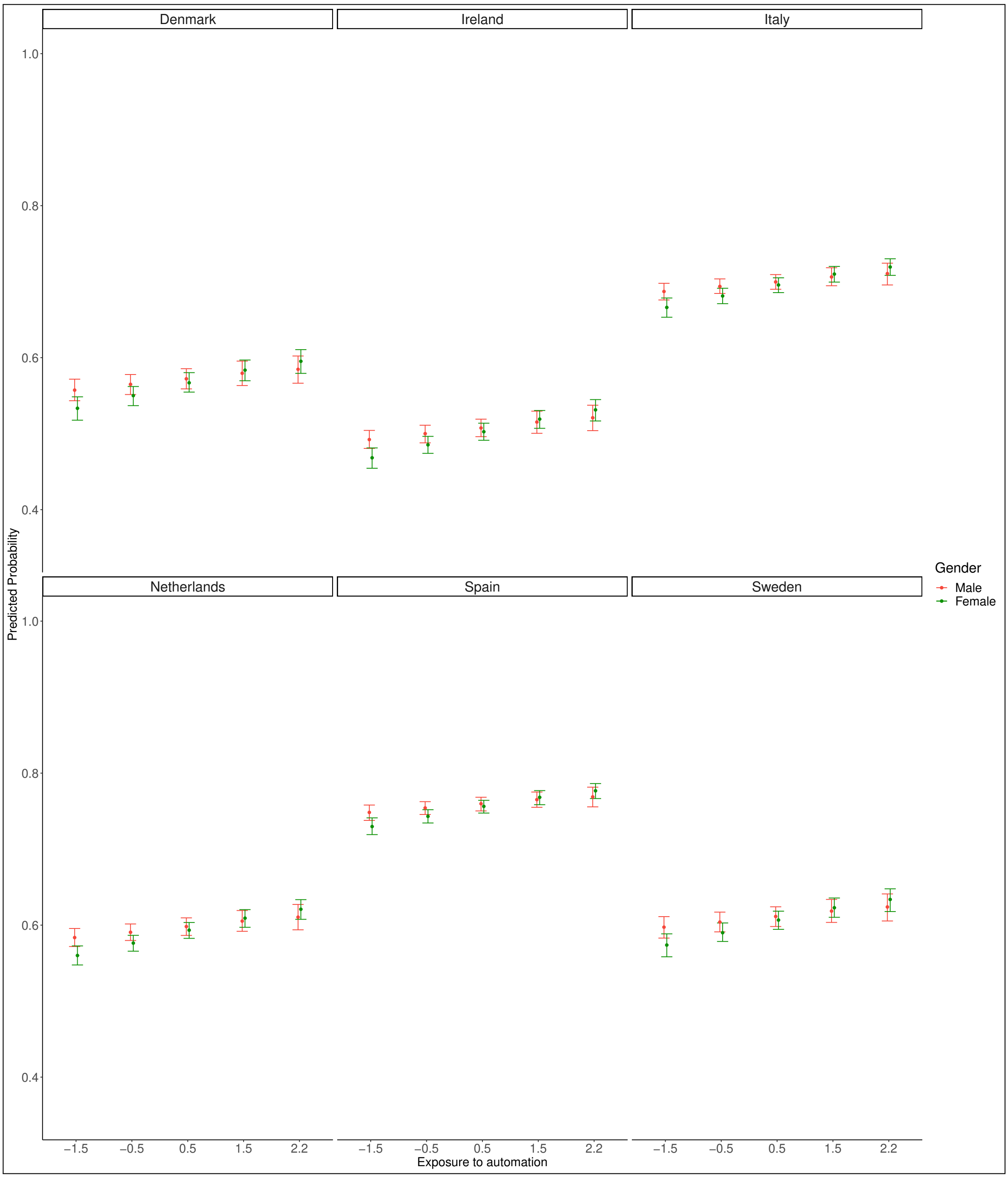
Table (4) Average effect of automation on social policy priorities by gender

	Index	Old-age pensions	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
RTI	-0.026^{***}	0.148	0.322^{***}	-0.226^{***}	0.397^{***}	-0.363^{***}	-0.277^{***}
	(0.005)	(0.132)	(0.082)	(0.049)	(0.068)	(0.061)	(0.074)
Female	0.022^{**}	-0.506^{**}	-0.569^{***}	-0.420^{***}	-0.468^{***}	0.690^{***}	1.273^{***}
	(0.007)	(0.158)	(0.106)	(0.067)	(0.088)	(0.092)	(0.096)
Age	-0.004^{***}	0.211^{***}	-0.073^{***}	-0.001	-0.008^{**}	-0.066^{***}	-0.063^{***}
	(0.000)	(0.005)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Education	0.045^{***}	-0.909^{***}	-0.589^{***}	0.385^{***}	0.297^{***}	0.759^{***}	0.057
	(0.002)	(0.048)	(0.030)	(0.023)	(0.027)	(0.029)	(0.030)
Income	0.022^{***}	-0.131^{***}	-0.480^{***}	0.014	-0.003	0.153^{***}	0.447^{***}
	(0.001)	(0.030)	(0.020)	(0.013)	(0.016)	(0.019)	(0.018)
Left-Right Position	-0.001	0.736^{***}	-0.214^{***}	-0.547^{***}	-0.019	0.039^{*}	0.005
	(0.002)	(0.033)	(0.025)	(0.015)	(0.018)	(0.018)	(0.019)
RTI*Female	0.010	0.613^{***}	-0.376^{***}	0.072	-0.463^{***}	0.156	-0.001
	(0.007)	(0.156)	(0.094)	(0.060)	(0.083)	(0.081)	(0.087)
Numb. obs	87824	87824	87824	87824	87824	87824	87824
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Covariates are age, education, income, left-right position, union membership. Data source: Welfare priorities data, 2020. Pooled data for Ireland, Italy, Netherlands, Spain, Sweden. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

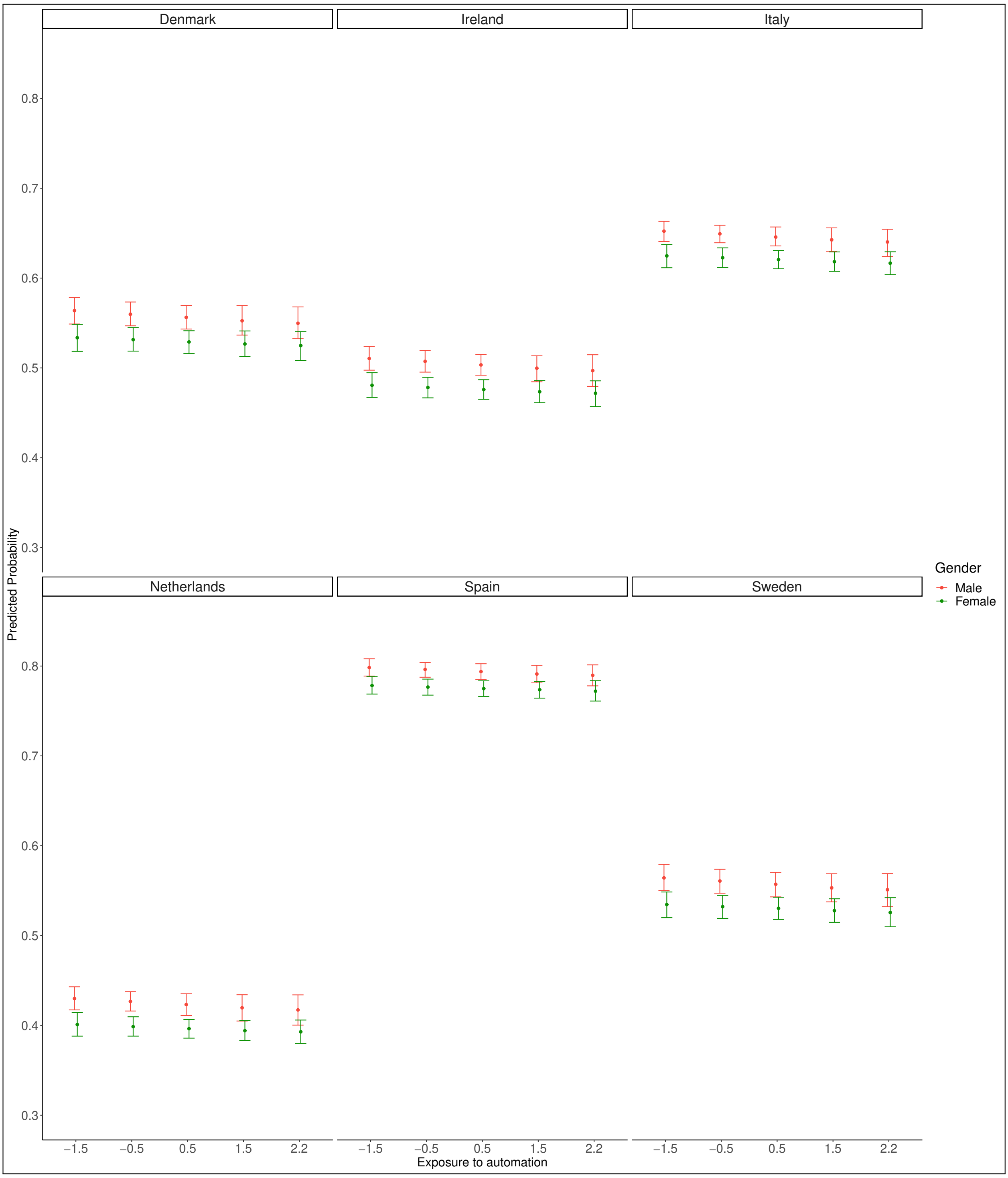
7.3 Additional country results

Figure (7) Preferences for old-age pensions with increasing exposure to automation by gender



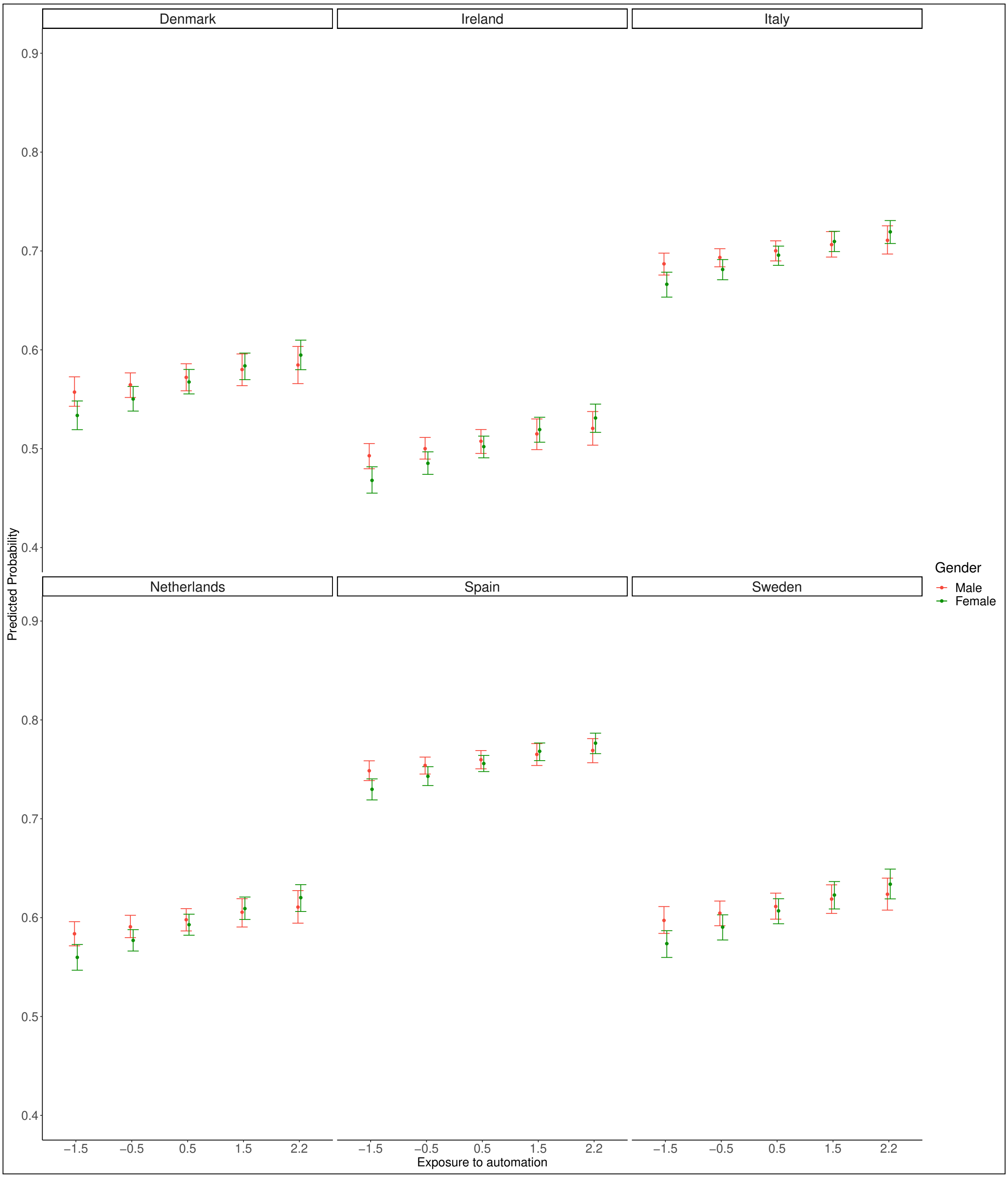
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (8) Preferences for unemployment benefits with increasing exposure to automation by gender



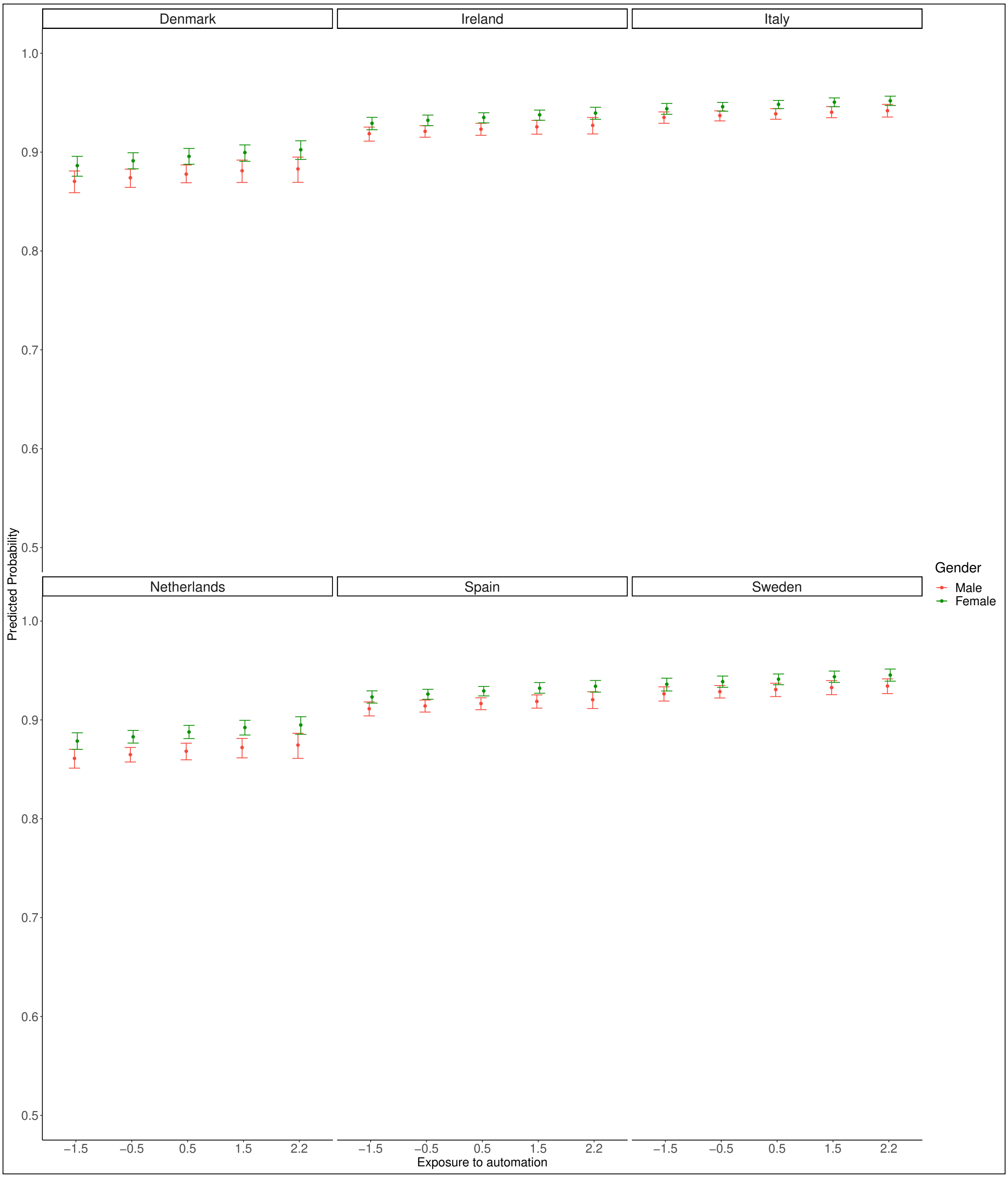
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (9) Preferences for welfare chauvinism with increasing exposure to automation by gender



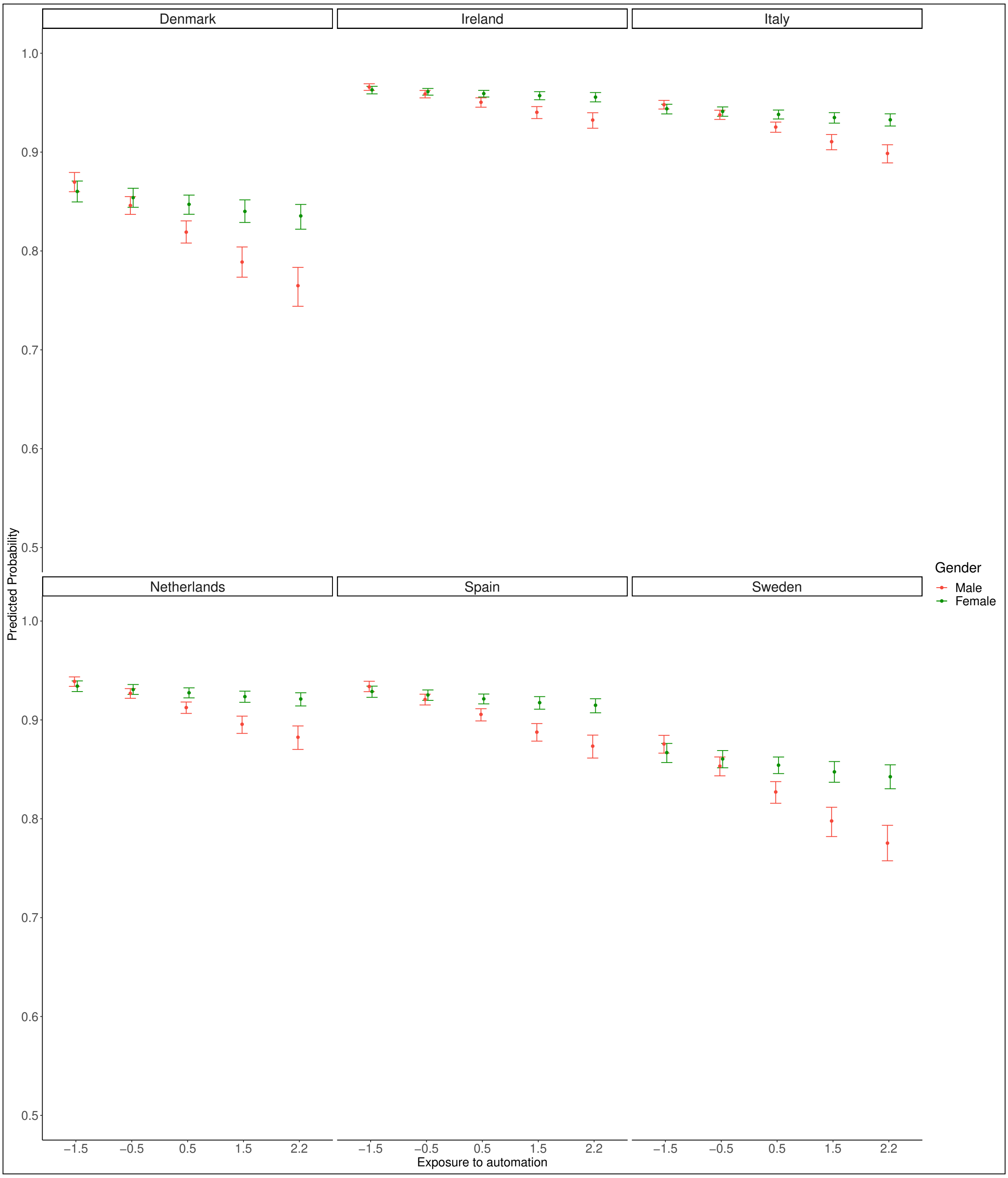
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (10) Preferences for reintegration services with increasing exposure to automation by gender



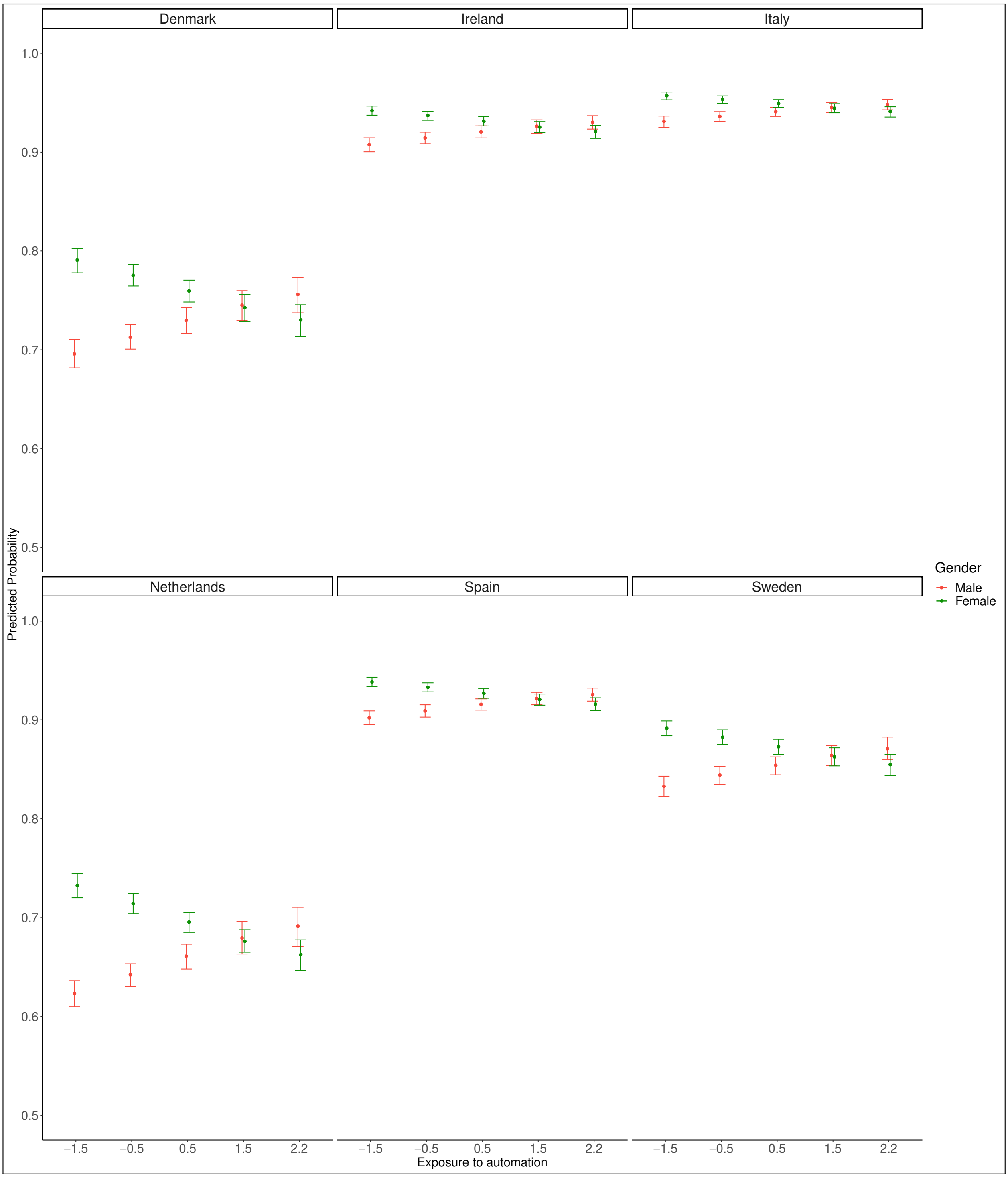
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (11) Preferences for education with increasing exposure to automation by gender



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (12) Preferences for childcare with increasing exposure to automation by gender



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

7.4 Analysis of trade-off scenarios

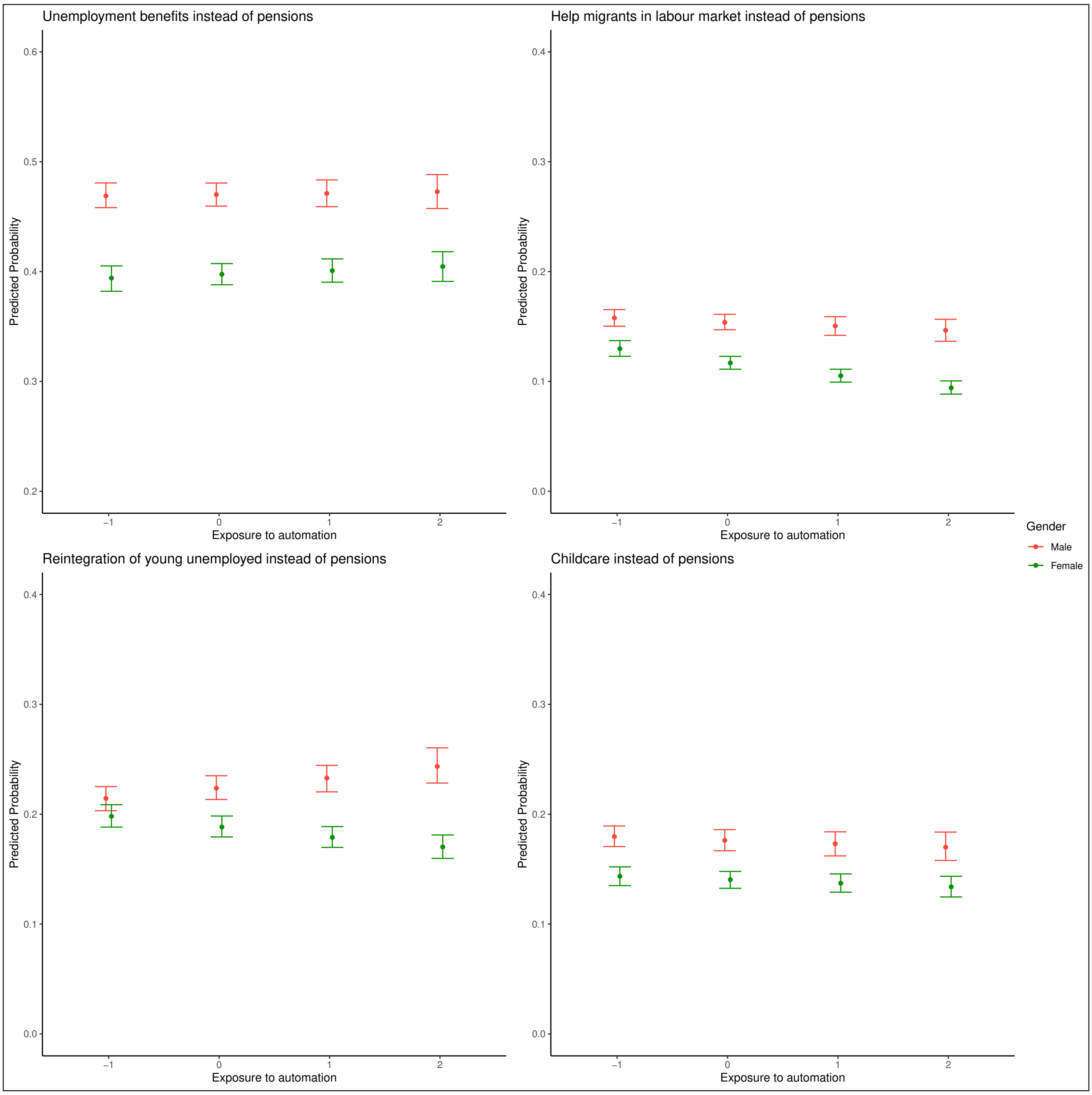
In this additional analysis, I examine what happens if men and women had to choose between compensatory or investing policies. Confronted with new welfare demands, but limited recourses, policymakers nowadays often must – explicitly or implicitly – prioritize one policy goal over another, a reality the literature on social policy preferences has started to incorporate (Boeri et al. 2001; Busemeyer and Garritzmann 2017; Fossati and Häusermann 2014). Old-age pensions are often the reference point of discussion. Pensions generally request a large part of the welfare budget. Yet, to cut them is often highly political as they are generally very popular among the population. In the context of this paper, I am most interested if women or men are more likely to accept reductions of old-age pensions in favour of childcare, unemployment benefits, reintegration measures and integrating migrants into labour market. Following the aforementioned and formulated expectations (see main analysis) on social policy preferences, I expect women to be less supportive to accept pension cut backs in order to increase unemployment benefits, reintegration measures and expenses to integrate migrants into the labour market. With regard to childcare, it is more difficult to formulate clear expectations since women are considered to be at the receiving end of both of these policies. Both possibilities are possible - either women prioritize old-age pensions or they prefer childcare.

The dependent variable here provides a scenario where the government can improve "certain social benefits. However it can only do so by cutting back on other social benefits. To what extent to you find the following cutbacks acceptable?" For the analysis, I use increasing benefits for the unemployed, services for migrants to find a job, training for unemployed young people and childcare at the cost of lowering the maximum old age pension benefits. The range of answers reaches from completely inacceptable (1) to completely acceptable (4). For the sake of compactness, I dichotomize the variables in supporting or being against it. This variable captures most closely the situation many governments are in: confronted with new welfare demands, but limited resources, policymakers often must – explicitly or implicitly – prioritize one policy goal over another (Garritzmann and Schwander 2021, e.g.).

Figure 13 presents the predicted probabilities of respondents at different levels of automation risk to support increasing unemployment benefits, integration measures for migrants, reintegration of young unemployed and childcare at the expense of old-age pension benefits.[7] The results provide us with a clear picture: Even though genders do not differ necessarily with regard to their support

[7] The dataset does not provide any trade-off questions on education at the expense of old-age pensions. I present the results for Germany (unemployment benefits and help migrants) and Sweden (for the other two since Germany is missing) as example countries.

Figure (13) Trade-off positions with increasing exposure to automation by gender



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. For the sake of compactness, here only shown the results for Germany respectively Sweden. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. For reintegration of pensions and childcare provisions without Germany and the UK.

to increase old-age pensions, women are less willing to accept reductions in order to increase expenditures on any other social policy, compared to men. These results confirm my expectations for

Table (5) Average effects of automation on social policy trade-offs by gender

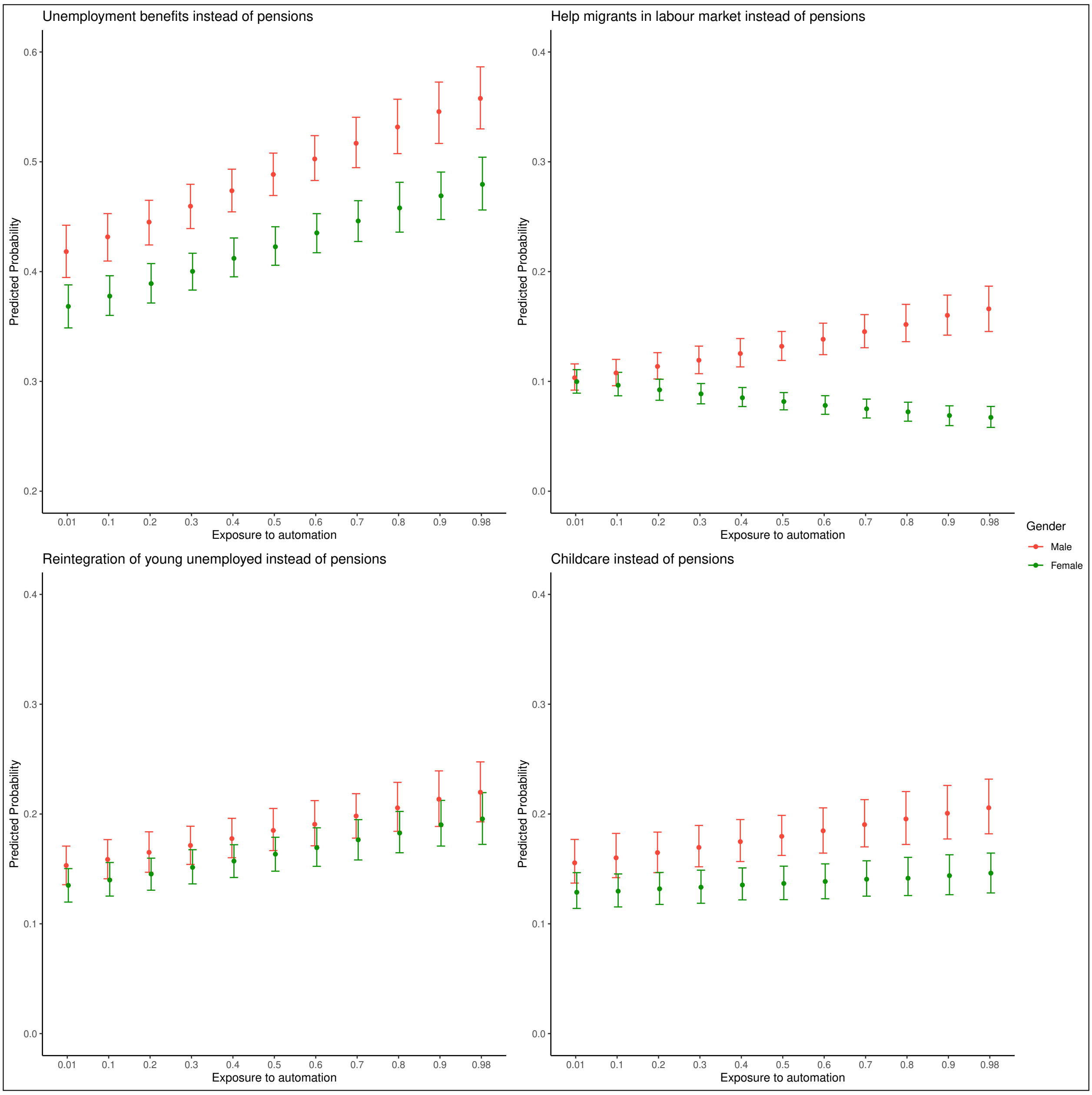
	Unemployment benefits	Integration of migrants	Reintegration	Childcare
RTI	0.005	-0.029^{*}	0.055^{***}	-0.021
	(0.011)	(0.014)	(0.014)	(0.015)
Female	-0.297^{***}	-0.319^{***}	-0.217^{***}	-0.269^{***}
	(0.016)	(0.019)	(0.018)	(0.020)
Age	-0.013^{***}	-0.020^{***}	-0.018^{***}	-0.021^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.025^{***}	0.073^{***}	0.043^{***}	0.025^{***}
	(0.005)	(0.006)	(0.006)	(0.006)
Income	-0.080^{***}	0.005	-0.040^{***}	-0.012^{**}
	(0.003)	(0.003)	(0.003)	(0.004)
Left-Right Position	-0.054^{***}	-0.103^{***}	-0.062^{***}	-0.046^{***}
	(0.003)	(0.004)	(0.004)	(0.004)
RTI*Female	0.010	-0.091^{***}	-0.117^{***}	-0.006
	(0.015)	(0.018)	(0.017)	(0.018)
Num. obs	90592	90592	90592	90592
Country fixed effects	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted and logistic country fixed-effect models with clustered and heteroskedasticity robust standard errors. For the sake of compactness, here only shown the results for Germany respectively Sweden. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. For reintegration of pensions and childcare provisions without Germany and the UK. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

unemployment benefits, integration measures for migrants and reintegration services. With regard to childcare, I theorized above that a priori it is unclear how women position themselves when having to make the difficult choice between old-age pensions and childcare. The results clearly show that women prioritize the maintenance of old-age pensions over the expansion of social investment and the integration of migrants, while men are significantly more likely to express support for social investment expansions and integration measures for migrants if these came at the expense of social compensation. The results are irrespective of the level of automation risk and remain very similar when using a different automation risk measure and when restricting the dataset to respondents with children as main beneficiaries of social activation policies. As Garritzmann and Schwander (2021) point out, this clear gender difference is likely to be related to women still needing to "catch up" with men's old-age pension benefits.

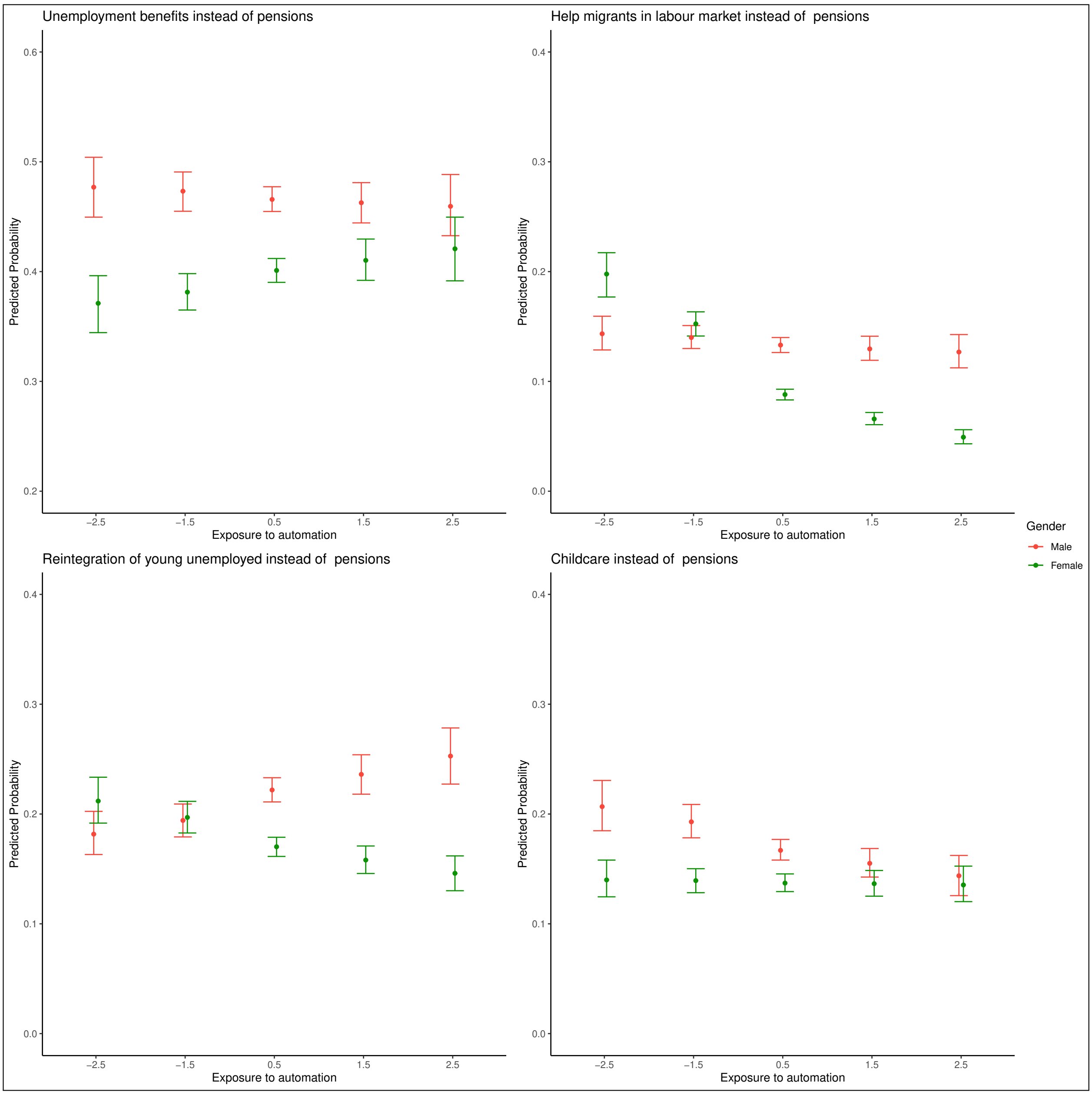
The results show that trade-off scenarios women are less willing to accept any reduction in old-age pensions in favour of any other social policy - here unemployment benefits, the integration of migrants, reintegration of young unemployed and childcare services - than men. This finding is in line with the results by Garritzmann and Schwander (2021) who examine trade-off scenarios in a general context and find that women are less willing than men to trade old-age pensions for alternative social policies. While this might not surprise in the cases of the first three social policies, it might come unexpected with regard to childcare benefits. A possible explanation for this finding is that women might want to first establish a safety net before seeking for social investment policies while men are more willing to trade pensions for childcare because of their more stable economic position. These results not only underline the importance of differentiating between welfare preferences and hard-cut trade-off scenarios but also show the complexity and difficulty that current governments are faced with in an era where welfare cuts might be increasingly necessary. In case governments hence would aim to cut old-age pensions, they would probably have to compensate women with a package of alternatives in order to gain their support. The following two figures (Figures 14 and 15 present the impact of automation on social policy preferences by gender with different measures of automation risk - once with the more future-oriented index by Frey and Osborne (2017) and once with the RTI provided by Owen and Johnston (2017) and restricted to respondents with children (see Figure 16).

Figure (14) Trade-off positions with increasing exposure to automation by gender - with Frey and Osborne (2017)



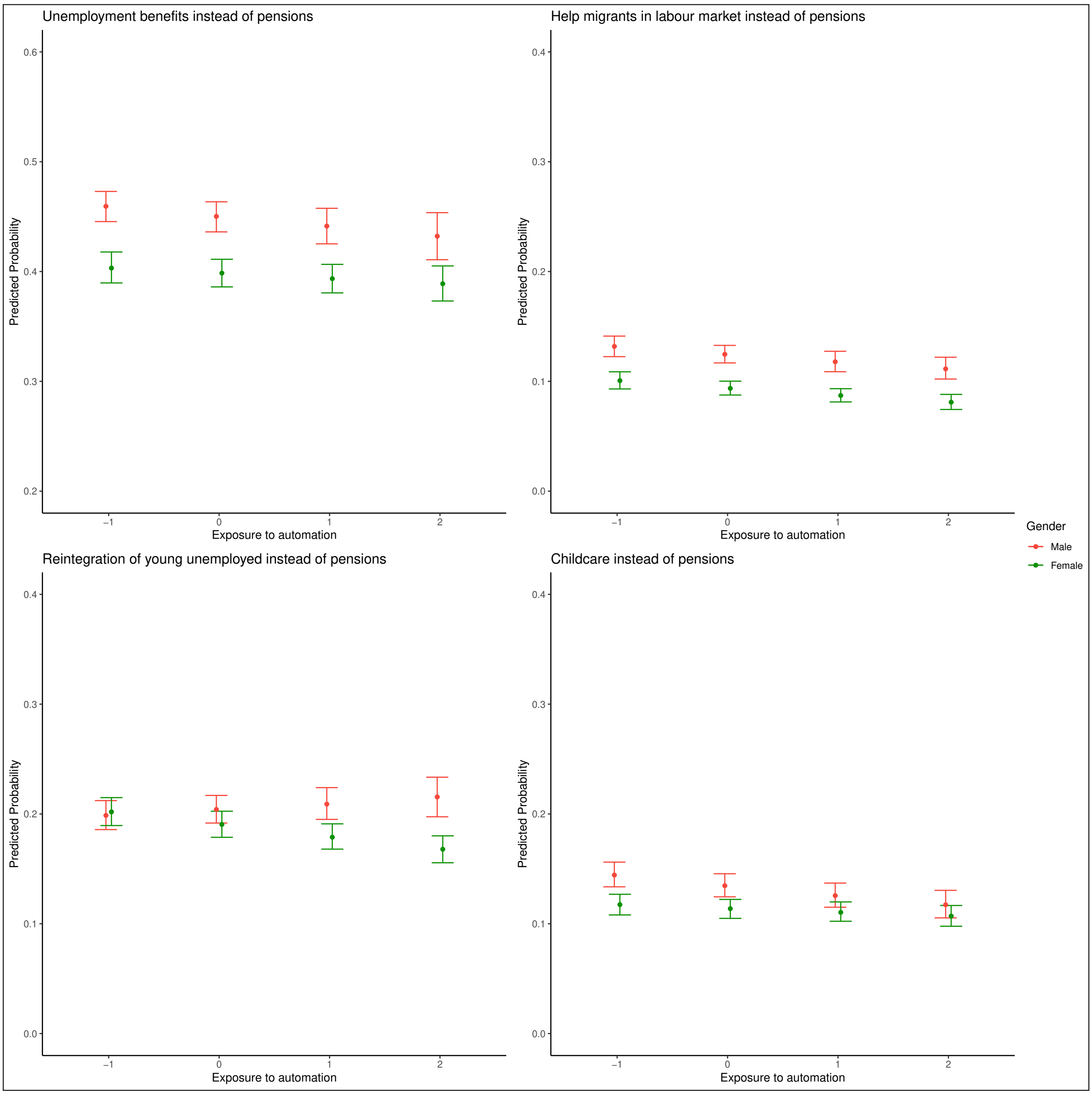
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. For the sake of compactness, here only shown the results for Germany respectively Sweden. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. For reintegration of pensions and childcare provisions without Germany and the UK.

Figure (15) Trade-off positions with increasing exposure to automation by gender - with Owen and Johnston (2017)



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. For the sake of compactness, here only shown the results for Germany respectively Sweden. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. For reintegration of pensions and childcare provisions without Germany and the UK.

Figure (16) Trade-off positions with increasing exposure to automation by gender - with children



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. For the sake of compactness, here only shown the results for Germany respectively Sweden. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. For reintegration of pensions and childcare provisions without Germany and the UK.

7.5 Exploratory mediation

This section presents results on the effect of social policy preferences mediating the relationship between gender and voting for right-wing populists for respondents with a higher exposure to automation than the mean exposure (highly exposed respondents). Gingrich and Kuo (forthcoming) show that women at high automation risk are less likely than men to vote for right-wing populist parties. At the same time, a broad range of literature has suggested that women are in general more supportive of social investment policies (Fossati and Häusermann 2014; Häusermann 2010). Following Enggist and Pinggera (2021) who show that right-wing populist parties support passive consumption but not social investment policies, one could hence expect that these differences along the consumption-activation line might explain some of the gender difference in voting for populist right parties when highly exposed to automation. In this paper, I have argued that the gender division, yet, is more complex and corresponds to insurance-based self-interest considerations rather than to a consumption-activation split.

The results confirm that the mediating effect of social policies is more complex than literature would suggest. Table 6 shows the results of the causal mediation analysis. ACME thereby stands for the average causal mediation effects which is the indirect effect of the independent on the dependent variable that goes through the mediator and reveals if the mediator significantly mediates the relationship. Figure 17 highlight the individual effects of the independent variable on the dependent and the mediator and the impact of the mediator on the dependent variable. The results show that social policy preferences do seem to matter in the explanation of gender difference in the support of right-wing populists. Yet, while women's preferences in unemployment benefits, education and childcare are in line with the literature as they suggest women to subsequently vote less for populist parties, the contrary is the case for females' assigned priority to old-age pensions, reintegration measures and the integration of migrants into the labour market. Analysing how social policy preferences matter for party and specifically right-wing populist support by gender might be a fruitful avenue for future research. From the results of the causal mediation analysis here, no clear conclusion can be reached.

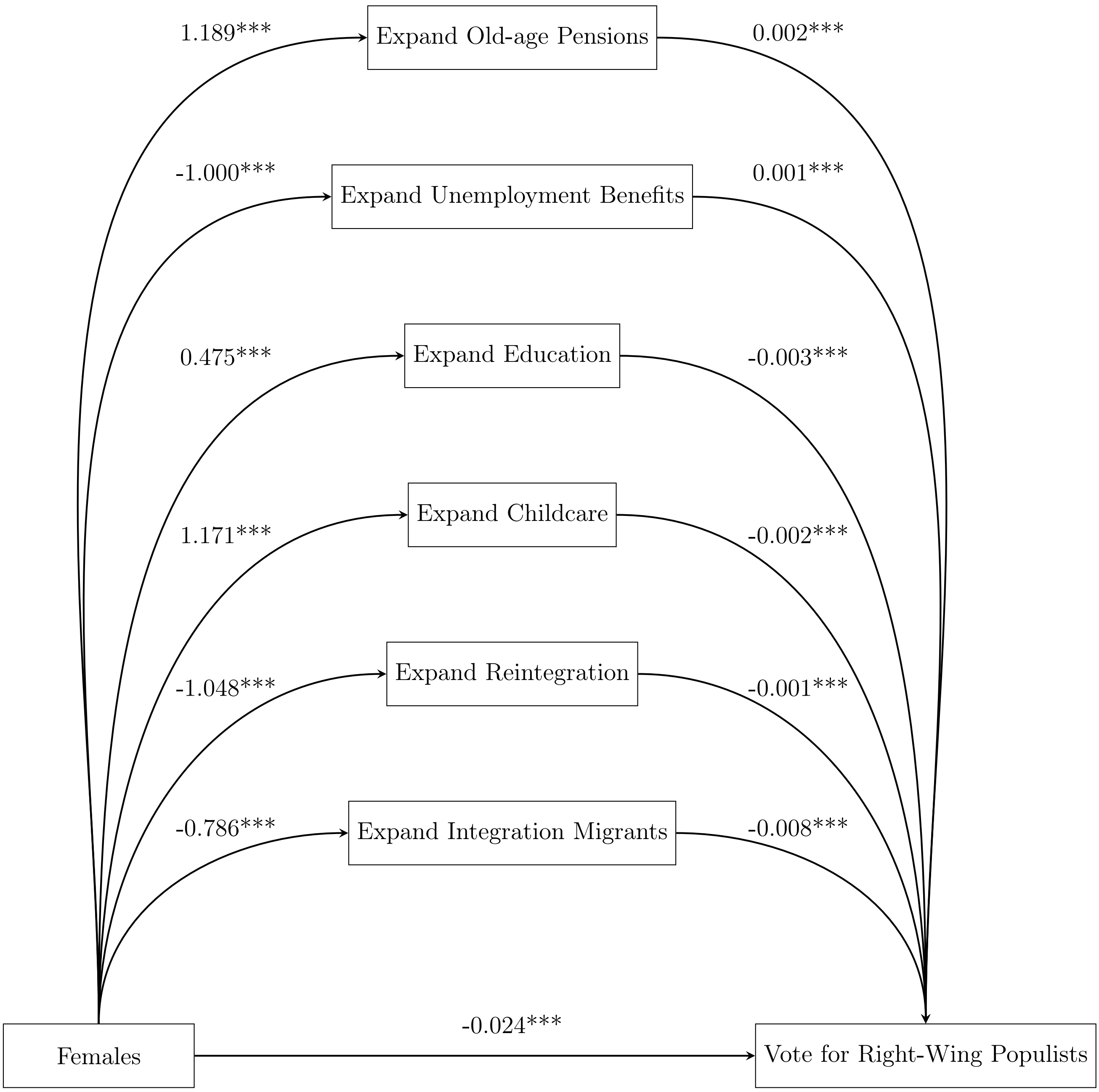
Table (6) Causal mediation of social policy preferences

	Social activation index		Consumption policies		Social activation policies			Welfare chauvinism
	Index	Index (Children)	Old-age pension	Unemployment benefits	Education	Childcare	Reintegration	Only for nationals
ACME	-0.000	-0.001	0.004***	-0.001***	-0.003***	-0.003**	-0.001***	-0.008***
ADE	-0.023***	-0.021***	-0.029***	-0.022***	-0.023***	-0.022***	-0.026***	-0.032***
Total Effect	-0.024***	-0.022***	-0.026***	-0.023***	-0.025***	-0.025***	-0.025***	-0.024***
Prop. Mediated	0.001	0.036	-0.145***	0.055***	0.100***	0.120***	-0.042***	-0.352***
Simulations	1000	1000	1000	1000	1000	1000	1000	1000
Num. obs.	26848	17872	26560	26624	26576	26576	26608	26672

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Results from a Causal Mediation Analysis. Nonparametric Bootstrap Confidence Intervals with the Percentile Method. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. ACME = Average causal mediation effects, ADE = average direct effects (IV on DV), Total effect = direct and indirect effect of IV onto the DV, Prop. Mediated = Proportion of the effect of the IV on the DV that goes through the mediator.

Figure (17) Mediation effect of preferences for individual social policies when highly exposed to automation

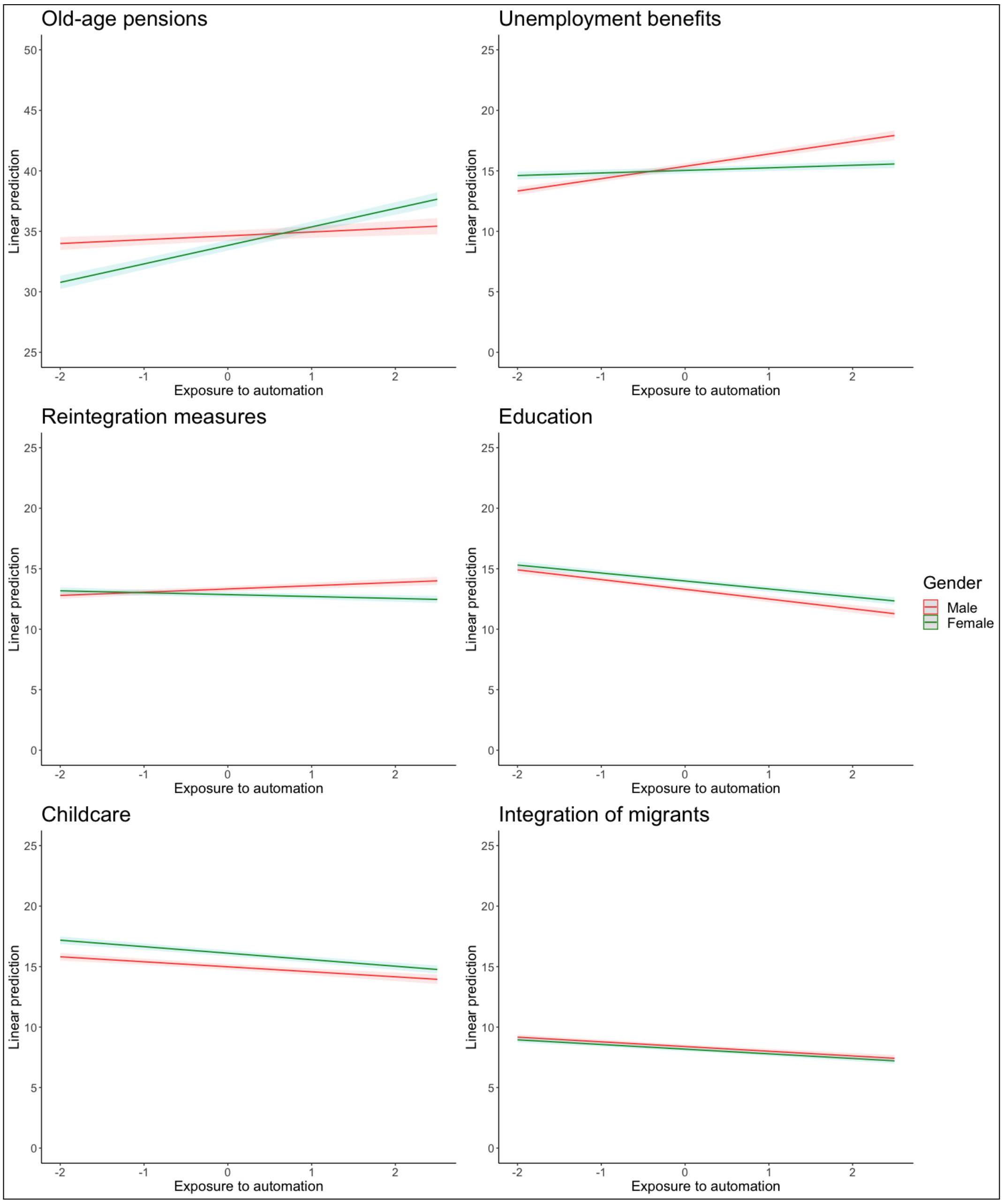


$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position and union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

7.6 Robustness of the results

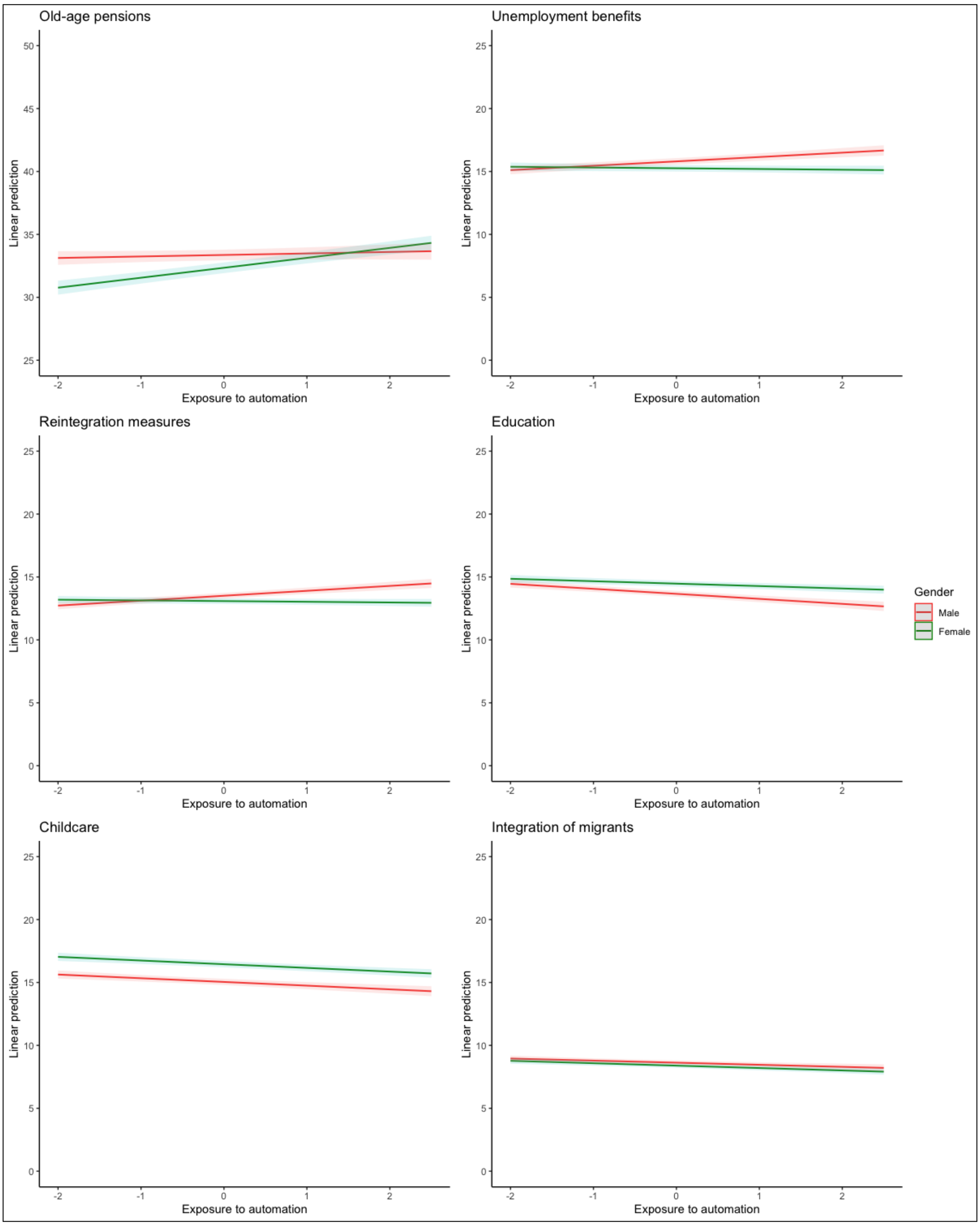
7.6.1 Different number of covariates

Figure (18) Social policy priorities with increasing exposure to automation by gender - no covariates



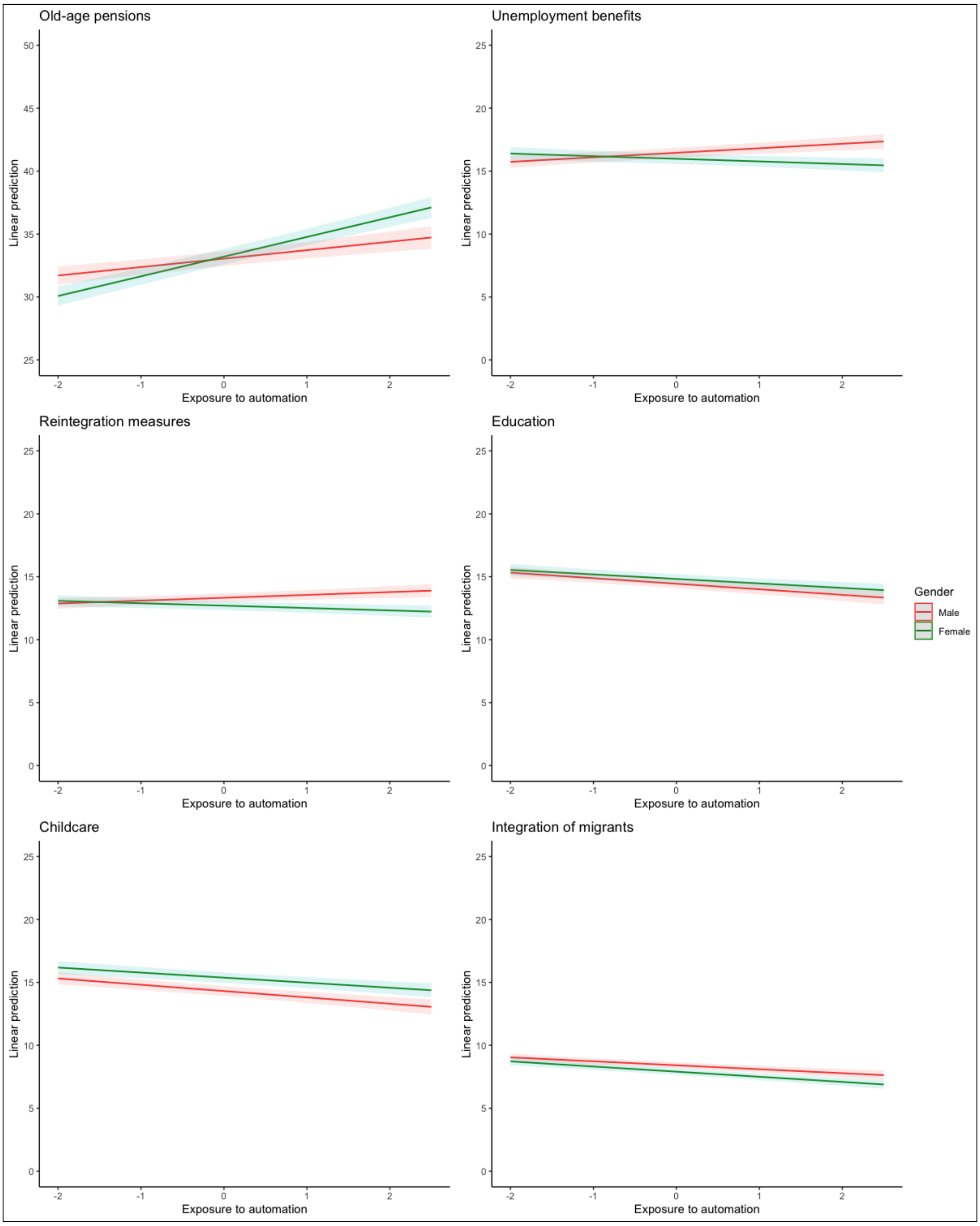
Binomial logistic regression with country fixed-effects and clustered robust standard errors. No additional covariates included. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (19) Social policy priorities with increasing exposure to automation by gender - only socio-economic variables



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Covariates included are education, age, income. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (20) Social policy priorities with increasing exposure to automation by gender - with additional covariables



Binomial logistic regression with country fixed-effects and clustered robust standard errors. Covariates included are education, age, income, left-right position, union membership, immigration as threat (cult), reduce income differences (econ), social benefits are strain on economy, chances of stable employment. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

7.6.2 Different measures of automation risk

The following tables and figures show the results with different indices of automation risk provided by Frey et al. (2017) and Owen and Johnston (2017). Tables 7, 8 and Figures 21, 22 highlight how genders differ in their general social policy positions with increasing automation risk. Subsequently, Figures 23, 24 and Tables 9, 10 present the corresponding results for social policy priorities. Lastly, Figures 25, 26 demonstrate how women and men differ in their consumption versus activation policy preferences with increasing risk exposure.

Table (7) Average effects of automation on social policy positions by gender - with Frey and Osborne (2017)

	Old-age pension	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
Frey	−0.018	0.282***	0.155***	0.120***	−0.024	−0.023
	(0.031)	(0.032)	(0.036)	(0.024)	(0.026)	(0.027)
Female	−0.078***	0.004	0.025	0.140***	0.032*	0.049**
	(0.018)	(0.018)	(0.019)	(0.014)	(0.015)	(0.016)
Age	0.004***	−0.000	0.001**	0.003***	0.001**	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.009*	−0.009*	−0.051***	0.002	−0.001	−0.004
	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Income	−0.006*	−0.048***	−0.002	−0.012***	−0.001	−0.008***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Left-Right Position	−0.009**	−0.051***	0.070***	−0.007***	−0.042***	−0.027***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)
Frey*Female	0.324***	−0.108**	0.062	−0.308***	0.256***	0.087**
	(0.036)	(0.038)	(0.040)	(0.029)	(0.030)	(0.030)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Num obs.	27856	27856	27856	27856	27856	27856

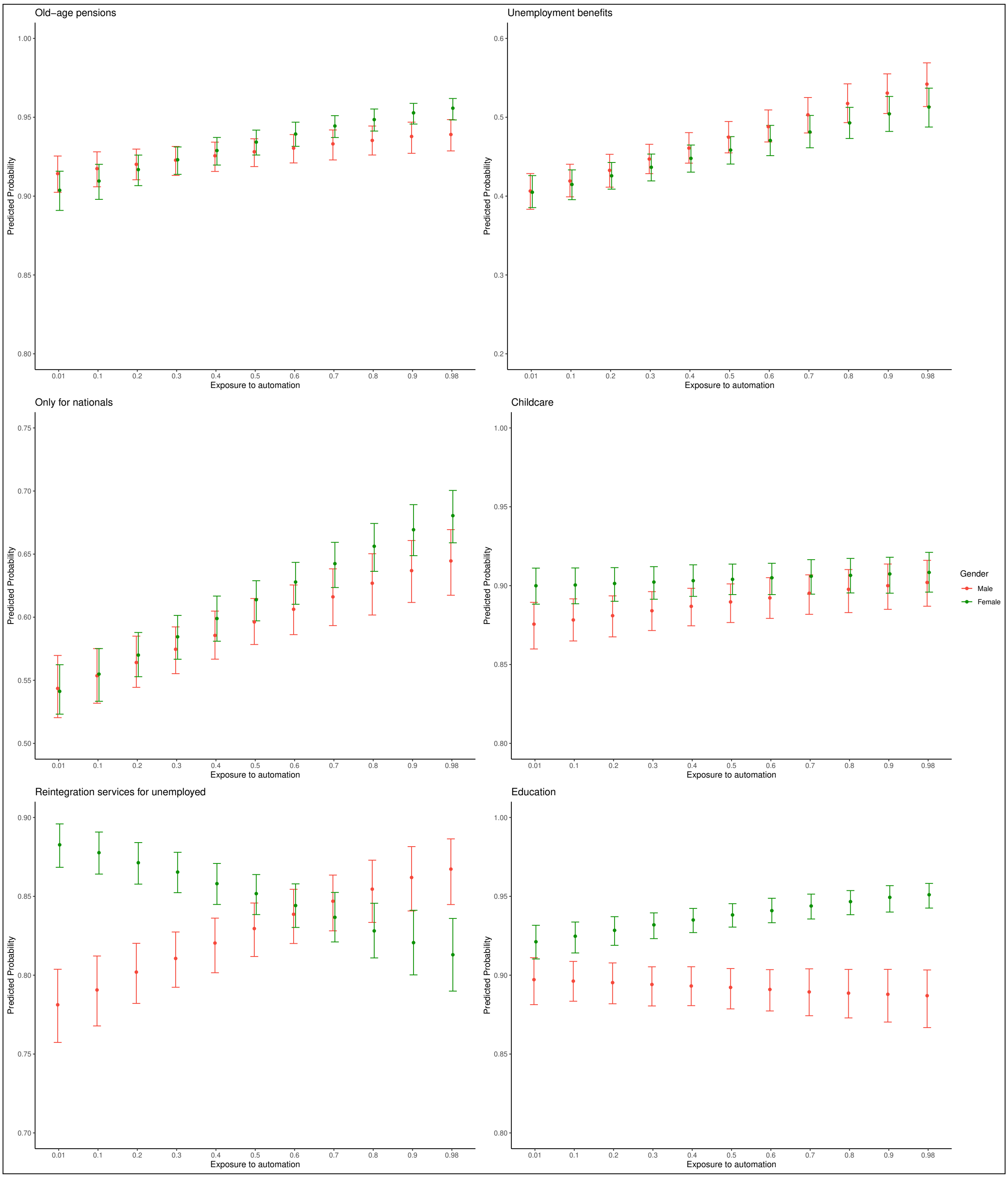
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculations. Weighted and logistic country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Regression tables are extracted from R using texreg (Leifeld 2013).

Table (8) Average effects of automation on social policy positions by gender - with Owen and Johnston (2017)

	Old-age pension	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
rti2	0.011	0.012	0.031**	0.019*	0.002	−0.030***
	(0.009)	(0.009)	(0.010)	(0.007)	(0.008)	(0.008)
Female	0.014*	−0.062***	−0.009	0.020***	0.039***	0.071***
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
Age	0.005***	0.001***	0.001*	0.003***	0.001***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	−0.015***	−0.035***	−0.047***	0.005**	−0.001	−0.011***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income	−0.015***	−0.049***	−0.015***	−0.004***	−0.011***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Left-Right Position	−0.009***	−0.066***	0.077***	−0.016***	−0.047***	−0.032***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
rti2*Female	0.055***	0.023	0.030*	0.004	0.033***	0.004
	(0.012)	(0.012)	(0.013)	(0.009)	(0.010)	(0.010)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Num obs.	27856	27856	27856	27856	27856	27856

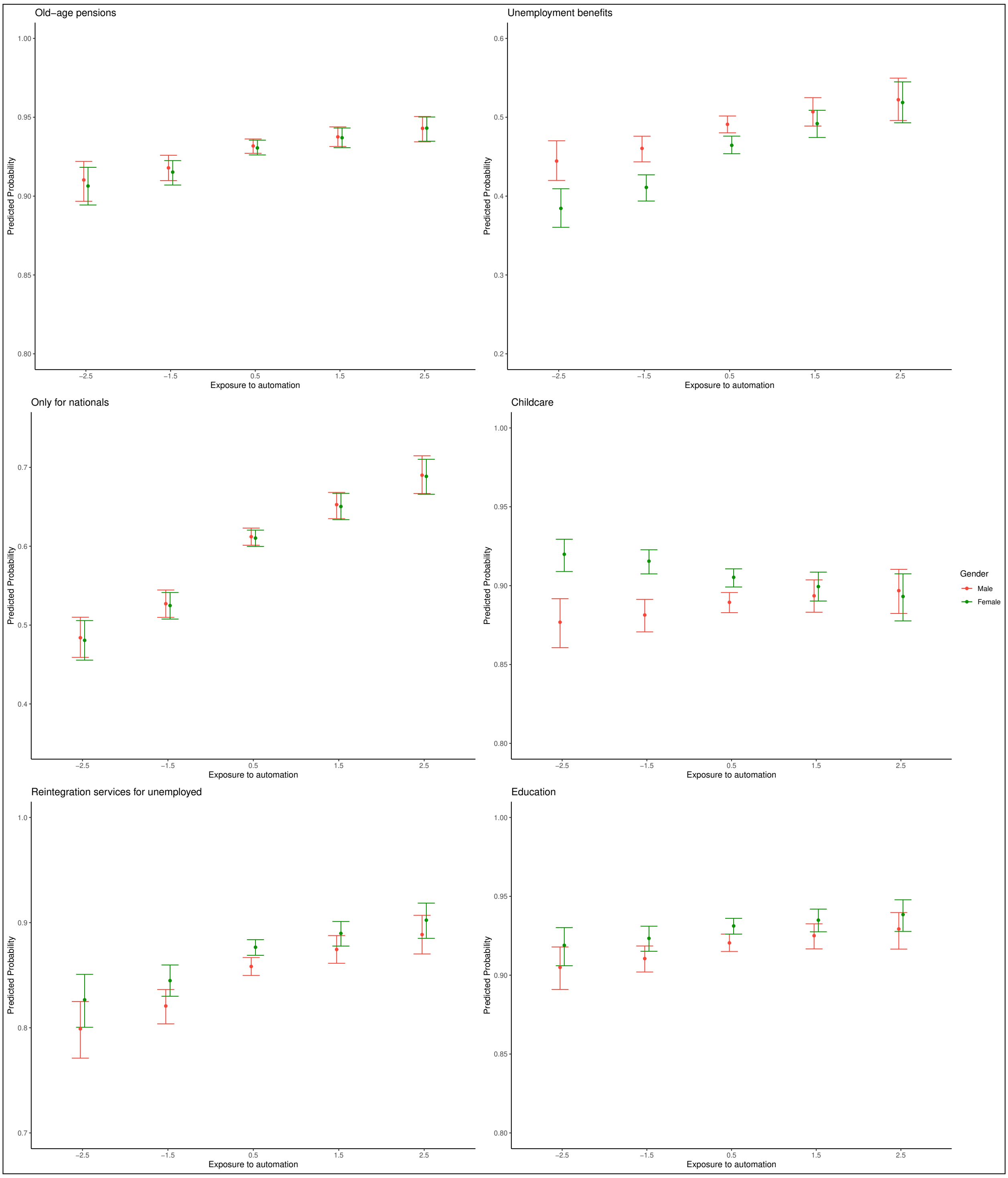
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculations. Weighted and logistic country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

Figure (21) Social policy positions with increasing exposure to automation by gender - with Frey and Osborne (2017)



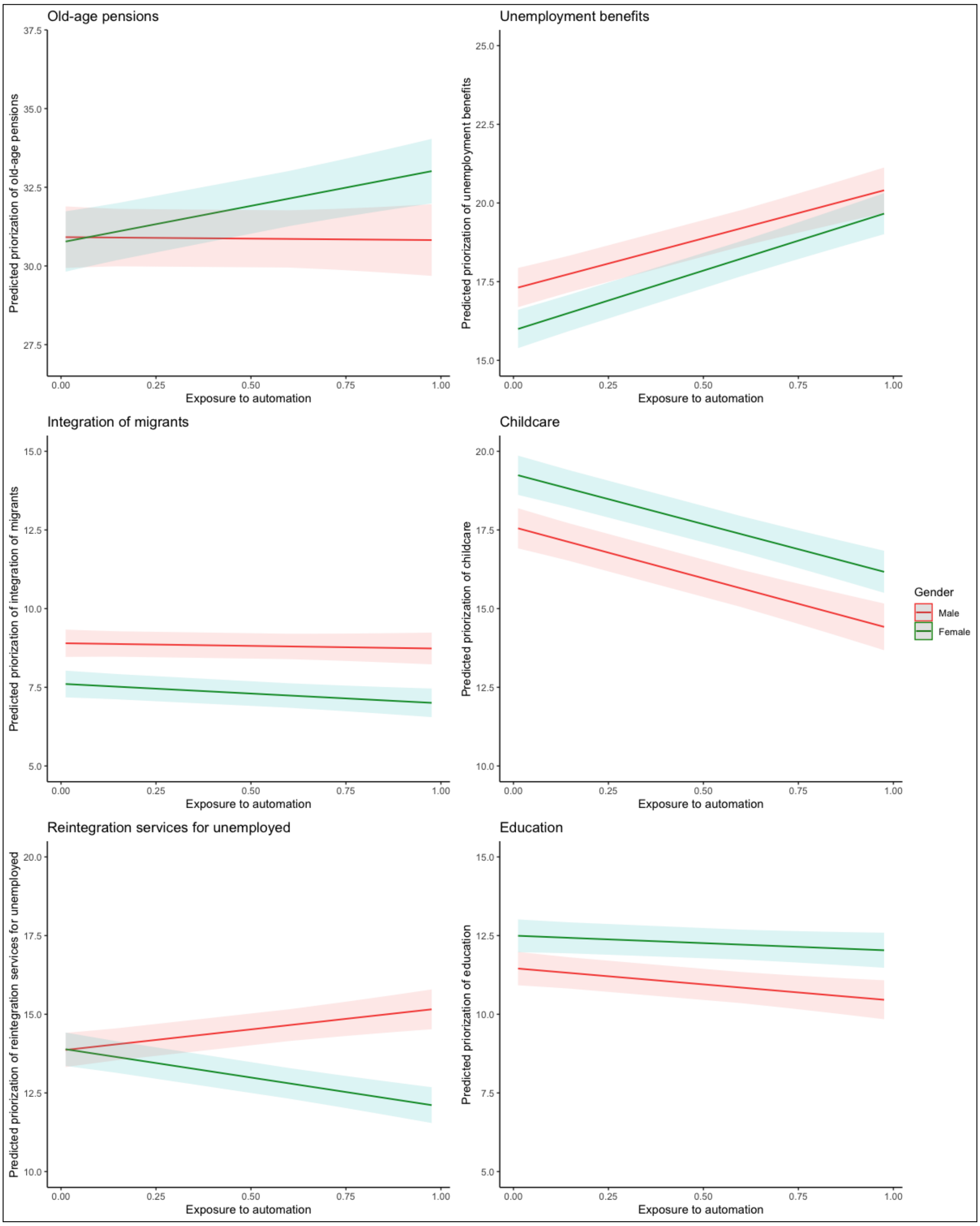
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (22) Social policy positions with increasing exposure to automation by gender - with Owen and Johnston (2017).



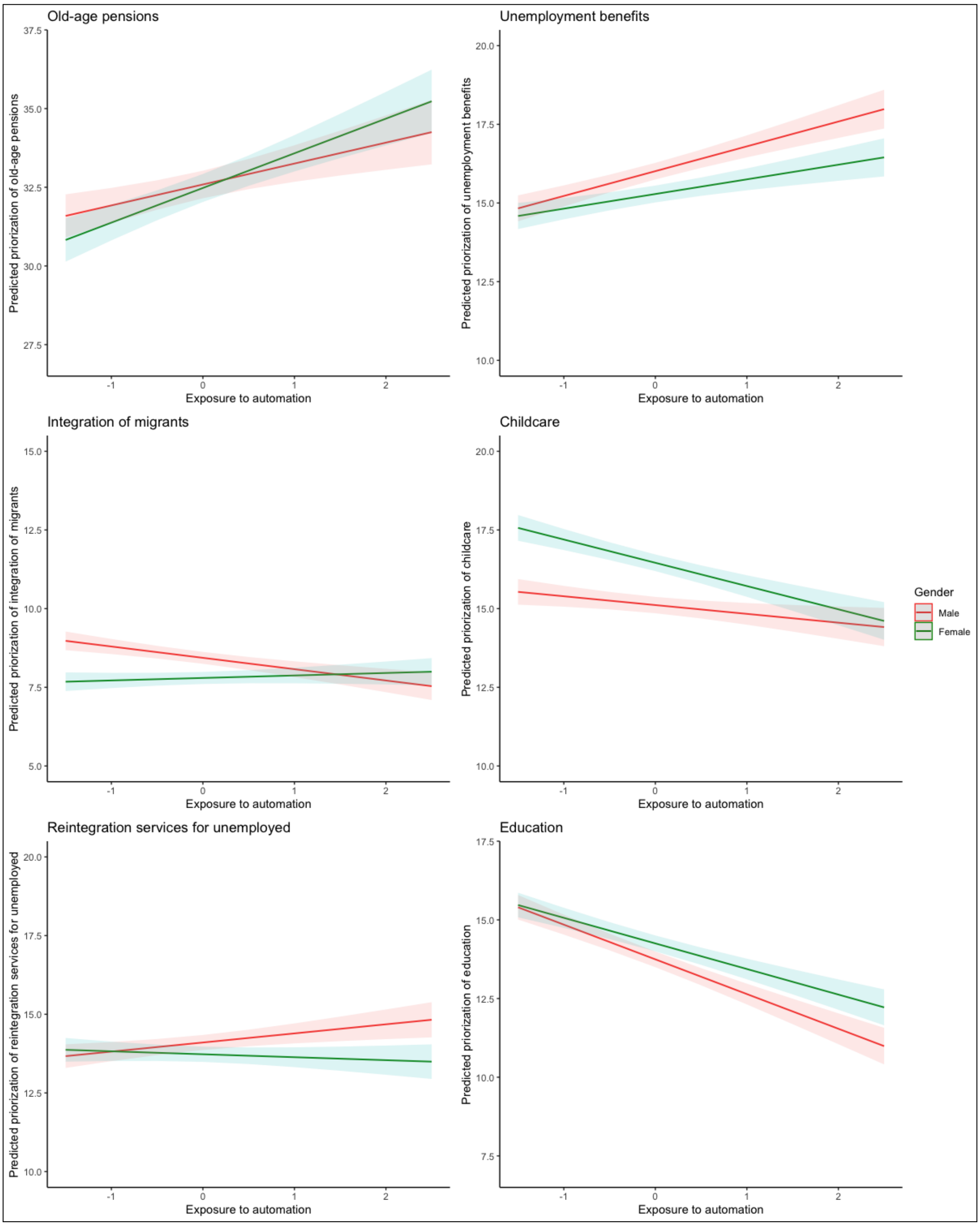
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (23) Social policy priorities of respondents with increasing exposure to automation by gender - with Frey and Osborne (2017)



Linear regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark,Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (24) Social policy priorities of respondents with increasing exposure to automation by gender - with Owen and Johnston (2017)



Linear regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark,Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Table (9) Average effect of automation on social policy priorities by gender - with Frey and Osborne (2017)

	Index	Old-age pensions	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
Frey	0.156^{***}	-0.096	3.207^{***}	-0.173	1.340^{**}	-1.029^{*}	-3.250^{***}
	(0.033)	(0.721)	(0.437)	(0.320)	(0.426)	(0.437)	(0.560)
Female	0.212^{***}	-0.168	-1.323^{***}	-1.290^{***}	0.061	1.035^{***}	1.685^{***}
	(0.018)	(0.439)	(0.276)	(0.210)	(0.256)	(0.271)	(0.313)
Age	-0.003^{***}	0.157^{***}	-0.049^{***}	0.025^{***}	0.001	-0.031^{***}	-0.103^{***}
	(0.000)	(0.009)	(0.007)	(0.004)	(0.005)	(0.005)	(0.006)
Education	0.032^{***}	-0.245^{**}	-0.167^{**}	0.384^{***}	0.158^{**}	0.389^{***}	-0.520^{***}
	(0.004)	(0.094)	(0.061)	(0.046)	(0.054)	(0.055)	(0.068)
Income	0.009^{***}	0.184^{***}	-0.567^{***}	-0.090^{***}	0.066^{*}	0.165^{***}	0.242^{***}
	(0.003)	(0.053)	(0.043)	(0.025)	(0.029)	(0.032)	(0.036)
Left-Right Position	-0.009^{**}	0.646^{***}	0.028	-0.513^{***}	-0.039	-0.020	-0.102^{**}
	(0.003)	(0.058)	(0.059)	(0.032)	(0.034)	(0.034)	(0.039)
Frey*Female	-0.339^{***}	2.417^{**}	0.596	-0.448	-3.183^{***}	0.553	0.066
	(0.039)	(0.834)	(0.583)	(0.386)	(0.466)	(0.488)	(0.583)
Numb. obs	27568	27568	27568	27568	27568	27568	27568
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, United Kingdom, Ireland, Italy, Netherlands, Spain, Sweden. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

Table (10) Average effect of automation on social policy priorities by gender - with Owen and Johnston (2017)

	Index	Old-age pensions	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
	(0.023)	(0.510)	(0.369)	(0.227)	(0.272)	(0.331)	(0.309)
RTI2	-0.001	0.665^{**}	0.788^{***}	-0.360^{***}	0.289^{*}	-1.103^{***}	-0.280^{*}
	(0.010)	(0.213)	(0.136)	(0.093)	(0.120)	(0.157)	(0.139)
Female	0.041^{***}	-0.110	-0.726^{***}	-0.640^{***}	-0.374^{***}	0.506^{***}	1.344^{***}
	(0.007)	(0.147)	(0.099)	(0.063)	(0.080)	(0.085)	(0.088)
Age	-0.003^{***}	0.171^{***}	-0.066^{***}	0.014^{***}	0.008^{**}	-0.059^{***}	-0.068^{***}
	(0.000)	(0.005)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
Education	0.046^{***}	-0.721^{***}	-0.595^{***}	0.368^{***}	0.334^{***}	0.624^{***}	-0.011
	(0.002)	(0.048)	(0.029)	(0.023)	(0.027)	(0.030)	(0.031)
Income	0.018^{***}	-0.100^{***}	-0.489^{***}	0.031^{*}	0.044^{**}	0.144^{***}	0.370^{***}
	(0.001)	(0.028)	(0.020)	(0.012)	(0.016)	(0.019)	(0.018)
Left-Right Position	-0.001	0.818^{***}	-0.339^{***}	-0.537^{***}	-0.003	0.095^{***}	-0.033
	(0.001)	(0.032)	(0.024)	(0.014)	(0.017)	(0.021)	(0.018)
RTI2*Female	-0.043^{***}	0.436	-0.322	0.439^{**}	-0.383^{*}	0.290	-0.460^{**}
	(0.013)	(0.290)	(0.172)	(0.137)	(0.157)	(0.194)	(0.175)
Numb. obs	27568	27568	27568	27568	27568	27568	27568
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, United Kingdom, Ireland, Italy, Netherlands, Spain, Sweden. Regression tables are extracted from R using texreg (Leifeld 2013).

Figure (25) Position on activation-consumption index with increasing exposure to automation by gender - with Frey and Osborne (2017)

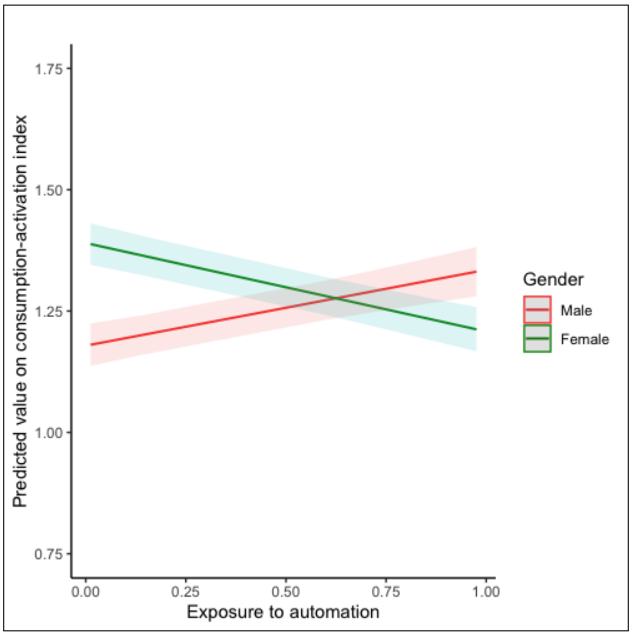
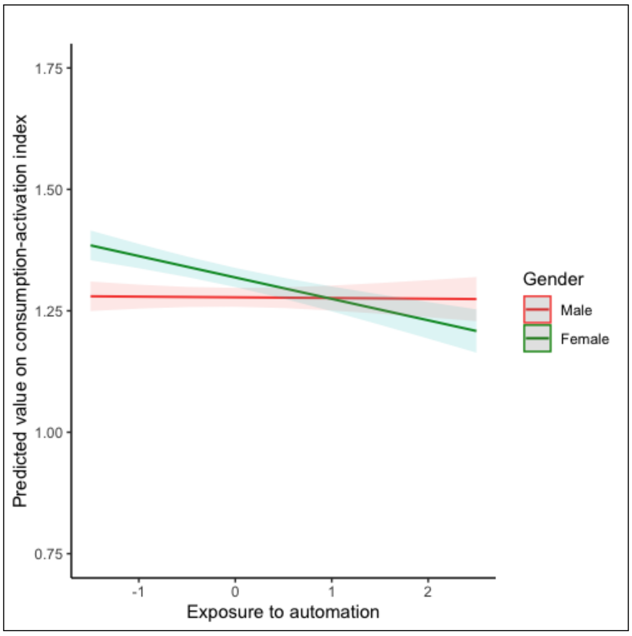


Figure (26) Position on activation-consumption index with increasing exposure to automation by gender - with Owen and Johnston (2017)



Linear regressions with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

7.6.3 Different regression models

The following tables and figures present the analysis with different regression specifications. Table 11 and Figure 27 show the results for policy positions in form of a linear instead of a binomial logistic regression. Table 12 and Figure 28 show the same results for more fine graded (1-4) social policy positions instead of an "approve/oppose." Table 13 highlights the results when using a different package in R to calculate the fixed-effects (plm) to analyse the sensitivity of the models to small calculation changes.

Table (11) Average effect of automation on social policy positions by gender, linear regressions

	Old-age pensions	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
RTI	-0.001	-0.000	0.011	-0.003	-0.036^{***}	-0.003
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)
Female	0.028^{***}	-0.050^{***}	-0.015^{*}	0.007	0.046^{***}	0.097^{***}
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Age	0.005^{***}	0.001^{***}	-0.001^{***}	0.002^{***}	0.001^{***}	-0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education	-0.024^{***}	-0.043^{***}	-0.051^{***}	0.001	-0.014^{***}	-0.008^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Income	-0.014^{***}	-0.051^{***}	-0.017^{***}	-0.004^{***}	-0.011^{***}	0.003^{**}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Left-Right Position	-0.001	-0.059^{***}	0.086^{***}	-0.012^{***}	-0.043^{***}	-0.024^{***}
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
RTI*Female	0.009	0.001	-0.003	0.021^{***}	0.020^{***}	-0.020^{***}
	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)
Numb. obs	86752	86752	86752	86752	86752	86752
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Regression tables are extracted from R using `texreg` (Leifeld 2013).

Figure (27) Social policy positions of respondents with increasing exposure to automation by gender, linear regressions

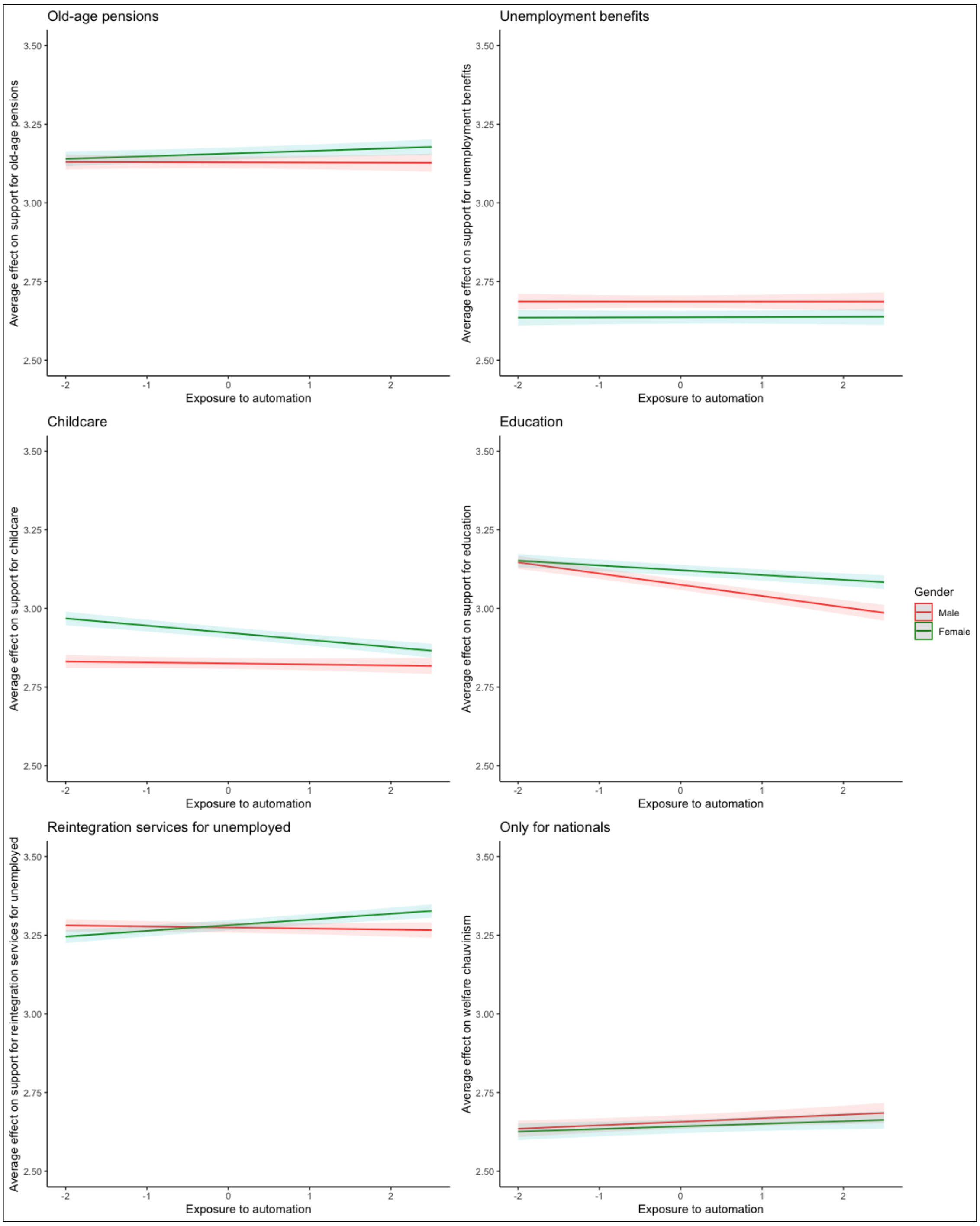


Table (12) Average effect of automation on social policy positions by gender - more fine-graded position variable

	Old-age pensions	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
rti	-0.003	-0.000	0.011	-0.003	-0.036^{*}	-0.003
	(0.020)	(0.027)	(0.030)	(0.020)	(0.018)	(0.013)
Female	0.007	-0.050	-0.015	0.007	0.046^{**}	0.097^{***}
	(0.022)	(0.054)	(0.038)	(0.022)	(0.017)	(0.022)
Age	0.002^{**}	0.001	-0.001	0.002^{**}	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	0.001	-0.043^{**}	-0.051^{***}	0.001	-0.014	-0.008
	(0.008)	(0.014)	(0.007)	(0.008)	(0.009)	(0.005)
Income	-0.004	-0.051^{***}	-0.017	-0.004	-0.011	0.003
	(0.005)	(0.009)	(0.013)	(0.005)	(0.007)	(0.005)
Left-Right Position	-0.012^{***}	-0.059^{***}	0.086^{***}	-0.012^{***}	-0.043^{***}	-0.024^{***}
	(0.004)	(0.013)	(0.013)	(0.004)	(0.007)	(0.006)
rti*Female	0.021	0.001	-0.003	0.021	0.020	-0.020
	(0.021)	(0.040)	(0.037)	(0.021)	(0.015)	(0.018)
Numb. obs	86544	86544	86544	86544	86544	86544
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Ireland, Italy, Netherlands, Spain, Sweden. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

Figure (28) Social policy positions of respondents with increasing exposure to automation by gender - more fine-graded position variable

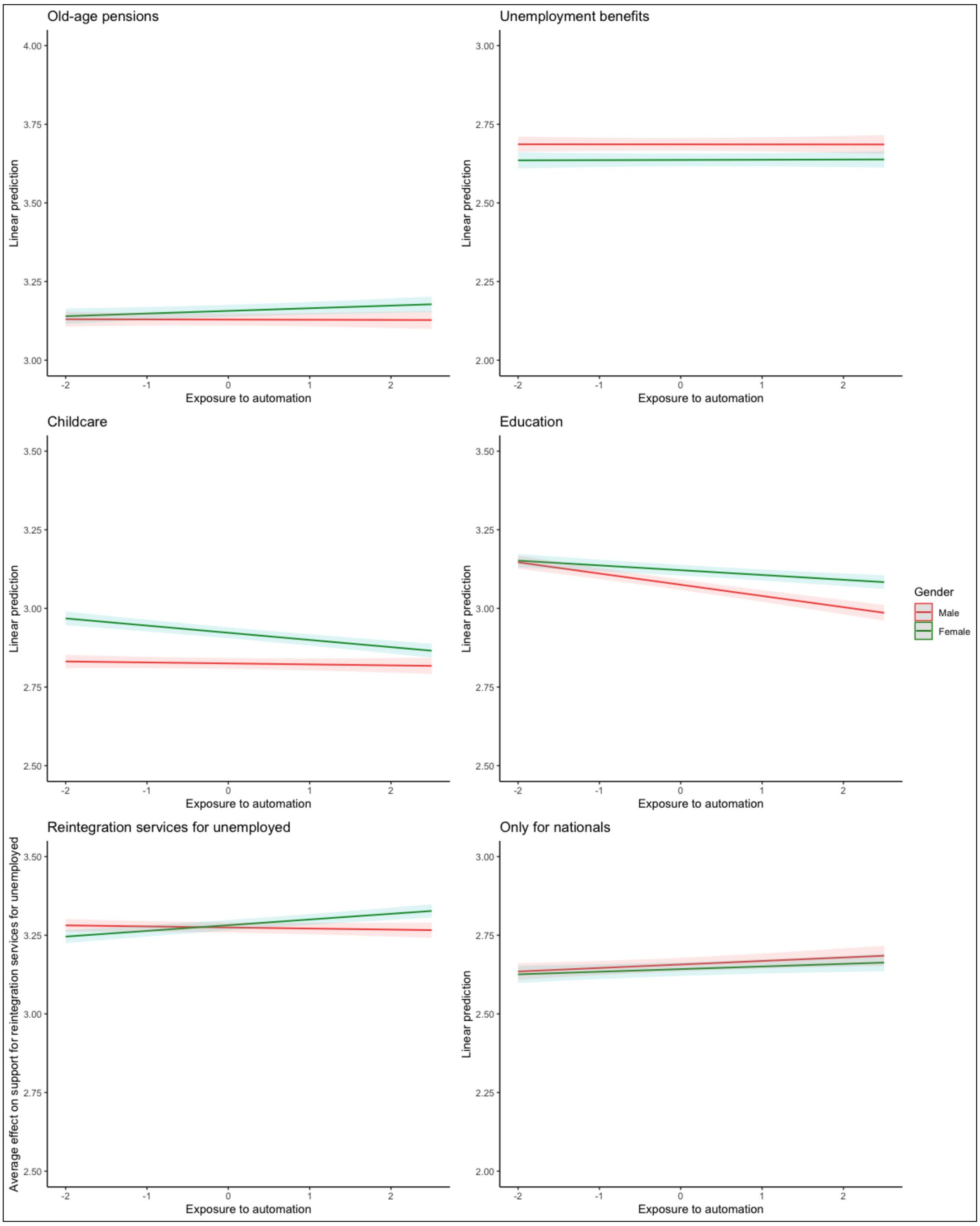


Table (13) Average effect of automation on social policy priorities by gender - with plm

	Old-age pensions	Unemployment benefits	Integration of migrants	Reintegration	Education	Childcare
rti	0.242^{*}	0.431^{***}	-0.167^{***}	0.024	-0.397^{***}	-0.134^{*}
	(0.097)	(0.058)	(0.042)	(0.053)	(0.054)	(0.058)
Female	0.363^{**}	-1.004^{***}	-0.344^{***}	-0.525^{***}	0.298^{***}	1.213^{***}
	(0.134)	(0.081)	(0.058)	(0.073)	(0.074)	(0.080)
Age	0.242^{***}	-0.069^{***}	-0.014^{***}	-0.012^{***}	-0.078^{***}	-0.069^{***}
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Education	-0.904^{***}	-0.513^{***}	0.364^{***}	0.238^{***}	0.699^{***}	0.116^{***}
	(0.042)	(0.025)	(0.018)	(0.023)	(0.023)	(0.025)
Income	-0.009	-0.500^{***}	0.007	-0.044^{**}	0.161^{***}	0.384^{***}
	(0.025)	(0.015)	(0.011)	(0.014)	(0.014)	(0.015)
Left-Right Position	0.878^{***}	-0.300^{***}	-0.584^{***}	-0.068^{***}	0.025	0.049^{**}
	(0.028)	(0.017)	(0.012)	(0.015)	(0.016)	(0.017)
rti*Female	0.715^{***}	-0.320^{***}	-0.133^{*}	-0.051	0.060	-0.271^{***}
	(0.124)	(0.074)	(0.053)	(0.068)	(0.068)	(0.074)
R^2	0.066	0.039	0.035	0.003	0.041	0.025
Adj. R^2	0.066	0.039	0.035	0.003	0.041	0.025
Num. obs.	90464	90464	90464	90464	90464	90464
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

Own calculation. Linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Ireland, Italy, Netherlands, Spain, Sweden. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

7.6.4 Subgroup analysis for respondents with children

This subsection highlights how social policy preferences change with increasing automation risk - for women and men with children. Figure 29 and Table 14 demonstrate the results for general social policy positions. Figure 30 and Table 15 present the corresponding results for social policy priorities. Lastly, Figure 31 highlights how genders differ in their social investment versus consumption priorities with increasing risk.

Table (14) Average effects of automation on social policy positions by gender - with children

	Old-age pension	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
RTI	-0.028	-0.069^{***}	0.002	0.015	-0.241^{***}	0.018
	(0.022)	(0.014)	(0.015)	(0.023)	(0.022)	(0.019)
Female	-0.072^{**}	-0.059^{**}	0.005	0.261^{***}	-0.041	0.288^{***}
	(0.026)	(0.019)	(0.019)	(0.033)	(0.031)	(0.028)
Age	0.010^{***}	-0.002^{**}	-0.004^{***}	0.018^{***}	0.015^{***}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Education	-0.041^{***}	-0.096^{***}	-0.120^{***}	0.073^{***}	-0.049^{***}	0.009
	(0.008)	(0.006)	(0.006)	(0.010)	(0.009)	(0.008)
Income	-0.061^{***}	-0.128^{***}	-0.042^{***}	-0.026^{***}	-0.051^{***}	-0.014^{**}
	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.005)
Left-Right Position	-0.043^{***}	-0.164^{***}	0.185^{***}	-0.070^{***}	-0.162^{***}	-0.064^{***}
	(0.005)	(0.004)	(0.004)	(0.007)	(0.007)	(0.006)
RTI*Female	0.122^{***}	0.023	0.039^{*}	-0.004	0.229^{***}	-0.023
	(0.026)	(0.017)	(0.018)	(0.030)	(0.029)	(0.025)
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes
Num obs.	58554	58554	58554	58554	58554	58554

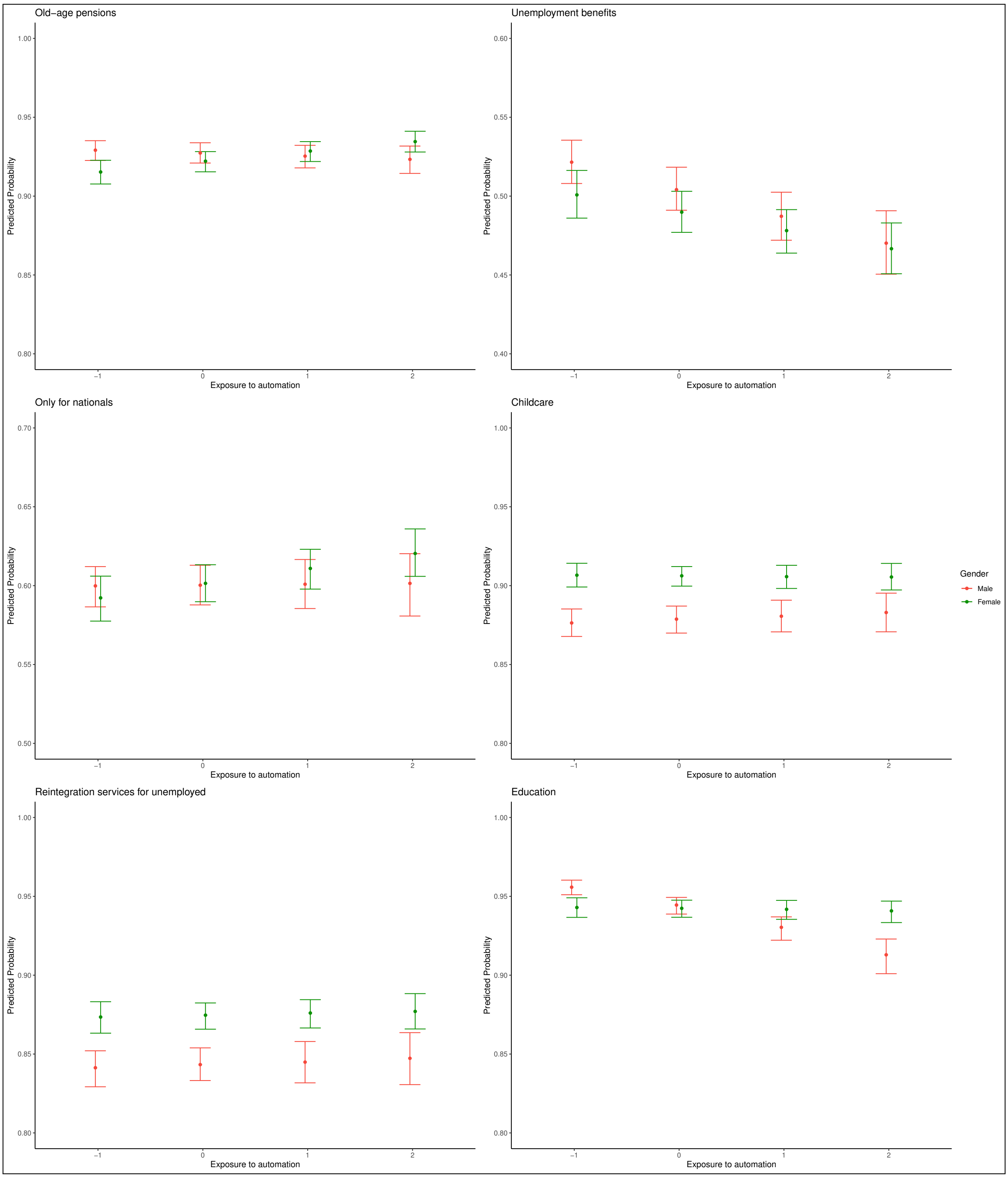
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculations. Weighted and logistic country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Pooled data for Germany,Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Regression tables are extracted from R using texreg (Leifeld 2013).

Table (15) Average effect of automation on social policy priorities by gender - with children

	Index	Old-age pensions	Unemployment benefits	Only for nationals	Reintegration	Education	Childcare
Intercept	1.191***	26.318***	24.164***	7.383***	10.682***	11.264***	20.190***
	(0.029)	(0.670)	(0.421)	(0.283)	(0.345)	(0.373)	(0.426)
RTI	−0.020**	−0.176	0.128	−0.118*	0.380***	−0.346***	0.132
	(0.007)	(0.170)	(0.107)	(0.055)	(0.089)	(0.078)	(0.101)
Female	0.022*	−0.463*	−0.299*	−0.495***	−0.518***	0.886***	0.888***
	(0.009)	(0.200)	(0.130)	(0.080)	(0.111)	(0.106)	(0.126)
Age	−0.005***	0.213***	−0.060***	0.014***	0.001	−0.041***	−0.127***
	(0.000)	(0.007)	(0.004)	(0.003)	(0.004)	(0.004)	(0.005)
Education	0.040***	−1.093***	−0.590***	0.491***	0.379***	0.639***	0.175***
	(0.003)	(0.060)	(0.034)	(0.025)	(0.034)	(0.034)	(0.039)
Income	0.026***	−0.391***	−0.422***	0.054***	0.048*	0.264***	0.447***
	(0.002)	(0.038)	(0.026)	(0.015)	(0.021)	(0.021)	(0.023)
Left-Right Position	−0.002	0.688***	−0.157***	−0.487***	−0.043*	−0.017	0.015
	(0.002)	(0.040)	(0.030)	(0.016)	(0.021)	(0.021)	(0.023)
RTI*Female	0.026**	0.382	−0.182	0.061	−0.315**	0.403***	−0.348**
	(0.008)	(0.195)	(0.118)	(0.070)	(0.104)	(0.099)	(0.116)
Numb. obs	87824	87824	87824	87824	87824	87824	87824
Country fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered and robust SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

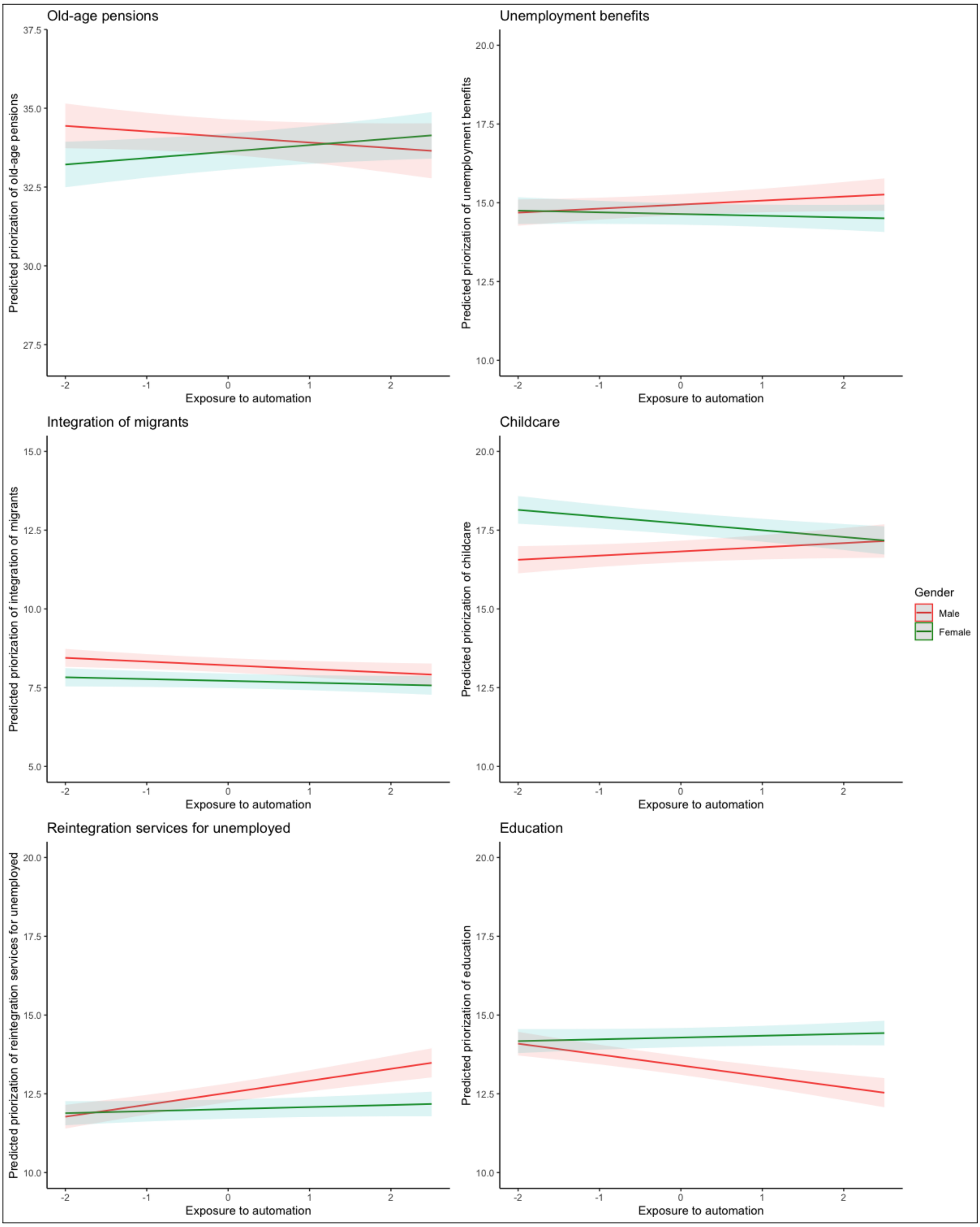
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.
Own calculation. Weighted linear country fixed-effect models with clustered and heteroskedasticity robust standard errors. Data source: Welfare priorities data, 2020. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom. Regression tables are extracted from `R` using `texreg` (Leifeld 2013).

Figure (29) Social policy positions with increasing exposure to automation by gender - with children



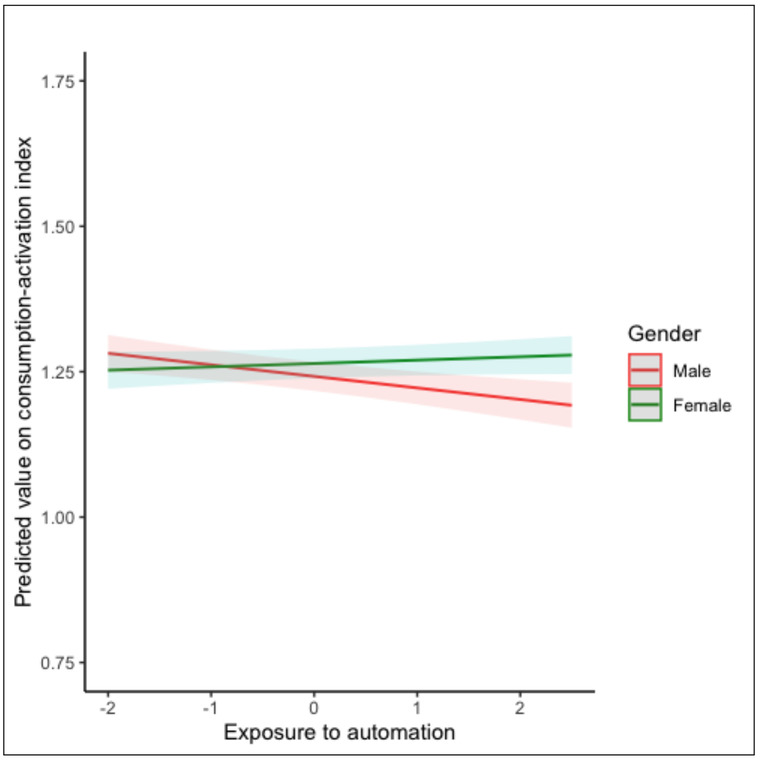
Binomial logistic regression with country fixed-effects and clustered robust standard errors. Predicted probabilities with R package by (Schlegel 2021). Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data for Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (30) Social policy priorities of respondents with increasing exposure to automation by gender - with children



Linear regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

Figure (31) Position on activation-consumption index with increasing exposure to automation by gender - with children



Linear regression with country fixed-effects and clustered robust standard errors. Covariates included are age, education, income, left-right position, union membership. Own calculations. Data source: Welfare priorities data, 2020. Pooled data, including Germany, Denmark, Ireland, Italy, Netherlands, Spain, Sweden, United Kingdom.

7.7 Additional descriptive figures

Figure (32) Preferences with regard to the generosity of the welfare state by gender

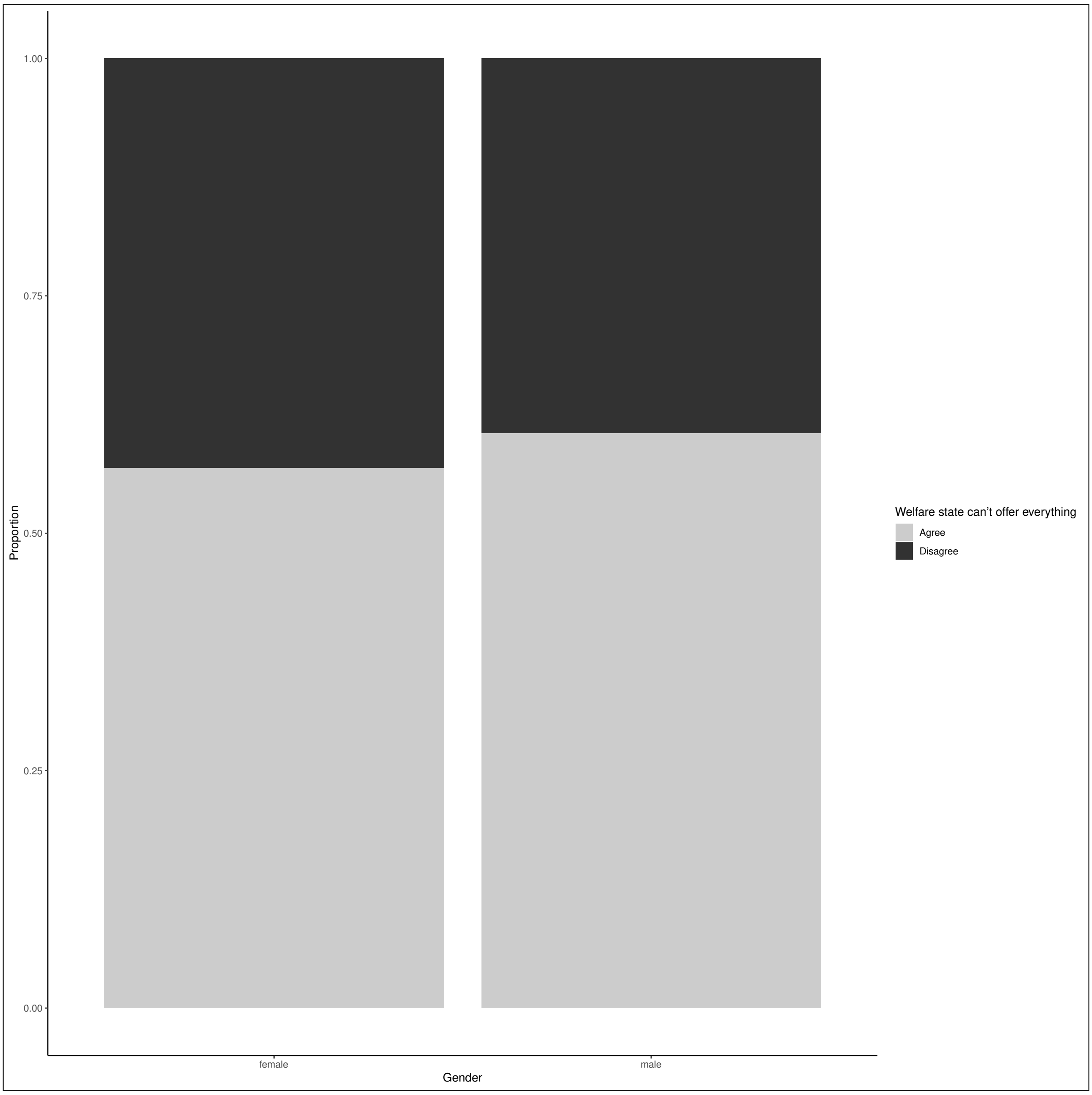


Figure (33) Welfare policy priorities of respondents highly exposed to automation by gender

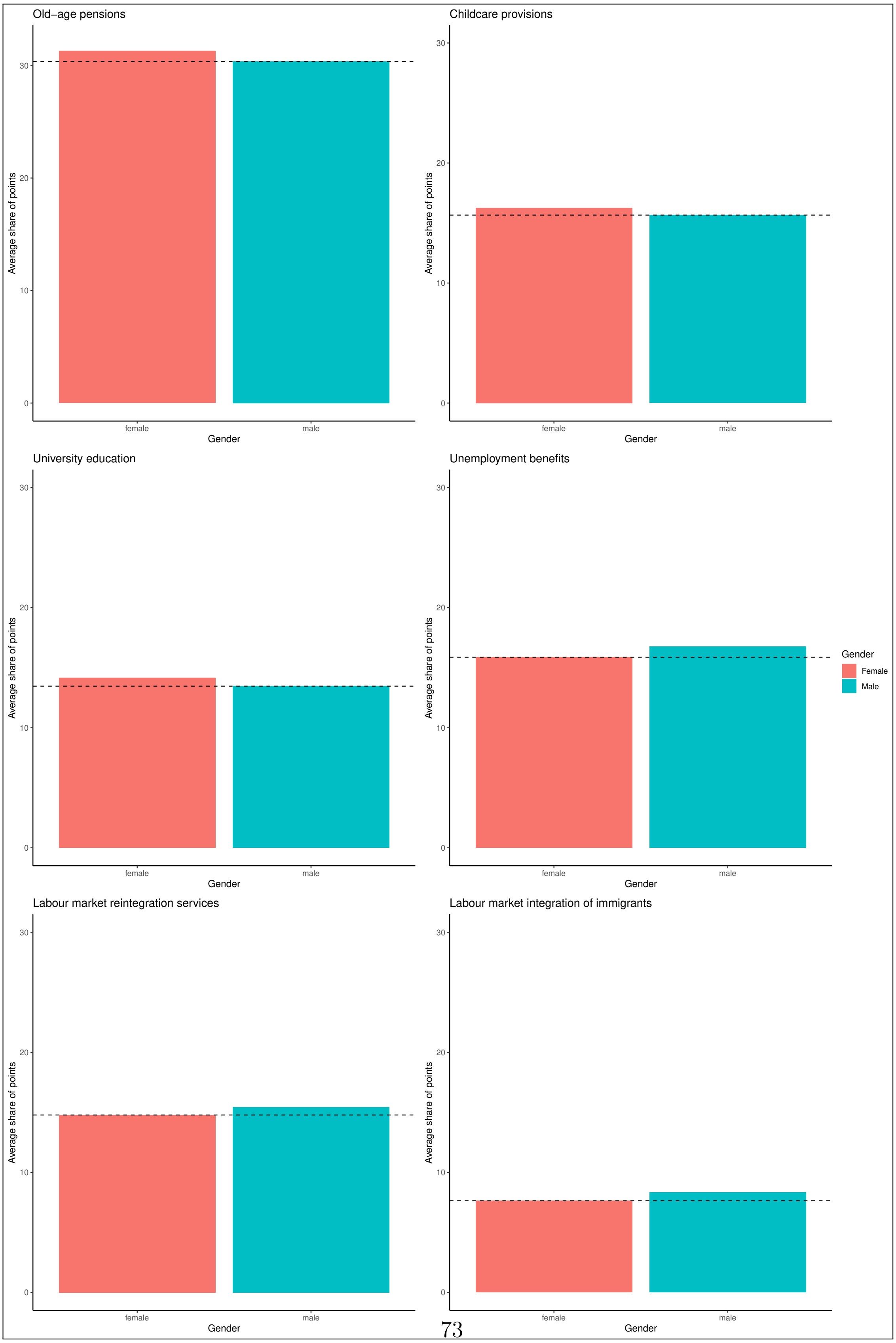


Figure (34) Trade-off social policy decisions of respondents highly exposed to automation by gender

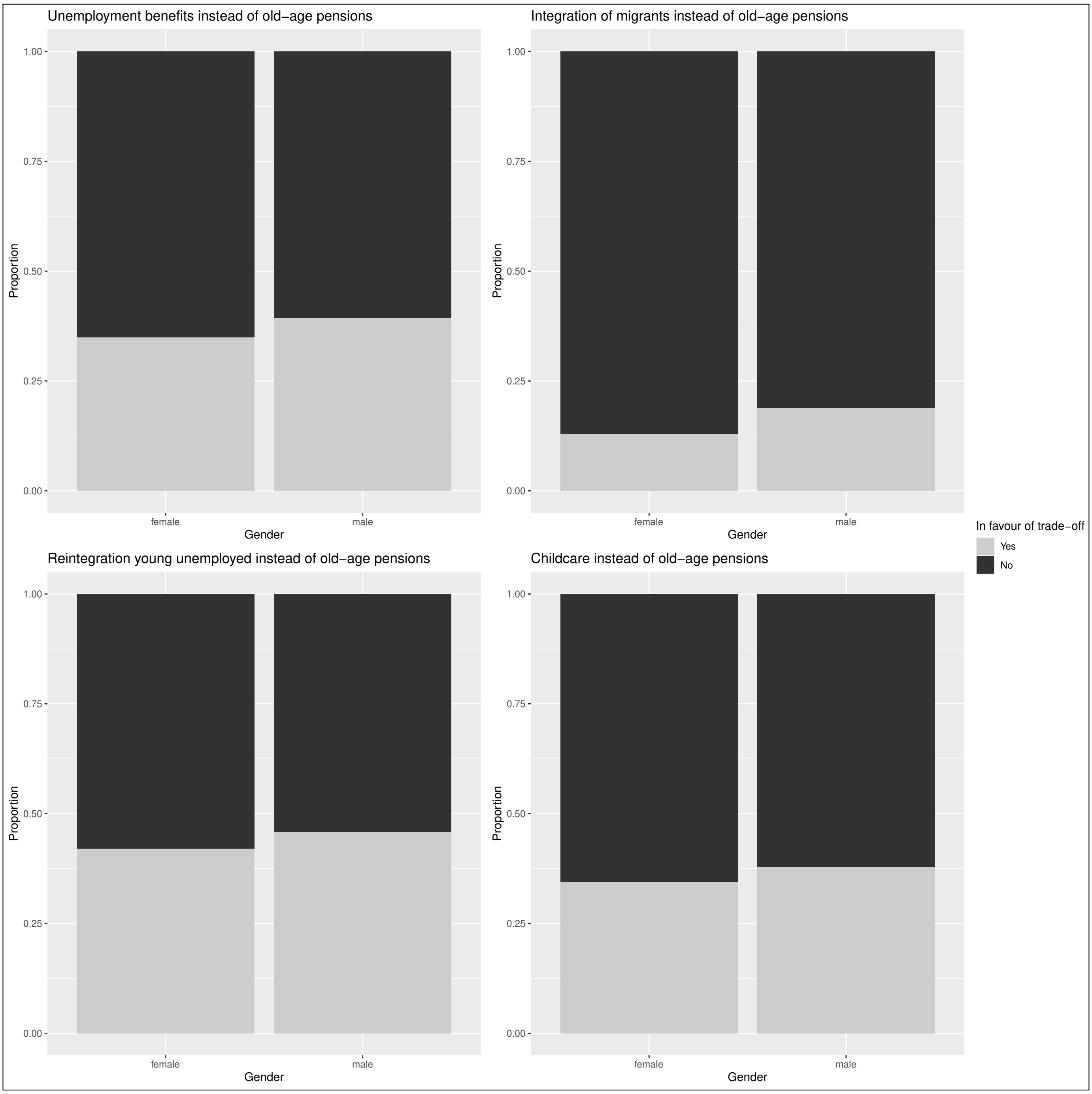


Figure (35)   General social policy positions by gender

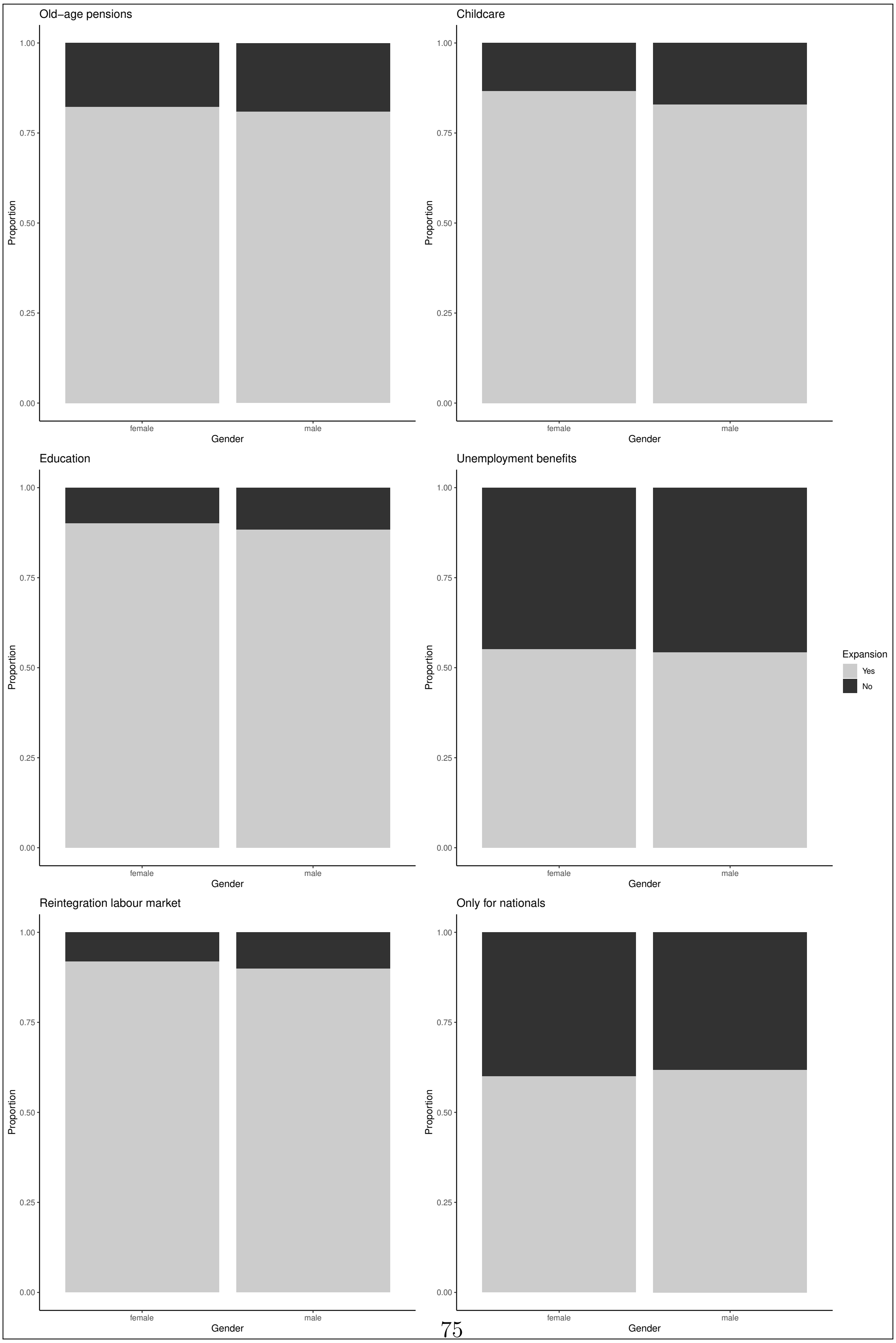
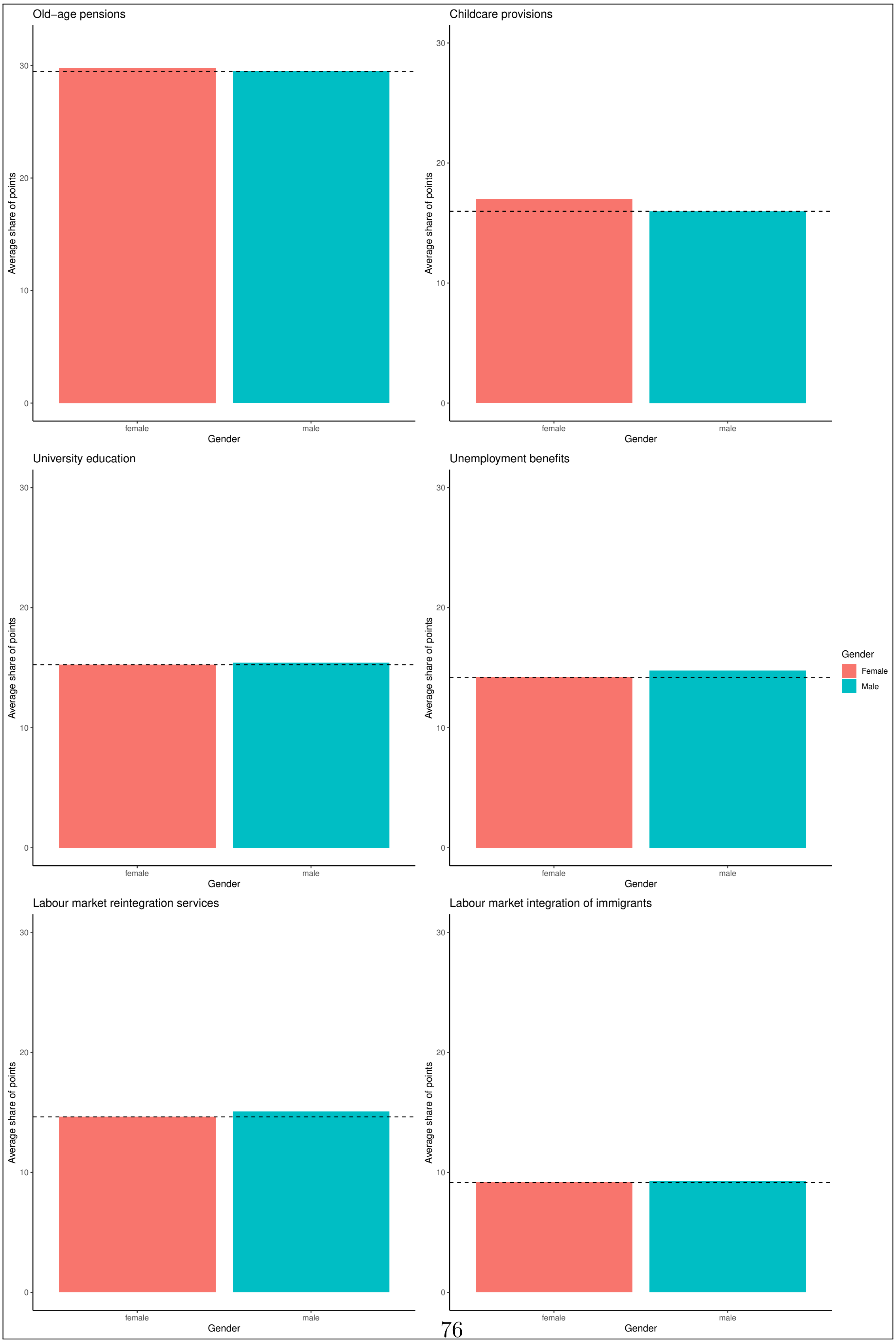


Figure (36) General social policy priorities by gender



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