Subjective Technology Risk and Education Preferences: VET as a Safe Haven or Dead End?

Matthias Haslberger
University of St.Gallen
Müller-Friedberg-Strasse 8
9000 St. Gallen
Switzerland
matthias.haslberger@unisg.ch

Scherwin M. Bajka
University of St.Gallen
Müller-Friedberg-Strasse 8
9000 St. Gallen
Switzerland
scherwinmichael.bajka@unisg.ch

March 13, 2025

Abstract

Education equips individuals with valuable skills to protect them against employment risks associated with the digital transition. As scholars debate whether vocational education and training (VET) or general education better insures against technology-induced employment risk, we ask how this type of risk, as perceived by individuals, shapes their education preferences. Our analyses, based on a survey of over 11,500 respondents across seven European countries, show that VET is regarded as a safe haven by those perceiving heightened risk. This relationship remains robust when controlling for various alternative explanations and is consistent across countries. Subgroup interactions indicate that men, high-income earners, respondents with tertiary education, and those politically on the right more strongly favor VET in response to subjective technology risk. Hence, our study suggests that VET's practical, job-oriented focus is perceived as better protection against the growing uncertainty over skill demands in the twin transition than general education.

We thank the participants of the special issue workshop as well as the special issue editors for their helpful feedback. All remaining errors are our own. This work was supported by the Swiss State Secretariat for Education, Research, and Innovation (SERI) in the framework of the GOVPET research project.

The authors declare no competing interests. Replication data will be made available on Harvard Dataverse upon publication.

1 Introduction

The rapid technological progress underpinning the twin transition creates fundamental uncertainty for workers by reshaping skill requirements at unprecedented rates. Yet, as Streeck (1989, 92) has argued, undertaking costly investments in skills "presupposes a degree of certainty as to what one is likely to need and value in the future." The digital and green transitions erode existing certainties about the expected value and security provided by different educational paths, raising the stakes when it comes to educational choices. As fundamental uncertainty complicates objective judgments (Beckert, 1996), people's subjective perceptions come into focus. Yet, how technology-induced risk as perceived by individuals shapes their education preferences has received surprisingly little attention.

One of the most consequential choices people face in their educational career is that between different tracks at the upper secondary level. In most European countries, adolescents choose between a vocational and a general track (Giudici et al., 2023; Shavit and Müller, 2000). Later choices, such as whether to go to university or which major to enroll in, have received greater scholarly attention, but the choice of upper secondary track may arguably be even more foundational for later economic outcomes (Hanushek et al., 2017; Hampf and Woessmann, 2017; Korber and Oesch, 2019). The climate of heightened uncertainty due to the twin transition is bound to influence people's thinking about which track offers better prospects. Yet, neither the existing literature nor first principles offer an unambiguous answer to this question.

Two contrasting perspectives dominate the existing literature. Scholars influenced by human capital theory have presented vocational education and training (VET) as the risk-averse choice — an educational "safety net" (Shavit and Müller, 2000). For example, it lowers the relative cost of acquiring post-compulsory education for working-class youth by offering them a straightforward path to stable employment (Breen and Goldthorpe, 1997). This, in turn, reduces the incidence of unskilled work in countries like Germany (Freeman and Schettkat, 2001). Moreover, dual VET promises to align training content and labor market needs through the involvement of firms in the definition of training content (blinded_3). While opportunities for wage growth may be more limited (Hanushek et al., 2017), VET therefore presents a favorable risk profile compared to general education (GE) according to this perspective. However, a contrasting view holds that VET is now a riskier choice. This view, inspired by the varieties of capitalism literature's characterization of vocational skills as highly specific and therefore inherently risky (Estevez-Abe, Iversen and Soskice, 2001; Streeck, 2011), argues that general skills as provided by academic education better prepare people for future skill needs (Iversen and Soskice, 2019; Diessner, Durazzi and Hope, 2022). Durazzi (2021) points out that this may even be true of countries whose growth model relies on advanced manufacturing, where the literature has traditionally assumed a symbiotic relationship with vocational education (Thelen, 2014; Wren, 2013).

Neither strand of literature, however, has investigated people's subjective response to increased uncertainty due to the twin transition.

In this paper, we therefore ask how people's educational preferences at the upper secondary level are shaped by subjective technology risk? We use novel data from a large, representative survey of educational attitudes and preferences in seven European countries (Denmark, England, France, Germany, Portugal, Sweden, Switzerland) with 11,508 respondents. We focus on the choice between vocational and general education at the upper-secondary level because at this stage young people sort into tracks in most countries (Giudici et al., 2023). Our main dependent variable is whether respondents personally prefer the vocational or general track. Our respondents are representative of the working-age population in their country and thus have already completed secondary education. They are not facing the decision they are asked about themselves, but are likely to, in their role as parents, relatives, or family friends, influence the sociocultural context in which young people make their decision (Schoon and Parsons, 2002) — indeed, they may in practice even make the choice for them. Moreover, unlike adolescents who do not yet have labor market experience, working-age respondents are in a position to link technology risk and educational choices, allowing us to study this important question.[1] Our main independent variable is whether respondents fear losing their job due to a lack of technological skills, capturing subjective technology risk (henceforth STR).

Our analyses show that VET is widely perceived as a safe haven — it appears particularly attractive to individuals who in their own estimation face significant employment risk from technological change. Crucially, this association remains robust and strong when we condition on a range of control variables and the main alternative explanations, that is, occupations as a proxy for objective technology risk and educational background to account for status quo bias. Moreover, the relationship is consistent across seven countries with very different education systems. Yet while the relationship is robust, it is not homogeneous. Interaction analyses show that men, high-income, highly educated, and right-leaning individuals increase their favorability towards VET more strongly in response to STR. Our findings point to a hitherto underappreciated implication of the growing uncertainty over skill needs in the twin transition. As technology skills become more important, people perceive VET to offer an advantage. VET policy may be able to build on this to prepare VET systems for the future and increase their attractiveness for qualified students.

The paper proceeds as follows. The next section situates the role of education in the wider literature on technological change. Section 3 introduces the competing perspectives on VET and argues that high risk people who experience elevated technology risk are likely to view VET as a safe haven. Section 4 describes our data and analytical approach and section 5 presents the results. A final section concludes.

[1] Our approach is by no means unprecedented in the literature. For example, Abrassart et al. (2020) study adult preferences for VET in Switzerland.

2 Literature Review

The existing literature on individual educational choices and preferences has generally paid relatively little attention to the role of technology risk. Social stratification research building on established rational choice models of educational decisions (e.g. Breen and Goldthorpe 1997) has at least tried to integrate risk and uncertainty, although without explicit reference to new technologies. Breen, Van De Werfhorst and Jaeger (2014) work with Danish register data to show that individuals with high risk aversion and high discount rates on future expected income are less likely to enroll in the academic upper secondary track. Complementary work by Holm, Hjorth-Trolle and Jæger (2019) furthermore shows that low-SES individuals are more likely to drop out of academic education if they receive a negative information shock regarding the difficulty of the track. This research highlights the subjective nature of risk perceptions, as individuals often have incomplete information when making educational decisions. Moreover, it indicates that sensitivity to risk may differ between groups of people.

Other studies in economics zoom in on the role of the social prestige of occupations or cultural differences between natives and immigrants in explaining preferences for vocational or academic education. Abrassart and Wolter (2020) find that in Switzerland occupations requiring vocational education are perceived as less prestigious, but expansion of VET at the tertiary level could raise the social prestige of such occupations. Abrassart et al. (2020) show that first-generation immigrants in Switzerland tend to have a stronger preference for academic education over VET, while the preferences of second-generation immigrants are more similar to those of natives. Taken together, research on individual-level educational choices highlights uncertainty over payoffs, concerns over occupational prestige, and cultural influences as factors pushing people to pursue one upper secondary track over the other. However, none of these studies systematically take into account STR, that is, the expectation that one might lose one's job because of technological change. Where risk is considered at all (Breen, Van De Werfhorst and Jaeger, 2014; Holm, Hjorth-Trolle and Jæger, 2019), it is as a catch-all category for uncertainty over payoffs to education and the authors remain agnostic regarding the source of the uncertainty.

By contrast, the political science literature has established subjective technology risk as a distinct concept that merits explicit attention. As Ahrens (2024) and Bicchi, Kuo and Gallego (2024) argue, subjective risk is the theoretical channel through which objective risk filters through to political preferences.[2] However, education is strangely absent in the growing literature that deals with the effects of automation and digitalization on political behavior. Whereas economists and sociologists have focused on structural changes, documenting

[2] Bicchi, Kuo and Gallego (2024) furthermore point out that substitution risk is not the only relevant dimension of subjective risk, as concerns over the need to continually adapt ("technostress") and the impact of technological change on job autonomy and satisfaction may affect people's preferences.

upgrading and sometimes polarization in the employment and wage structure (Haslberger, 2021; Oesch and Piccitto, 2019; Cortes, 2016; Autor and Dorn, 2013; Acemoglu and Autor, 2011), political scientists grapple with the downstream effects of these trends. A growing body of work investigates the effects of technology on social policy preferences and voting behavior (for overviews see, e.g., Gallego and Kurer 2022; Weisstanner 2023; Kurer and Häusermann 2022; Kurer and Van Staalduinen 2022), but education preferences have remained a blind spot. Early work focused mostly on "objective" measures of exposure to technology, such as routine intensity scores (Autor, Levy and Murnane, 2003; Fernández-Macías and Hurley, 2017; Haslberger, 2022), and established that risk exposure increases right-wing populist voting and support for some forms of social policy (for examples, see Thewissen and Rueda (2019), Dermont and Weisstanner (2020), and Im et al. (2019)).[3] As the field matured, people's subjective risk perceptions have increasingly come into focus. Scholars have pointed out that objective measures of exposure and subjective risk perceptions often do not correspond closely, and the latter tend to have greater explanatory power (Gallego et al., 2022; Bicchi, Kuo and Gallego, 2024; Busemeyer and Tober, 2023). Recently, the literature has begun to incorporate generative AI as a new form of technology risk (see, e.g., Magistro et al. 2024)(blinded_1), but it has remained focused on social policy preferences and voting behavior. In summary, sociologists and economists working on educational choices have paid little attention to technology risk and political scientists working on technological change have largely ignored education preferences. As a result, we know very little about how digitalization and the attendant risks affect education preferences.

Yet, one of the most fundamental impacts of digitalization is on skill formation, requiring new skill sets and tasking education policy with adapting skill formation systems to an environment characterized by rapid change and uncertainty (REF to introductory chapter). Against this backdrop, policy proposals increasingly promote high-quality VET as a means to address emerging skill demands (Lee, 2024). National and international actors, including the European Union, have long championed VET reform and expansion (Bonoli and Emmenegger, 2022; European Commission, 2010, 2016), and recent initiatives such as the European Green Deal and reports on Europe's (lack of) competitiveness have added a renewed sense of urgency (European Commission, 2024b,a). Many advanced economies already face skill shortages in occupations requiring vocational qualifications (Cedefop, 2025), underscoring the importance of VET in strategies to address labor market needs.

VET indeed appears attractive for several reasons: it facilitates school-to-work transitions and reduces youth unemployment (Breen, 2005), provides substantial labor market returns for individuals without higher education (Bol et al., 2019; Schulz, Solga and Pollak, 2023; Hanushek et al., 2017), and is associated with

[3] Scholars generally distinguish between investment, compensation, and steering policies (Bürgisser, 2023). The evidence is not conclusive, but on balance, risk appears to increase support for compensation and steering policies, but not investment policies.

lower wage inequality (blinded_3). High-quality vocational training has helped countries like Germany and Switzerland more evenly distribute the economic benefits of technological innovation (Lee, 2024). Moreover, VET systems can play an integrative role, offering pathways into the labor market for migrants and less academically inclined individuals (Bonoli and Wilson, 2019; Bonoli and Emmenegger, 2021; Bonoli and Otmani, 2023). However, despite these advantages and widespread political support, there remains a disconnect between macro-level evidence on benefits of VET and the limited research on individuals' motivations to choose vocational or general education — particularly in light of the fundamental uncertainty associated with the twin transition. In the next section, we outline how two contrasting perspectives rooted in the extant political economy literature would lead people to view VET either as a "dead end" or as a "safe haven" and argue why we ultimately expect the safe-haven view to prevail.

3 Theory: Subjective Technology Risk and Education Preferences under "Vast Uncertainty"

Autor (2022) argues that current technological change is taking place in a climate of "vast uncertainty" which makes predictions over the future impact difficult. This gives rise to what we may call subjective technology risk (STR): a perception that one may lose one's job due to an inability to keep up with changing skill requirements. We expect that STR influences people's educational preferences. Research shows that people who worry about losing their job due to technological change are more likely to support social protection policies such as unemployment benefits and less likely to support social investment policies (Busemeyer and Tober, 2023; Weisstanner, 2023). Generalizing from this, almost by definition, people who believe that they face high risks due to technology, are likely to be risk averse (see, e.g., Hetschko and Preuss 2020). In the case of upper secondary education, this means that they should favor the track which they expect to provide secure employment and a high degree of adaptability — that is, a track that reduces uncertainty as much as possible.

However, it is not obvious which would be the low-risk alternative in the context of the digital transition — the "safe haven" for those who worry about the consequences of technological change. We argue that despite a recent literature which portrays VET as an outdated model, and investment in vocational skills as inherently risky, VET still offers promising career prospects and in any case, public perceptions are slow to change. Hence, we expect that STR is nevertheless associated with a preference for vocational upper secondary education. Moreover, we discuss which demographic groups are most likely to experience STR and how the relationship between STR and education preferences may differ between them.

3.1 VET as a Dead End

Much recent research implies that GE is the safer educational option in the twin transition, while VET risks becoming a dead end (see (blinded_3) for a detailed critical discussion of this view). Building on the work of labor economists who documented an increase in demand for cognitive tasks (Autor and Dorn, 2013), political economy scholars have argued that in post-Fordist knowledge economies, "complementarities in production between skilled and semiskilled workers have been replaced by complementarities between skilled workers and new ICTs" (Hope and Martelli, 2019, 243), with the implication that VET skills would be less in demand (see also Iversen and Soskice 2019 and Wren 2021). Moreover, Iversen and Soskice (2019) among others explicitly point to the uncertainty about skill demands created by the twin transition to argue that academic education provides more general and transferable skills which increase adaptability.

One might therefore expect that years of emphasis on the increasing importance of general and transferable skills, and the equation of these skills with higher education — in rhetoric if not in reality (Streeck, 2011) — have created a perception that vocational education leaves people ill-equipped to deal with rapid labor market change due to technology. The very visible (and effective, see OECD 2021) push towards academization in many countries also sends a strong signal that VET is "yesterday's model" (blinded_3), not fit for the knowledge economy. Concurrent efforts to promote VET may have been less visible to the general public than the ongoing academization, undermining the salience of arguments in favor of VET. The decline of stereotypical VET occupations such as skilled manufacturing jobs could exacerbate this perception (Autor, Dorn and Hanson, 2019; Kollmeyer, 2009). Following this logic, individuals who experience high STR should be less inclined to look to VET for the skills that are necessary for labor market success in a world of fast-changing technology. Empirically, we would expect this to manifest in a negative relationship between STR and preference for VET.

3.2 VET as a Safe Haven

However, we contend that the perspective of VET as a dead end has two important flaws which make it unlikely that people with high STR prefer GE. First, it discounts the continuing substantive benefits of VET. Second, even if the pessimistic view of the merits of VET were true, public attitudes likely lag behind. Hence, we expect people with high STR to prefer VET over GE.

There are a number of reasons to reject the view that VET is a dead end in terms of the labor market prospects it provides. As reported by Cedefop (2025), numerous VET occupations face skill shortages across Europe, alleviating fears of a lack of demand. Moreover, VET systems are able to quickly react to changing labor market conditions, especially in countries where employers are involved in the definition of training content (Emmenegger and Bonoli, 2022)(blinded_2). In practice, this has led to a broadening and upgrading of the skills provided in vocational programs, which in turn has shored up the labor market returns to VET (Schulz, Solga and Pollak, 2023; Adda and Dustmann, 2023)(blinded_3). In addition, the increasing awareness and availability of lifelong learning and adult education opportunities can assuage fears of skill obsolescence (OECD, 2020). For the growing migrant populations across Europe, VET can help reconcile the twin imperatives of labor market integration and skill development (Bonoli and Otmani, 2023). Finally, in a world where generative AI is substituting workers in cognitive tasks (Gmyrek, Berg and Bescond, 2023; Felten, Raj and Seamans, 2023; Hui, Reshef and Zhou, 2024), jobs with a physical component, which tend to be associated with VET, may be relatively less exposed to technology risk. In the words of Autor (2024, 2), "AI used well can assist with restoring the middle-skill, middle-class heart of the ... labor market that has been hollowed out by automation and globalization." Hence, VET still provides attractive employment prospects to many individuals in labor markets undergoing the twin transition, owing to the responsiveness and flexibility of VET systems and the potential impact of AI on cognitive jobs requiring tertiary education. These individual-level benefits of VET, along with macro-level benefits such as reduced youth unemployment and lower wage inequality, have been excessively discounted in portrayals of VET as an outdated model (blinded_3).

However, members of the public are unlikely to be well-informed about the details of such debates. Instead, they are likely to rely on heuristics and basic cues (Althaus, 2003; Zaller and Feldman, 1992). Hence, it matters that VET has long been and still is viewed as a safe and dependable choice (Cedefop, 2017) — absent a highly salient information shock, this perception is unlikely to change. Indeed, influential sociological research has argued that people from non-academic backgrounds prefer the vocational track because it offers secure job prospects and a good salary at a young age, while general and academic education are seen as inherently more risky (Breen and Goldthorpe, 1997). More recent survey evidence confirms that this perception is not limited to marginalized individuals and still predominates across Europe (Cedefop, 2017). For these reasons, it is easy to see how VET can still be considered an attractive educational path in a digitalizing economy. There are strong substantive reasons to do so, which are aided by the inertia of public opinion. Thus, our central expectation in this study is that *subjective technology risk is associated with a stronger preference for vocational upper secondary education.*[4]

[4]Readers unconvinced by our substantive argument might object that people who hold this view are misinformed. This is possible, but it would not change our empirical expectation. However, if our substantive argument is correct, it would be more accurate to say that while the recent literature fails to fully appreciate the benefits of VET in the twin transition, the general public does.

3.3 Moderating Factors in the Relationship between Subjective Technology Risk and Educational Preferences

Neither risk exposure nor risk aversion are evenly distributed across the population. We therefore expect the relationship between STR and education preferences to vary between socio-demographic groups. Few empirical studies have studied such interactions. However, the rich literature on risk and social policy preferences suggests several margins which may shape the relationship between technology risk and educational preferences analogously. In this study, we zoom in on gender, income, educational background, and political orientation.

Despite a convergence of the roles of women and men in the labor market (Goldin, 2014), there is growing evidence that automation affects women and men in different ways. For example, Gingrich and Kuo (2022) argue that women face higher non-technological labor market risks, limiting the potential impact of technology risk on social policy preferences through a ceiling effect. By the same logic, we might also expect technology risk to affect women's education preferences less strongly than men's. On the other hand, women are generally more risk-averse than men (Borghans et al., 2009; Falk et al., 2018), and there is evidence that women have more negative attitudes towards digital technologies (Borwein et al., 2024; Carvajal, Franco and Isaksson, 2024)(blinded_1), suggesting that they view such technologies as inherently more risky and might show a stronger reaction. Hence, the net effect of these forces is an empirical matter.

When it comes to the moderating role of income, the existing literature points to a clear expectation that richer individuals, while generally less likely to prefer VET, should show a stronger shift towards VET with increasing risk. This reasoning mirrors Thewissen and Rueda (2019), who contend that richer individuals are generally opposed to redistribution, but that automation risk has a stronger positive effect on their redistribution preferences since they have more to lose. The negative main effect of income reflects simple self-interest following the Meltzer and Richard (1981) framework, whereas the positive interaction captures increased demand for insurance (Moene and Wallerstein, 2001). In our case, lower preference for VET at low risk does not necessarily reflect self-interest, but rather the link between education and income. Insurance is provided by vocational education, which at-risk individuals perceive as providing secure employment. Thus, the expectation of a positive interaction follows from the analogous application of an established theoretical mechanism.

In a similar vein, a person's educational background may affect the relationship between subjective risk and education preferences. We expect individuals who experience high subjective risk and who do not have a VET background to view VET as more appealing, and vice versa, as they are unhappy with the current state of affairs and imagine the alternative to be better. Existing research has mostly looked into how risk and educational background affect preferences for redistribution, but we can again extrapolate from this literature. For example, Häusermann, Kurer and Schwander (2015) find that highly skilled individuals are particularly sensitive to labor market risk. Applying this logic to education preferences, tertiary educated individuals with high subjective risk should be particularly prone to think that "the grass is greener on the other side" and increase their preference for VET, while people with a VET background should experience a more moderate preference shift towards GE.

Finally, we expect that right-leaning individuals react more strongly to high subjective risk. They tend to be more favorable towards VET to begin with (Busemeyer, Cattaneo and Wolter, 2011), but more importantly, we expect that they are more sensitive to technology risk and disproportionately increase their preference for VET. This follows from psychological research which links fear of loss and uncertainty avoidance to conservative ideology (Jost et al., 2003). If, as we argue, VET is perceived as a safe haven offering attractive job prospects in the twin transition, right-leaning individuals who fear losing their job to technology should therefore favor this educational path particularly strongly.

4 Data and Analytical Strategy

We test our arguments using data from a large online survey with 11,508 working-age respondents from seven European countries: Denmark, England, France, Germany, Portugal, Sweden and Switzerland. They are all advanced democracies but represent different welfare state models and varieties of capitalism (Hall and Soskice, 2001; Esping-Andersen, 1990). Hence, they face varied institutional challenges while transitioning to knowledge economies and reforming their skill formation systems (Bonoli and Emmenegger, 2022). This allows us to posit a high degree of external validity for our findings in a European context. To ensure the representativeness of our sample, we used country-specific quotas for gender, age, and education. We fielded our survey in collaboration with the survey company Bilendi in May and June 2024.[5]

Our dependent variable is respondents' educational preference for VET or GE. We asked: "Which upper secondary education track do you personally prefer?" Responses are measured on an 11-point scale, where "1" indicates a strong preference for general education and "11" a strong preference for vocational education. It is worth reiterating that the respondents, being of working age, do not face the decision between VET and GE themselves. However, like Abrassart et al. (2020), we study the preferences of adults because only working-age individuals meaningfully experience technology risk and their preferences moreover influence the choices of young people in their social environment (Schoon and Parsons, 2002).

[5]Some components of the survey were pre-registered, see here. Before being fielded, the survey received the approval of the University of St. Gallen Ethics Board.

Our independent variable is subjective technology risk. Our operationalization follows Busemeyer and Tober (2023) and is based on agreement with the statement that over the next five years, "I will lose my job because I am not good enough with new technology or because I will be replaced by someone with better technological skills." The variable takes values from "very unlikely" (1) to "very likely" (5), with a middle category "can't choose". For the analysis, we created a dummy where "0" indicates low subjective risk (values 1-3) and "1" indicates high subjective risk (values 4-5).[6] Conceptually, we conceive of our measure of STR as a function of three key components that we cannot measure separately: objective risk exposure, risk aversion, and misperceptions (which we assume are random and hence can be treated like an error term). This allows us to derive hypotheses regarding heterogeneous relationships based on established findings on group differences in risk exposure and risk aversion.

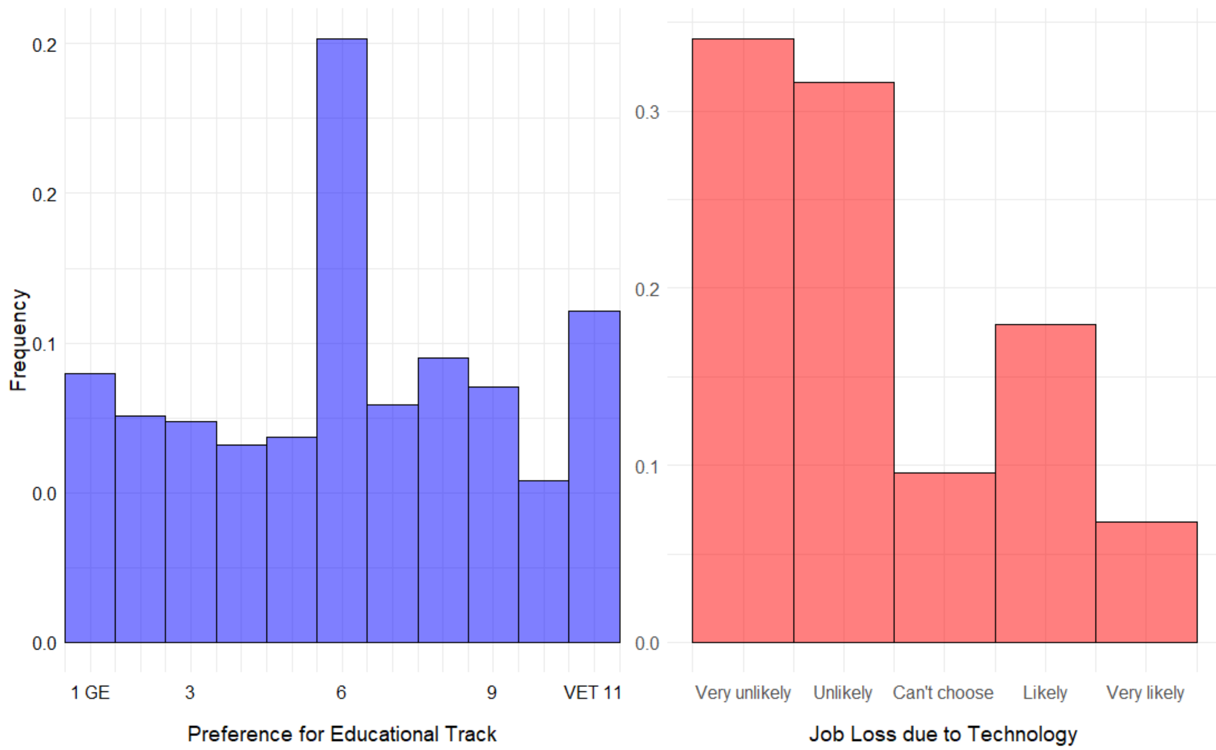
Moreover, we collected data on a comprehensive set of controls, including age, gender, education background (VET or GE), employment status, occupation (1-digit codes), personal income (18-category scale), parenthood status (has children or not), and political orientation (7-point scale, recoded to a dummy; left-center = 1 to 5 and right-wing = 6 and 7). Many of these socio-demographic variables are standard controls in studies on individual preferences. In addition, since we study education preferences, we consider it crucial to account for whether the respondent has children or a VET background, as well as their political orientation. The presence of children is likely to raise the salience of education-related questions, status-quo bias may increase the preference of respondents for the track they have attended themselves, and political orientation may shape risk aversion and views on education.

Figure 1 shows the pooled distribution of the two main variables. The left panel shows the distribution of education preferences which, with a mean of 6.12 (SD = 3.05), indicates a relatively even split between respondents who prefer VET and those who prefer GE, and a large number of undecided respondents. In the right panel we see that 24.8 percent of respondents experience high levels of STR (answered that they will "likely" or "very likely" lose their job due to technology over the next five years), a slightly lower share than in Busemeyer and Tober (2023). A glance at the summary statistics for the control variables in Table A1 provides reassurance concerning the socio-economic representativeness of the sample.

To test our argument, we regress individuals' education preference ($Pref_i$) on their subjective technology risk (STR_i) and a vector of individual-level controls (X_i) via ordinary least squares. We include country fixed-effects ($v_{country(i)}$) to absorb unobserved country-specific factors, and cluster standard errors at the country

[6] The survey included additional items capturing subjective risk perceptions: 1) "My job will be replaced by a robot, computer software, an algorithm, or artificial intelligence," and 2) "My job will be replaced by a person providing a similar service on an internet platform." Analyses using these items instead, or the first component based on a rotational principal component analysis (PCA) as in Busemeyer and Tober (2023), yield substantively identical results. For ease of presentation, we therefore focus on the item with the most comprehensive conceptualization of subjective risk and present additional results in Appendix B.

Figure 1: Educational Preferences and Subjective Risk



level to correct for potential correlation in errors among individuals within the same country. Formally, the core specification is:

$$Pref_i = \alpha + \beta_1 STR_i + \hat{\beta}_2 X_i + v_{country(i)} + \epsilon_i \tag{1}$$

To examine heterogeneous relationships, we add an interaction term with the moderating variable M_i (e.g., gender). Formally:

$$Pref_i = \alpha + \beta_1 STR_i + \beta_2 M_i + \beta_3 STR_i \times M_i + \hat{\beta}_4 X_i + v_{country(i)} + \epsilon_i, \tag{2}$$

5 Results

The empirical analysis is divided into two parts. The first part investigates the direct relationship between STR and education preferences. The second part focuses on how socio-demographic factors moderate this relationship. To preview the results, we find support for our argument that people who experience high STR tend to prefer vocational education as a "safe haven" in uncertain times. Moreover, we find that groups which the existing literature on social policy preferences argues are more sensitive to technology risk — such as men, high-income and highly educated as well as right-leaning individuals — also show a stronger increase in their preference for VET if they express high STR.

5.1 Subjective Technology Risk Increases Preferences for VET

Our regression analyses provide strong evidence for the argument that STR is associated with a preference for VET. In Table 1, we build up our models in four steps. In model 1, which includes only country fixed-effects, STR is positively and significantly associated with a preference for VET ($\beta_1 = 0.54; p < 0.001$). As we add controls in models 2 - 4, β_1 remains consistently significant and essentially unchanged in size. This indicates that individuals who worry about losing their job due to technology are more likely to prefer vocational education over general education, highlighting the substantial influence of subjective risk perceptions on educational decision-making. The estimated effect size is substantial, amounting to approximately 1/6 of a standard deviation (see Table A1).

With the addition of controls in model 2, the size of β_1 even increases by about 10 percent. Meanwhile, the controls largely behave as expected. Women, parents, people who are in paid employment and those with higher incomes are significantly less likely to prefer VET, while right-wing individuals have a strong preference for VET, similar in size to the coefficient for STR. The coefficient on age is not significant, indicating that the greater preference for VET among older cohorts is likely due to compositional factors. However, this still leaves our analysis vulnerable to two obvious alternative explanations: status-quo bias and objective replacement risk.

To account for status-quo bias, in model 3 we control for whether the respondent has a VET background. Unsurprisingly, the coefficient is positive and large, indicating that status-quo bias is indeed present and respondents tend to prefer the educational track they have completed themselves. Nevertheless, this leaves the coefficient on STR unaffected. Thus, our main finding is not simply a result of people with a VET background feeling more at risk. In model 4, we additionally account for the possibility that STR is merely a function of objective automation risk by including occupation dummies. In the absence of more detailed occupational information which would allow us to use routine intensity scores (see, e.g., Autor and Dorn 2013 and Fernández-Macías and Hurley 2017), 1-digit occupation dummies nevertheless capture a large portion of the variation in substitutability as commonly understood in the labor economics literature (Acemoglu and Autor, 2011). Again, however, the estimate effect of STR remains unaffected.[7] We conclude therefore that the association between STR and a preference for VET in advanced European democracies is independent of educational background, objective automation risk, and other individual characteristics. Moreover, as

[7]Including occupation dummies also leads to some interesting changes on other control variables. Notably, the coefficient on income goes to zero and the coefficient on being female is reduced by almost half, highlighting the role of occupations in income stratification and the impact of occupational sorting by gender.

Table 1: Subjective Technology Risk Is Associated with Preference for VET

Models	(1)	(2)	(3)	(4)
STR	0.5362***	0.5939***	0.5683***	0.5390***
	(0.0830)	(0.0849)	(0.0715)	(0.0671)
Age		0.0018	-0.0050	-0.0054
		(0.0065)	(0.0061)	(0.0059)
In Paid Employment		-0.2208*	-0.2468*	-0.1917*
		(0.1056)	(0.1228)	(0.0879)
Has Children		-0.4891***	-0.4286***	-0.3806***
		(0.0914)	(0.0960)	(0.0831)
Female		-0.2307**	-0.2272***	-0.1226**
		(0.0677)	(0.0580)	(0.0481)
Personal Income		-0.0760**	-0.0473*	-0.0111
		(0.0263)	(0.0242)	(0.0203)
Right-wing		0.6569**	0.5913**	0.5907**
		(0.1838)	(0.1945)	(0.2009)
VET Background			1.601***	1.266***
			(0.1268)	(0.1327)
Occupation Dummies	No	No	No	Yes
Fit statistics				
Observations	11,451	8,983	8,843	8,843
R^2	0.01814	0.04372	0.09598	0.12990
Within R^2	0.00583	0.03044	0.08327	0.05408

Note: All models include country fixed-effects. Standard errors are clustered by country. Full results, including estimates for occupations, in Table C1.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

supplementary analyses in Table B2 show, we obtain identical results when using alternative measures of STR.

With the inclusion of country fixed-effects, we abstract from differences between countries and identify β_1 purely from within-country variation in individual characteristics. To be sure about the generalizability of the results, we must therefore consider the possibility that the relationship differs qualitatively between different groups of countries. In Table 2, we estimate model 4 from Table 1 for each country individually. The effect is statistically significant in Germany, Denmark, England, France, Portugal and Sweden, with the largest coefficients in Germany (0.69) and France (0.72). In the case of Switzerland the effect points in the same positive direction, but does not reach statistical significance. Hence, our findings suggest that individuals perceiving higher automation risk tend to favor vocational education, though the strength of this relationship varies across countries. This variation highlights the importance of national contexts, but there is no obvious pattern corresponding to the perceived quality of VET systems or differences in welfare state models or varieties of capitalism (Esping-Andersen, 1990; Hall and Soskice, 2001), which constitutes prima facie evidence against an institutional explanation. Thus, the main takeaway is that the finding that people who experience high STR tend to favor VET holds across a range of contexts.

In summary, STR is a significant factor in explaining educational preferences, independent of educational background, objective automation risk, and other individual characteristics, as well as across countries. This finding offers valuable insights into the dynamics of educational preferences in advanced economies. It suggests that the attractiveness of VET is bolstered by automation anxiety, creating a potential dilemma for policymakers seeking to reduce automation anxiety while strengthening VET.

Table 2: Subjective Risk on Educational Preferences by Country

	Country						
	CH	DE	DK	EN	FR	PT	SE
STR	0.2393	0.6817***	0.4728**	0.3820**	0.7306***	0.4414**	0.6257***
	(0.1836)	(0.1845)	(0.1907)	(0.1833)	(0.1794)	(0.2064)	(0.1751)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	1,210	1,411	1,182	1,165	1,165	1,365	1,345
R^2	0.11946	0.15723	0.20594	0.10573	0.12427	0.09440	0.19635
Adjusted R^2	0.10615	0.14633	0.19365	0.09168	0.11052	0.08229	0.18544

Note: Full results, including control variables, in Table C2. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

5.2 Heterogeneous Effects of Subjective Technology Risk

We have argued that risk exposure and risk aversion are unevenly distributed across the population. Since STR can be understood as a function of objective risk exposure and underlying risk aversion, we expect significant differences between socio-demographic subgroups. Moreover, these factors may matter more or less for different subgroups, giving rise to heterogeneous relationships between STR and education preferences. We therefore investigate the interactions between STR and 1) gender, 2) income, 3) educational background, and 4) political orientation. First, Figure 2 provides descriptive insights into the density distributions of subjective risk and education preferences by subgroup. Gender differences are small, with men expressing slightly higher technology risk and a stronger preference for VET, on average. Lower-income groups display more variability in preferences and higher concerns about automation, highlighting the complex relationship between economic vulnerability, education, and technological change.[8] We can see that individuals who themselves have a VET background prefer the vocational path and experience slightly higher anxiety about technological change.[9] Right-wing individuals tend to favor VET while people on the left and in the center have more ambiguous preferences. Additionally, supporters for the right perceive higher automation risks than their center-left counterparts.[10]

The descriptive picture provides prima facie evidence that the theorized subgroup differences merit a systematic exploration. We thus re-estimate the full model in column 4 of Table 1 with added interaction terms. Our analyses in Figure 3 (full output in Table C3) reveal that indeed all four factors moderate the relationship between STR and education preferences — so not only do social groups differ in how much technology risk they experience, but also in the extent to which this shapes their education preferences. In the case of gender, the interaction term and the main effect of STR are statistically significant, but the main effect of gender is not. Thus, at low levels of subjective risk there is no gender difference in education preferences, but among women the perception of VET as a safe haven is less pronounced (see Panel A of Figure 3). The size of the coefficients implies that the estimated effect of subjective risk is 51 percent smaller than for men.[11] This finding aligns with Gingrich and Kuo (2022), who argue that since women face higher non-technological labor market risks, there is a ceiling to the potential effect of technology risk on social policy preferences. We show that this logic extends to education preferences as well.

With regard to income, we find no difference between the three groups at low levels of STR. All groups express a stronger preference for VET at high levels of subjective risk, but the estimated effect is partic-

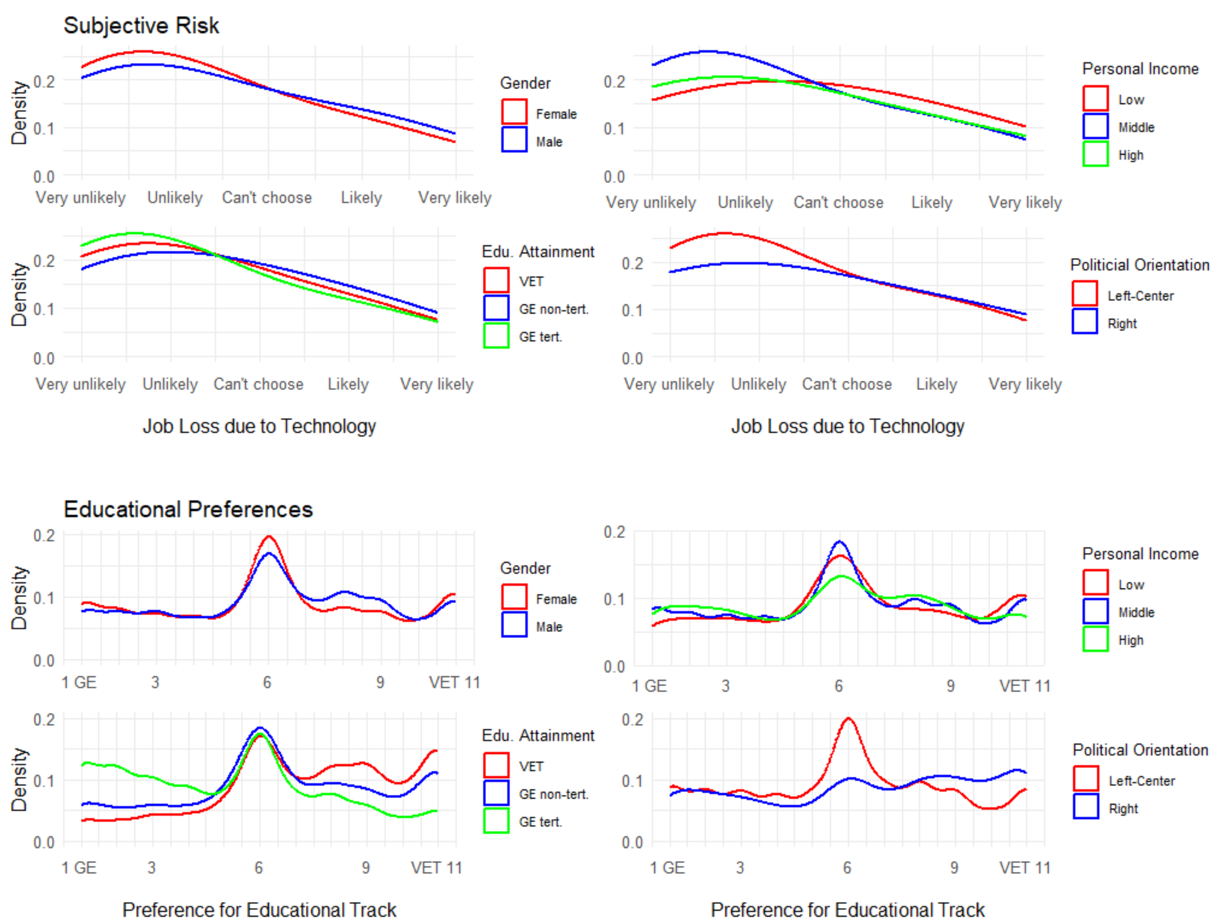
[8] For simplicity, we recoded the income variable into three categories: low (< Mean - 1SD), middle (Mean ± 1SD), and high (> Mean + 1SD).

[9] To paint a more detailed picture, we distinguish between VET, non-tertiary GE, and tertiary GE in the interaction analyses.

[10] Pairwise t-tests reveal that all mean differences are statistically significant except between the VET and GE tertiary groups for STR and between the high income and middle income groups for education preferences.

[11] $(0.6876 - 0.3488)/0.6876 = 0.4927$

Figure 2: Educational Preferences and Subjective Risks across Subgroups



ularly strong for high-earners, at more than triple the size of the coefficient for low-earners (see Panel B of Figure 3).[12] The statistically significant interaction implies that high-income individuals in particular regard VET as a safe haven when they experience technology risk. Our finding for education preferences thus conforms to what Thewissen and Rueda (2019) have established for redistribution preferences: rich individuals' demand for insurance is more sensitive to risk because they have more to lose. In the case of education, insurance comes from vocational education which is perceived to better prepare people for the labor market in uncertain times.

We find that educational background likewise significantly shapes the relationship between STR and education preferences. Distinguishing between VET and GE with and without a tertiary qualification, we see a clear gradient (see Panel C of Figure 3). At low levels of risk, people with tertiary GE are almost 2 points less likely to choose VET than VET graduates (amounting to approximately 2/3 of a standard deviation on the 11-point scale), with GE graduates without a tertiary qualification in between. The main effect of STR is zero, indicating that the education preferences of VET graduates are not affected by whether they fear losing their job due to technology. Both interaction terms are positive, but only that for GE graduates with a tertiary degree is significant, reducing the difference in preferences between both groups by half. Thus, as we argued with reference to the findings of Häusermann, Kurer and Schwander (2015) for high-skilled labor market outsiders, the most educated individuals appear to be most sensitive to STR and increase their demand for what they perceive to be an educational safe haven. However, since VET graduates do not significantly move towards GE, there is no general "the grass is greener on the other side"-effect when it comes to education and STR.

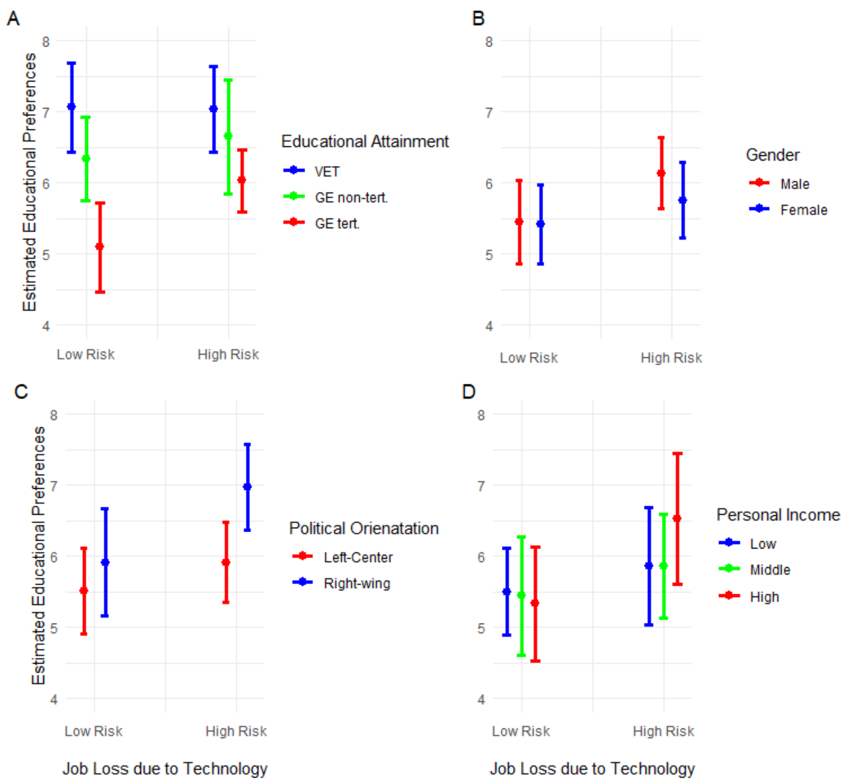
Finally, the analysis by political orientation indicates that right-wing individuals are more likely to choose VET to begin with, compared to people who identify as politically left or centrist. In line with our expectation, their preference for VET increases more strongly when they perceive high levels of technology risk (see Panel D of Figure 3). The estimated increase is more than twice as strong as for center-left individuals.[13] While the significant main effect can be attributed to VET being associated with traditional occupations that appeal to conservatives, the interaction effect is consistent with conservatism being linked to psychological traits such as uncertainty avoidance (Jost et al., 2003).

These analyses show that the relationship between STR and education preferences is not homogeneous. Gender, income, educational background, and political ideology all play a moderating role. In line with arguments about risk exposure and risk aversion that have been made elsewhere in the literature (for example with regard to social policy preferences), we show that men, high-income and highly educated individuals,

[12] $(0.3586 + 0.8417)/0.3586 = 3.3472$

[13] $(0.3965 + 0.6654)/0.6654 = 2.6782$

Figure 3: Predicted Education Preferences by Moderating Factors



Note: Full results in Table C3.

as well as politically right-leaning people all react more strongly to STR and substantially increase their preference for VET. The consistent analogy with established findings lends credibility to our results. VET appears to be perceived as a safe haven in times of heightened uncertainty due to the twin transition, but not to the same extent by everyone.

6 Conclusion

Based on the observation that rapid technological change associated with the twin transition is increasing uncertainty over future skill requirements, this article argues that individuals today make educational choices in a context of heightened risk. One of the most consequential choices people face in their educational career is that between vocational and general education at the upper secondary level (Shavit and Müller, 2000; Hanushek et al., 2017). However, research so far has little to say about how people's appraisal of the technology-induced risks they face shapes their preference between these alternatives. Sociological and economic research relies on rational choice arguments to explain education preferences, but has largely neglected the increased uncertainty precipitated by the twin transition. Concurrently, political science research emphasizes the effect of subjective risk on social policy and voting preferences, but not education. Our study links these literatures and helps us understand how macro-level trends interact with micro-level decision-making.

We contrast two extant perspectives. On the one hand, a recent literature argues that VET increasingly constitutes a risky choice, as the specificity of vocational skills may quickly render them obsolete during times of rapid change (Iversen and Soskice, 2019). On the other hand, some scholars object that VET remains an attractive option during the twin transition, as VET systems are highly adaptable and inculcate skills that are in high demand (blinded_3). Against the background of this unresolved debate, our study aims to establish how subjective technology risk shapes individuals' preference between vocational and general upper secondary education. Drawing on the literature linking automation risk to demand for social insurance, we posit that STR is associated with a preference for an educational "safe haven." We further argue that because of the continuing substantive benefits of VET, and because public opinion lags behind expert debates, VET is widely considered this safe haven. We test this argument using data from a large, representative survey in seven European countries (Denmark, England, France, Germany, Portugal, Sweden, Switzerland).

Our study thus offers novel insights into the micro-foundations of education preferences in times of heightened uncertainty. We make two contributions to the literature. First, we show that individuals who experience high STR view VET as a "safe haven" that provides attractive employment prospects and insurance against uncertainty over future skill demands. Second, we demonstrate that the relationship between STR and education preferences is not uniform across groups. In line with existing literature on risk exposure and risk aversion, we find that STR matters more for male, high-income, highly educated, and right-leaning respondents. Our results thus mirror prominent findings from the literature on automation risk and social policy preferences (Thewissen and Rueda, 2019; Häusermann, Kurer and Schwander, 2015; Gingrich and Kuo, 2022).

While our findings are not causal, they are highly robust and generalizable. We control for a wide range of individual characteristics and account for alternative explanations such as objective technology risk (proxied by education) and status quo bias (captured by educational background), and find our results substantively unaffected. Supplementary analyses furthermore show that the relationship is robust to using different measures of subjective technology risk. The association between STR and a preference for vocational over general upper secondary education also holds across diverse national contexts, including different welfare state types and varieties of capitalism (Esping-Andersen, 1990; Hall and Soskice, 2001). This inspires confidence in the robustness of the relationship and its generalizability across advanced European democracies.

These findings offer important insights which can help policymakers craft effective skills policies for the twin transition. The predictability and security that citizens seek may remain elusive. How, then, can public policy promote adaptability without fanning anxiety? First, it is necessary to recognize that the fundamental uncertainty accompanying the twin transition imposes risks on people. Skills policies should aim to alleviate these risks by putting people in a position where they can adapt to changing circumstances and requirements. As argued elsewhere in this special issue (REF to introductory chapter), this "is not to be confused with an emphasis on general skills because skill requirements during the twin transition might still be highly specific, but individuals may need to be empowered to [gain] immediate access to affordable high-quality training that prepares them for the next phase of their labor market career." VET systems are well placed to provide initial training that inculcates up-to-date specific skills, but additional efforts are needed to make access to high-quality training throughout the labor market career a reality. Such efforts can build on existing VET infrastructure to identify emerging skill needs and offer suitable training formats in coordination with employers. For this to succeed, it is crucial to cultivate healthy industrial relations and especially employer buy-in (Emmenegger, Bajka and Ivardi, 2023).

Second, our findings highlight the political dimension of uncertainty over skill needs. Framing efforts to strengthen VET and lifelong learning as a way of enabling people to deal with the requirements of the twin transition may prove electorally popular with a broad and unlikely coalition. This is because rising macro-level uncertainty unites knowledge economy winners who are otherwise less positively disposed towards VET, such as high-income and highly educated individuals, and knowledge economy losers, such as men and those on the political right, in strengthening preferences for VET. This may open a window of opportunity for substantive and sustainable reform. However, policymakers should resist the temptation to fan anxiety over technological change to drive up support for VET. Such a policy could invite a host of unintended consequences, such as strengthening radical parties or backlash against the twin transition as such (Kurer and Häusermann, 2022; Kurer, 2020). Ultimately, how well individuals feel able to respond to uncertainty over skill requirements is partially shaped by the education and training opportunities open to them. But policymakers will only be able to build institutions providing these opportunities if they remain attuned to people's anxieties and preferences.

As we seek to chart a new line of research that takes seriously the role of subjective risk perceptions in shaping education preferences, we suggest three avenues for future research to further expand on our findings. First, other heterogeneous relationships between STR and education preferences, for example with regard to age and immigration background, are likely and merit further study. Second, future work should investigate the preferences and choices of adolescents. While they lack labor market experience, as the workforce of the future their perspective on technology risk and education is particularly relevant. Third, such studies should include an experimental component that manipulates information about technology risk or returns to different educational tracks. This would provide causal evidence and important insights into the mechanisms through which STR affects education preferences. We hope that our paper will serve as a starting point for further efforts to understand how citizens think about education during the twin transition.

References

Abrassart, Aurélien, Marius R. Busemeyer, Maria A. Cattaneo and Stefan C. Wolter. 2020. "Do adult foreign residents prefer academic to vocational education? Evidence from a survey of public opinion in Switzerland." Journal of Ethnic and Migration Studies 46(15):3314–3334.

Abrassart, Aurélien and Stefan C Wolter. 2020. "Investigating the image deficit of vocational education and training: Occupational prestige ranking depending on the educational requirements and the skill content of occupations." Journal of European Social Policy 30(2):225–240.

Acemoglu, Daron and David Autor. 2011. Skills, tasks and technologies: Implications for employment and earnings. In Handbook of Labor Economics. Vol. 4b Elsevier B.V. pp. 1043–1171. arXiv: 1011.1669v3 ISSN: 15734463.

Adda, Jérôme and Christian Dustmann. 2023. "Sources of Wage Growth." Journal of Political Economy 131(2):456–503.

Ahrens, Leo. 2024. "Labor market risks and welfare preferences: a bounded rationality approach." Socio-Economic Review 22(1):327–348.

Althaus, Scott L. 2003. Collective preferences in democratic politics: Opinion surveys and the will of the people. Cambridge: Cambridge University Press.

Autor, David. 2022. "The Labor Market Impacts of Technological Change: From Unbridled Enthusiasm to Qualified Optimism to Vast Uncertainty." NBER Working Paper Series (30074).

Autor, David. 2024. "Applying AI to Rebuild Middle Class Jobs." NBER Working Paper Series (32140).

Autor, David and David Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." American Economic Review 103(5):1553–97. arXiv: 1011.1669v3 ISBN: 0002-8282.

Autor, David, David Dorn and Gordon Hanson. 2019. "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men." American Economic Review: Insights 1(2):161–178.

Autor, David, Frank Levy and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." The Quarterly Journal of Economics 118(4):1279–1333.

Beckert, Jens. 1996. "What is sociological about economic sociology? Uncertainty and the embeddedness of economic action." Theory and Society 25(6):803–840.

Bicchi, Nicolas, Alexander Kuo and Aina Gallego. 2024. "Unpacking Technological Risks: Different Sources of Concern and Policy Preferences." Political Studies p. 00323217241281575.

Bol, Thijs, Christina Ciocca Eller, Herman G van de Werfhorst and Thomas A. DiPrete. 2019. "School-to-Work Linkages, Educational Mismatches, and Labor Market Outcomes." American Sociological Review 84(2):275–307.

Bonoli, Giuliano and Anna Wilson. 2019. "Bringing firms on board. Inclusiveness of the dual apprenticeship systems in Germany, Switzerland and Denmark." International Journal of Social Welfare 28(4):369–379.

Bonoli, Giuliano and Ihssane Otmani. 2023. "Upskilling as integration policy: Making the most of refugees' human capital in a context of skill shortage." Social Policy & Administration 57(1):51–66.

Bonoli, Giuliano and Patrick Emmenegger. 2021. "The limits of decentralized cooperation: promoting inclusiveness in collective skill formation systems?" Journal of European Public Policy 28(2):229–247.

Bonoli, Giuliano and Patrick Emmenegger. 2022. Collective skill formation in a knowledge economy: Challenges and dilemmas. In Collective Skill Formation in the Knowledge Economy, ed. Giuliano Bonoli and Patrick Emmenegger. Oxford: Oxford University Press pp. 1–30.

Borghans, Lex, Bart H. H. Golsteyn, James J. Heckman and Huub Meijers. 2009. "Gender Differences in Risk Aversion and Ambiguity Aversion." Journal of the European Economic Association 7(2-3):649–658.

Borwein, Sophie, Beatrice Magistro, Peter Loewen, Bart Bonikowski and Blake Lee-Whiting. 2024. "The gender gap in attitudes toward workplace technological change." Socio-Economic Review p. mwae004.

Breen, R., H. G. Van De Werfhorst and M. M. Jaeger. 2014. "Deciding under Doubt: A Theory of Risk Aversion, Time Discounting Preferences, and Educational Decision-making." European Sociological Review 30(2):258–270.

Breen, Richard. 2005. "Explaining Cross-national Variation in Youth Unemployment." European Sociological Review 21(2):125–134.

Breen, Richard and John H. Goldthorpe. 1997. "Explaining Educational Differentials: Towards a Formal Rational Action Theory." Rationality and Society 9(3):275–305.

Busemeyer, Marius R., Maria Alejandra Cattaneo and Stefan C. Wolter. 2011. "Individual policy preferences for vocational versus academic education: Microlevel evidence for the case of Switzerland." Journal of European Social Policy 21(3):253–273.

Busemeyer, Marius R. and Tobias Tober. 2023. "Dealing with Technological Change: Social Policy Preferences and Institutional Context." Comparative Political Studies 56(7):968–999.

Bürgisser, Reto. 2023. "Policy Responses to Technological Change in the Workplace." JRC Working Paper Series .

Carvajal, Daniel, Catalina Franco and Siri Isaksson. 2024. "Will Artificial Intelligence Get in the Way of Achieving Gender Equality?" SSRN Electronic Journal .

Cedefop. 2017. Cedefop European public opinion survey on vocational education and training. LU: Publications Office.

Cedefop. 2025. "Cedefop Labour and Skills Shortage Index.".

Cortes, Guido Matias. 2016. "Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data." Journal of Labor Economics 34(1):63–105.

Dermont, Clau and David Weisstanner. 2020. "Automation and the future of the welfare state: basic income as a response to technological change?" Political Research Exchange 2(1):1757387.

Diessner, Sebastian, Niccolo Durazzi and David Hope. 2022. "Skill-Biased Liberalization: Germany's Transition to the Knowledge Economy." Politics & Society 50(1):117–155.

Durazzi, Niccolo. 2021. "Engineering the expansion of higher education: High skills, advanced manufacturing, and the knowledge economy." Regulation & Governance 17:121–141.

Emmenegger, Patrick and Giuliano Bonoli. 2022. How Collective Skill Formation Systems Adapt to a Knowledge Economy. In Collective Skill Formation in the Knowledge Economy, ed. Giuliano Bonoli and Patrick Emmenegger. Oxford: Oxford University Press pp. 334–349.

Emmenegger, Patrick, Scherwin M. Bajka and Cecilia Ivardi. 2023. "How Coordinated Capitalism Adapts to the Knowledge Economy: Different Upskilling Strategies in Germany and Switzerland." Swiss Political Science Review 29(4):355–378.

Esping-Andersen, Gøsta. 1990. The Three Worlds of Welfare Capitalism. Cambridge: Polity Press.

Estevez-Abe, Margarita, Torben Iversen and David Soskice. 2001. Social Protection and the Formation of Skills: A Reinterpretation of the Welfare State. In Varieties of Capitalism: The Institutional Foundations of Comparative Advantage, ed. Peter A Hall and David Soskice. Oxford: Oxford University Press.

European Commission. 2010. "The Bruges Communiqué on enhanced European Cooperation in Vocational Education and Training.".

European Commission. 2016. Developing skills for the labour market: The Riga conclusions: European cooperation in vocational education and training 2015-2020. LU: Publications Office of the European Union.

European Commission. 2024a. "The future of European competitiveness - Part A: A competitiveness strategy for Europe.".

European Commission. 2024b. "The future of European competitiveness - Part B: In-depth analysis and recommendations.".

Falk, Armin, Anke Becker, Thomas Dohmen, Benjamin Enke, David Huffman and Uwe Sunde. 2018. "Global Evidence on Economic Preferences." The Quarterly Journal of Economics 133(4):1645–1692.

Felten, Edward W., Manav Raj and Robert Seamans. 2023. "How will Language Modelers like ChatGPT Affect Occupations and Industries?" SSRN Electronic Journal .

Fernández-Macías, Enrique and John Hurley. 2017. "Routine-biased technical change and job polarization in Europe." Socio-Economic Review 15(3):563–585.

Freeman, Richard and Ronald Schettkat. 2001. "Skill compression, wage differentials, and employment: Germany vs the US." Oxford Economic Papers 3:582–603.

Gallego, Aina, Alexander Kuo, Dulce Manzano and José Fernández-Albertos. 2022. "Technological Risk and Policy Preferences." Comparative Political Studies 55(1):60–92.

Gallego, Aina and Thomas Kurer. 2022. "Automation, Digitalization, and Artificial Intelligence in the Workplace: Implications for Political Behavior." Annual Review of Political Science 25(1):463–484.

Gingrich, Jane and Alexander Kuo. 2022. Gender, Technological Risk, and Political Preferences. In Digitalization and the Welfare State, ed. Marius R Busemeyer, Achim Kemmerling, Paul Marx and Kees van Kersbergen. Oxford University Press pp. 157–173.

Giudici, Anja, Jane Gingrich, Tom Chevalier and Matthias Haslberger. 2023. "Center-Right Parties and Post-War Secondary Education." Comparative Politics 55(2):193–218.

Gmyrek, Pawel, Janine Berg and David Bescond. 2023. "Generative AI and Jobs: A global analysis of potential effects on job quantity and quality." ILO Working Paper 96.

Goldin, Claudia. 2014. "A grand gender convergence: Its last chapter." American Economic Review 104(4):1091–1119.

Hall, Peter A and David Soskice. 2001. An Introduction to Varieties of Capitalism. In Varieties of Capitalism: The Institutional Foundations of Comparative Advantage, ed. Peter A Hall and David Soskice. Oxford: Oxford University Press. arXiv: 1011.1669v3 ISSN: 0032-3292.

Hampf, Franziska and Ludger Woessmann. 2017. "Vocational vs. General Education and Employment over the Life Cycle: New Evidence from PIAAC." CESifo Economic Studies .

Hanushek, Eric A., Guido Schwerdt, Ludger Woessmann and Lei Zhang. 2017. "General Education, Vocational Education, and Labor-Market Outcomes over the Lifecycle." Journal of Human Resources 52(1):48–87.

Haslberger, Matthias. 2021. "Routine-biased technological change does not always lead to polarisation: Evidence from 10 OECD countries, 1995–2013." Research in Social Stratification and Mobility 74(4):100623.

Haslberger, Matthias. 2022. "Rethinking the measurement of occupational task content." The Economic and Labour Relations Review 33(1):178–199.

Hetschko, Clemens and Malte Preuss. 2020. "Income in jeopardy: How losing employment affects the willingness to take risks." Journal of Economic Psychology 79:102175.

Holm, Anders, Anders Hjorth-Trolle and Mads Meier Jæger. 2019. "Signals, Educational Decision-Making, and Inequality." European Sociological Review 35(4):447–460.

Hope, David and Angelo Martelli. 2019. "The Transition to the Knowledge Economy, Labor Market Institutions, and Income Inequality in Advanced Democracies." World Politics 71(2):236–288.

Hui, Xiang, Oren Reshef and Luofeng Zhou. 2024. "The Short-Term Effects of Generative Artificial Intelligence on Employment: Evidence from an Online Labor Market." Organization Science p. orsc.2023.18441.

Häusermann, Silja, Thomas Kurer and Hanna Schwander. 2015. "High-skilled outsiders? Labor market vulnerability, education and welfare state preferences." Socio-Economic Review 13(2):235–258.

Im, Zhen Jie, Nonna Mayer, Bruno Palier and Jan Rovny. 2019. "The "losers of automation": A reservoir of votes for the radical right?" Research & Politics 6(1):2053168018822395.

Iversen, Torben and David Soskice. 2019. Democracy and Prosperity : Reinventing Capitalism through a Turbulent Century. Princeton: Princeton University Press.

Jost, John T., Jack Glaser, Arie W. Kruglanski and Frank J. Sulloway. 2003. "Political conservatism as motivated social cognition." Psychological Bulletin 129(3):339–375.

Kollmeyer, Christopher. 2009. "Explaining deindustrialization: How affluence, productivity growth, and globalization diminish manufacturing employment." American Journal of Sociology 114(6):1644–1674.

Korber, Maïlys and Daniel Oesch. 2019. "Vocational versus general education: Employment and earnings over the life course in Switzerland." Advances in Life Course Research 40:1–13.

Kurer, Thomas. 2020. "The Declining Middle: Occupational Change, Social Status, and the Populist Right." Comparative Political Studies 53(10-11):1798–1835.

Kurer, Thomas and Briitta Van Staalduinen. 2022. "Disappointed Expectations: Downward Mobility and Electoral Change." American Political Science Review 116(4):1340–1356.

Kurer, Thomas and Silja Häusermann. 2022. Automation Risk, Social Policy Preferences, and Political Participation. In Digitalization and the Welfare State, ed. Marius R Busemeyer, Achim Kemmerling, Paul Marx and Kees van Kersbergen. Oxford University Press pp. 139–156.

Lee, Neil. 2024. Innovation for the Masses: How to Share the Benefits of the High-Tech Economy. Oakland: University of California Press.

Magistro, Beatrice, Peter Loewen, Bart Bonikowski, Sophie Borwein and Blake Lee-Whiting. 2024. "Attitudes toward automation and the demand for policies addressing job loss: the effects of information about trade-offs." Political Science Research and Methods pp. 1–16.

Meltzer, Allan H. and Scott F. Richard. 1981. "A Rational Theory of the Size of Government." Journal of Political Economy 89(5):914–927.

Moene, Karl Ove and Michael Wallerstein. 2001. "Inequality, Social Insurance, and Redistribution." American Political Science Review 95(4):859–874.

OECD. 2020. Increasing Adult Learning Participation: Learning from Successful Reforms. Getting Skills Right OECD.

OECD. 2021. Education at a Glance 2021: OECD Indicators. Education at a Glance OECD.

Oesch, Daniel and Giorgio Piccitto. 2019. "The Polarization Myth: Occupational Upgrading in Germany, Spain, Sweden, and the UK, 1992-2015." Work and Occupations 46(4):441–469.

Schoon, Ingrid and Samantha Parsons. 2002. "Teenage Aspirations for Future Careers and Occupational Outcomes." Journal of Vocational Behavior 60(2):262–288.

Schulz, Wiebke, Heike Solga and Reinhard Pollak. 2023. "Vocational education, tertiary education, and skill use across career stages." European Sociological Review .

Shavit, Yossi and Walter Müller. 2000. "Vocational Secondary Education." European Societies 2(1):29–50.

Streeck, Wolfgang. 1989. "Skills and the Limits of Neo-Liberalism: The Enterprise of the Future as a Place of Learning." Work, Employment and Society 3(1):89–104.

Streeck, Wolfgang. 2011. Skills and Politics: General and Specific. In The Political Economy of Collective Skill Formation, ed. Marius R. Busemeyer and Christine Trampusch. Oxford: Oxford University Press.

Thelen, Kathleen Ann. 2014. Varieties of liberalization and the new politics of social solidarity. New York, NY: Cambridge University Press.

Thewissen, Stefan and David Rueda. 2019. "Automation and the Welfare State: Technological Change as a Determinant of Redistribution Preferences." Comparative Political Studies 52(2):171–208.

Weisstanner, David. 2023. Technological Change and Labour Market Policy Preferences. In Handbook of Labour Market Policy in Advanced Democracies, ed. Daniel Clegg and Niccolo Durazzi. Cheltenham: Edward Elgar Publishing.

Wren, Anne. 2013. The political economy of the service transition. Oxford scholarship online Oxford: Oxford University Press. Publication Title: The political economy of the service transition.

Wren, Anne. 2021. Strategies for Growth and Employment Creation in a Services-Based Economy: Skill Formation, Equality, and the Welfare State. In Growth & Welfare in Advanced Capitalist Economies: How Have Growth Regimes Evolved?, ed. Anke Hassel and Bruno Palier. Oxford: Oxford University Press pp. 255–288.

Zaller, John and Stanley Feldman. 1992. "A Simple Theory of the Survey Response: Answering Questions versus Revealing Preferences." American Journal of Political Science 36(3):579.

Online Appendix

Contents

A Descriptives

Table A1: Descriptive Overview of the Key Variables

Variables	**Min**	**Max**	**Mean**	**Median**	**SD**	**N**
Educational Preferences	1	11	6.12	6	3.05	11451
Age	18	64	42.71	43	12.74	11451
Political Orientation	1	7	4.16	4	1.5	9834
Personal Income	1	18	5.98	5	3.68	10190
	Yes	**No**				
In Paid Employment	8400	3051				
Has Children	6626	4825				
Education VET	7946	3265				
Female	5805	5646				
High STR	2835	8616				
	N					
All occupations	11451					
Professional and technical	2548					
Higher administration	1151					
Clerical	2324					
Sales	792					
Service	1338					
Skilled worker	801					
Semi-skilled worker	336					
Unskilled worker	556					
Farm worker	60					
Other	1180					
Not working	365					

B Principal Component Analysis

As mentioned in Footnote 6, we performed a (rotated) Principal Component Analysis to check the robustness of our main STR measure (cf. Busemeyer and Tober, 2023). Therefore, we built a factor-based weighted index out of the following three measures: 1) *Skills* "I will lose my job because I am not good enough with new technology or because I will be replaced by someone with better technological skills.", 2) *Person* "My job will be replaced by a person providing a similar service on an internet platform" and 3) *Robot* "My job will be replaced by a robot, computer software, an algorithm, or artificial intelligence" (all three variables take values from "very unlikely" (1) to "very likely" (5), with a middle category "can't choose"). We applied rotated PCA because unlike regular PCA it simplifies interpretation by redistributing variance, making it clearer which variables contribute to which components, and because we are interested in interpretable factors rather than pure variance maximization. The PCA revealed that the three survey items have a high degree of internal consistency (Cronbach's alpha = 0.82) and that each component (RC1-3) explains a similar proportion of the total variance and strongly loads on one of the STR items (see Table B1).

Table B1: Factor Loadings and Variance Explained

Variables	RC2	RC1	RC3
Skills	0.934	0.250	0.257
Person	0.267	0.301	0.915
Robot	0.257	0.919	0.298
SS Loadings	1.009	0.998	0.993
Proportion Var	0.336	0.333	0.331
Cumulative Var	0.336	0.669	1.000

Using the different STR indicators in our main model leads to comparable results (see Table B2). All models have similar coefficient sizes and explained variance, indicating the robustness of our findings to different operationalizations of STR.

Table B2: Educational Preferences by different STR Measures

Model	(PCA)	(Skills)	(Person)	(Robot)
STR	0.1776***	0.1801***	0.1569***	0.1455***
	(0.0339)	(0.0318)	(0.0304)	(0.0340)
Age	-0.0067	-0.0053	-0.0051	-0.0048
	(0.0062)	(0.0060)	(0.0060)	(0.0061)
In Paid Employment	-0.1912*	-0.1537*	-0.1778*	-0.1838*
	(0.0809)	(0.0766)	(0.0755)	(0.0783)
Has Children	-0.3847***	-0.3729***	-0.3813***	-0.3882***
	(0.0849)	(0.0831)	(0.0834)	(0.0853)
Female	-0.1276**	-0.1115**	-0.1180*	-0.1156**
	(0.0469)	(0.0451)	(0.0488)	(0.0464)
Personal Income	-0.0129	-0.0123	-0.0131	-0.0140
	(0.0209)	(0.0207)	(0.0211)	(0.0214)
Right-wing	0.1679**	0.1640**	0.1686**	0.1691**
	(0.0495)	(0.0483)	(0.0480)	(0.0484)
VET Background	1.252***	1.252***	1.260***	1.255***
	(0.1252)	(0.1249)	(0.1247)	(0.1245)
Controls				
Occupation Dummies	Yes	Yes	Yes	Yes
Fit statistics				
Observations	8,843	8,843	8,843	8,843
R^2	0.12863	0.13090	0.12959	0.12920
Within R^2	0.11638	0.11868	0.11735	0.11695

Note: The model includes country fixed-effects. Standard errors are clustered by country. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

C Full Model Output

Table C1: Full Output to Table 1 (Including Occupation Dummies)

Models	(Full 4)	
STR	0.5390***	(0.0671)
Age	-0.0054	(0.0059)
In Paid Employment	-0.1917*	(0.0879)
Has Children	-0.3806***	(0.0831)
Female	-0.1226**	(0.0481)
Personal Income	-0.0111	(0.0203)
Right-wing	0.5907**	(0.2009)
VET Background	1.266***	(0.1327)
Occupations		
Higher admin.	0.7119***	(0.0856)
Clerical	0.9058***	(0.1174)
Sales	1.046***	(0.1401)
Service	1.305***	(0.1667)
Skilled worker	1.843***	(0.2217)
Semi-skilled worker	1.933***	(0.3577)
Unskilled worker	1.868***	(0.1944)
Farm worker	1.419**	(0.5265)
Other	1.040***	(0.1399)
Not working	0.5583	(0.3678)
Fit statistics		
Observations	8,843	
R^2	0.12990	
Within R^2	0.05408	

Note: The reference category for all occupations is *Professional and technical*. All models include country fixed-effects. Standard errors are clustered by country. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table C2: Full Output to Table 2

	Country						
Models	CH	DE	DK	EN	FR	PT	SE
STR	0.2393	0.6817***	0.4728**	0.3820**	0.7306***	0.4414**	0.6257***
	(0.1836)	(0.1845)	(0.1907)	(0.1833)	(0.1794)	(0.2064)	(0.1751)
Age	-0.0059	-0.0144*	0.0225**	-0.0180**	-0.0115**	0.0069	-0.0054
	(0.0069)	(0.0067)	(0.0070)	(0.0068)	(0.0070)	(0.0082)	(0.0063)
In Paid Employment	-0.0518	-0.1181	-0.2806	-0.0897	-0.2306	0.0644	-0.4629*
	(0.2107)	(0.2175)	(0.1952)	(0.2154)	(0.2243)	(0.2368)	(0.1878)
Has Children	0.0309	-0.5805**	-0.2427	-0.2136*	-0.4960***	-0.4546**	-0.3758**
	(0.1709)	(0.1657)	(0.1853)	(0.1706)	(0.1759)	(0.2105)	(0.1620)
Female	-0.0631	-0.2448	-0.2837	0.1012	-0.1640	0.0333	-0.0536
	(0.1719)	(0.1687)	(0.1696)	(0.1679)	(0.1637)	(0.1829)	(0.1544)
Personal Income	-0.0016	-0.0437	-0.0019	0.0755*	-0.0568***	-0.0395	-0.0991**
	(0.0186)	(0.0260)	(0.0254)	(0.0259)	(0.0293)	(0.0382)	(0.0302)
Right-wing	0.8560***	1.496***	0.4976**	1.213***	0.4912**	0.3257	-0.0054
	(0.2236)	(0.2587)	(0.1998)	(0.2155)	(0.1822)	(0.2149)	(0.1707)
VET Background	1.026***	1.678***	1.764***	1.284***	0.9052***	1.118***	0.9659***
	(0.1761)	(0.1959)	(0.1846)	(0.2087)	(0.1945)	(0.2151)	(0.1805)
Controls							
Occupation Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	1,210	1,411	1,182	1,165	1,165	1,365	1,345
R^2	0.11946	0.15723	0.20594	0.10573	0.12427	0.09440	0.19635
Adjusted R^2	0.10615	0.14633	0.19365	0.09168	0.11052	0.08229	0.18544

Note: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table C3: Full Output to Figure 3

Models	(1)	(2)	(3)	(4)
STR	0.6876***	0.3981***	0.3586*	-0.0281
	(0.1030)	(0.0605)	(0.1597)	(0.1335)
Female	-0.0332	-0.1271**	-0.1084*	-0.0695
	(0.0613)	(0.0482)	(0.0458)	(0.0495)
Age	-0.0051	-0.0054	-0.0052	-0.0058
	(0.0058)	(0.0059)	(0.0058)	(0.0061)
In Paid Employment	-0.1990*	-0.1860*	-0.2191*	-0.0657
	(0.0894)	(0.0859)	(0.1108)	(0.0721)
Has Children	-0.3823***	-0.3810***	-0.3607***	-0.3429***
	(0.0830)	(0.0838)	(0.0826)	(0.0735)
Right-wing	0.5925**	0.3965*	0.5698**	0.5511**
	(0.2008)	(0.1894)	(0.2012)	(0.2071)
Personal Income	-0.0107	-0.0119		0.0059
	(0.0203)	(0.0198)		(0.0162)
VET Background	1.268***	1.268***	1.277***	
	(0.1340)	(0.1321)	(0.1294)	
STR×Female	-0.3488**			
	(0.1233)			
STR×Right-wing		0.6654***		
		(0.1643)		
Income Middle			-0.0603	
			(0.1883)	
Income High			-0.1689	
			(0.2225)	
STR×Income Middle			0.0557	
			(0.1523)	
STR×Income High			0.8417**	
			(0.2596)	
Educational Attainment(GE Non-tertiary)				-0.7241**
				(0.2062)
Educational Attainment(GE Tertiary)				-1.969***
				(0.1765)
STR×Edu.Attainment(GE Non-tertiary)				0.3385
				(0.2100)
STR×Edu. Attainment(GE Tertiary)				0.9660***
				(0.1874)
Controls				
Occupation Dummies	Yes	Yes	Yes	Yes
Fit statistics				
Observations	8,843	8,843	8,843	8,843
R^2	0.13051	0.13142	0.13175	0.14820
Within R^2	0.05474	0.05573	0.05609	0.07398

Note: All models include country fixed-effects. Standard errors are clustered by country.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.