The Missing Link: Technological Change, Dual VET, and Social Policy Preferences

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May 23, 2024

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Abstract

How does technological change affect social policy preferences? We advance the lively debate surrounding this question by focusing on the moderating role of education and training institutions. In particular, we develop a theoretical argument that foregrounds the role of dual VET systems. While existing literature would lead us to expect that dual VET systems increase demand for compensatory social policy and magnify the effect of automation risk on such demand, we contend that the opposite holds true. We hypothesize that dual VET systems weaken demand for compensatory social policy and dampen the effect of automation risk on demand for compensatory social policy through three non-mutually exclusive mechanisms that we refer to as (i) skill certification; (ii) material self-interest; and (iii) workplace socialization. Analyzing cross-national individual data from ESS, fine-grained data on individual educational background from the German ESS module as well as national-level OECD data on education and training systems, we find strong evidence in favor of our argument. The paper does not only advance the debate on social policy preferences in the age of automation but it also sheds new light on an old debate, namely the relationship between skill specificity and social policy preferences.

Introduction

How does technological change affect social policy preferences? This question has been at the core of recent literature in political science (see Gallego and Kurer 2022 for a review). Several studies have investigated the question from the perspective of the degree to which different occupations are exposed to the risk of automation, premised on the overarching hypothesis that individuals in occupations at high risk of automation would see their demand for social protection increase, primarily in the form of compensatory social policies (Thewissen and Rueda, 2019; Kurer and Häusermann, 2022; Gallego et al., 2022; Dermont and Weisstanner, 2020; Sacchi, Guarascio and Vannutelli, 2020). Yet, empirical evidence in support of this hypothesis has been mixed and susceptible to choice of variables and research designs. As such, more recent contributions started to unpack this relationship further by embedding "micro preferences" in "macro contexts" (cf. Gingrich and Ansell 2012), looking for instance at how existing welfare state institutions shape the relationship between individual labor market risks and social policy preferences (e.g., Busemeyer and Tober 2022). This paper concurs with the latter line of inquiry. We shift, however, the focus from welfare states to skill formation systems (cf. Busemeyer and Trampusch 2011). We focus in particular on the role played by dual vocational education and training (VET) in moderating the relationship between technology-induced automation risks and demand for compensatory social policies.[1]

Our contribution is anchored in a major theoretical puzzle, namely the conspicuous absence of "skills" from the recent debate on the relationship between technological change and social policy preferences. Received wisdom from labor economics and comparative political economy (CPE) highlights, respectively, the crucial role of educational *levels* in determining workers' fortunes in the context of technological change (e.g. Autor, Levy and Murnane 2003; Goos, Manning and Salomons 2014) and the key role of different *types* of upper-secondary education systems - and in particular the extent to which they produce "specific" skills - in shaping demand for compensatory social policies (e.g. Iversen and Soskice 2001; Estevez-Abe, Iversen and Soskice 2001). Yet, skills and cross-national variation in education and training systems have been thus far surprisingly absent from the debate on individual preferences for social policy in the context of increasing automation risks, as also pointed out by recent review articles (Gallego and Kurer, 2022; Özkiziltan and Hassel, 2020).

This paper fills this gap both theoretically and empirically, by showing that skill formation systems constitute a missing link in the relationship between automation risk and demand for compensatory social policies. In doing so, we propose a constructive dialogue between three streams of literature that - while

[1] In dual VET systems, training takes place in both schools and firms, the resulting occupational skills are portable, certified, and standardized beyond the firm level, and firms and their intermediary associations participate in the financing and administration of training, which presupposes inter-firm cooperation (Busemeyer and Trampusch, 2011, 14-15).

sharing obvious affinities - have mostly developed separately from one another thus far: the recent political behavior literature on the connection between technological change and social policy preferences; the labor economics literature that has investigated the relationship between skills and technology; and the Varieties of Capitalism (VoC) literature that focused on the relationship between skill specificity and social policy preferences. Taken together, these streams of literature put skills, technology, and social policy preferences under the spotlight - but they only analyze them in pairs. We suggest instead that skills, technology, and social policy preferences should be placed under a unified theoretical framework.

More specifically, we argue that dual VET systems moderate the relationship between automation risk and demand for compensatory social policies. However, departing from the expectations of the influential VoC literature (cf. Hall and Soskice, 2001a), we develop a theoretical argument that predicts dual VET systems in the context of automation to make individuals less supportive of compensatory social policies. We outline three (non-mutually exclusive) mechanisms that underpin this relationship, which we refer to as (i) skill certification, (ii) material self-interest, and (iii) workplace socialization mechanisms. We argue that these three mechanisms set dual VET systems apart from other forms of education and training and they jointly explain why dual VET graduates are surprisingly critical of compensatory social policies in the context of automation. Empirically, we first demonstrate that dual VET systems attenuate the positive effect of automation risk on support for compensatory social policies (compared to respondents with comparable levels of educational achievement) and we then move on to assess the three mechanisms through which this is hypothesized to happen. Mobilizing cross-national survey data with country-level information on education and training systems as well as zooming into the case of Germany to tap into more fine-grained information on individuals' educational background, we find overall strong support for our argument across a range of statistical analyses and model specifications.

Our argument and findings have important implications for the existing literature. By exploring how the institutional make-up of education and training systems moderates demand for compensatory social policies in the age of automation, we advance the flourishing literature on the effects of technological change on demand for compensatory social policies. We also enrich the labor economics literature on the relationship between skills and technology by showing that *types* of education and training matter, alongside *levels* of skills. The article also casts new light on an old debate, namely the relationship between skills and social policy preferences. The paper is organized as follows. The next section reviews the literature and highlights how the missing theorization of the role of education and training systems in the debate on automation risk and social policy preferences is theoretically puzzling. Subsequently, we develop our theoretical argument, explaining in detail the three mechanisms through which we hypothesize dual VET weakens the effect of automation risk on demand for compensatory social policies. After discussing the data and the statistical approach, we present the results of our empirical analysis. A final section concludes.

Literature review: Skills as the missing link between automation risk and social policy preferences

Skills, technology-induced automation, and social policy preferences have featured prominently in the debate on the transition to the knowledge economy (cf. Thelen 2019, Hall 2020, Bonoli and Emmenegger 2022, Hassel and Palier 2021). However, these three elements have been largely analyzed in pairs. Much recent political behavior literature has focused on the relationship between automation risk and social policy preferences but has paid little attention to skills. In contrast, the literature in labor economics has been preoccupied with the relationship between skills and automation but has shown little interest in demands for compensatory social policies. Finally, the prominent VoC literature within CPE scholarship has highlighted the relationship between skills and social policy preferences. Yet, technology-induced automation has not featured prominently in this literature. As a result, few scholars have explored the three-pronged relationship between skills, automation risk, and social policy preferences, which we argue is a crucial, yet overlooked aspect of the transition to the knowledge economy. The remainder of this section first illustrates the main analyses that have tackled the relationship between skills, automation risk, and social policy preferences in the current literature before spelling out the missing link between the three of them.

The relationship between skills and technology-induced automation has been a central theme in recent labor economics. Theories of skill-biased and routine-biased technological change (SBTC and RBTC) highlight the asymmetric effects that technology has on labor markets. Crucial reasons behind such asymmetry lie in the different relationships between occupations at various skills and task levels, on the one hand, and technology on the other (see e.g. Autor, Levy and Murnane 2003, Goos, Manning and Salomons 2014). SBTC and RBTC theorize, respectively, a linear and U-shaped relationship between skills and technology. The former suggests that technology is complementary to jobs at high levels of skills, while it replaces jobs lower down the skill distribution. Such jobs are thus at the highest risk of automation. The latter concurs on the complementary nature of technology and high skill levels (that are typically associated with non-routine cognitive tasks) and expects an effect of substitution in the middle of the skills distribution (where jobs characterized by routine tasks tend to concentrate). However, RBTC posits that occupations often found at the bottom of the skill distribution and characterized by interpersonal tasks are relatively unaffected by technological change because they are not easily replaceable by robots, algorithms, or other technological advancements.

Despite different expectations concerning the bottom of the skill distribution, both approaches point *de facto* in the same direction as far as the middle and top of the skill distribution are concerned. Knowledge economies are expected to "thrive" on high skill levels that fuel cognitively and analytically demanding occupations and that are complementary to technology. In contrast, they paint a rather bleak picture for those jobs in the middle of the skill distribution. The general take-home message from the labor economics literature that we highlight here is that skill levels matter in determining what jobs in the labor market face the highest automation risk. We shall return to this point later.

The relationship between technological change and social policy has been another hotly debated topic in the last few years, mostly among political scientists. A rapidly growing scholarship in political behavior has been interested in theorizing how (perceived and/or real) exposure to the risk of automation affects individual demand for social protection. Thus far, results have been somewhat mixed.

Based on perceived automation risk, Kurer and Häusermann (2022) find that at-risk individuals demand traditional passive insurance against the risk of job loss. Similarly, based on routine task intensity (RTI) at the occupational level, Thewissen and Rueda (2019) observe that individuals in routine occupations demand more redistribution to compensate for their greater risk of losing their jobs due to automation. Mobilizing experimental evidence, Gallego et al. (2022), however, do not find strong support for the compensation hypothesis in the case of Spain. Rather than demanding more public spending on unemployment benefits, they find that workers at risk of automation would prefer policies that "slow down" the pace of technological change. Golin and Rauh (2023), on the other hand, document an association in the US between fear of automation and a range of outcomes such as intention to join a union and preferences for government handouts and higher taxation. Moreover, they show experimentally that information about occupation-specific job loss probabilities has a causal effect on these outcomes, driven mainly by respondents who learn that they underestimated their automation risk. Focusing primarily on the case of universal basic income (UBI), Dermont and Weisstanner (2020) find that higher RTI does not trigger greater support for UBI, while Sacchi, Guarascio and Vannutelli (2020) find that for the case of Italy some groups display stronger support for UBI at high levels of RTI.

Busemeyer and Tober (2022) focus on the interaction between the risk of automation, demand for social protection, and existing welfare state institutions. They find that both the perception of technology-related employment risks and RTI increase demand for generous unemployment benefits, although the relationship is moderated by the generosity of the already existing compensation schemes. Most notably, they find that welfare state institutions make a difference in shaping social policy preferences only for individuals at low perceived risk of automation, while those at high risk privilege compensatory social policies regardless of existing welfare institutions. Finally, they find little relationship between automation risk and support for more investment-oriented labor market policies (see also Kurer and Häusermann 2022; Busemeyer and Tober 2022).

Taken together, this fast-growing political behavior literature suggests a complex relationship between automation risk and demand for compensatory social policies. While the "risk increases demand for social protection" framework is appealing for its parsimoniousness, the extent to which it accurately captures the determinants of preferences for compensatory social policies in the age of automation seems to be susceptible to data sources, specifications, and the exact policy manifestations that such preferences take.

Given the degree of ambiguity in findings thus far, we must conclude that there are missing links in the theorization of the relationship between automation risk and social policy preferences. From our vantage point, and especially given the importance of the skill-technology relationship as established by labor economists, an issue that stands out in the recent political science literature is the limited theoretical and empirical role assigned to education and training systems as potentially influencing the relationship between automation risk and demand for compensatory social policies. These studies typically treat education as a control variable (expressed in years of education, thereby ignoring type of education) or they use an occupational-based (rather than education-based) measures of skill specificity as an alternative specification. But the role of education and skills systems is not systematically embedded in the theoretical apparatus underpinning this research (Thewissen and Rueda, 2019). Reviewing the state-of-the-art on the impact of automation on the labor market, Özkiziltan and Hassel (2020, 23) conclude that "a new research agenda should incorporate institutional factors, such as workers' voice and the role of existing training regimes (VET), with the differentiated effects on specific socio-economic groups and the best practices for workers to cope with labor market restructuring." Similarly, reviewing the implications of technological change in the workplace for political behavior, Gallego and Kurer (2022, 479) urge that "[d]ifferences in education and, particularly, vocational education and training regimes should have a more prominent role in this research agenda."

Approaching this debate from the perspective of social policy preference formation, the lack of explicit theorization of education and skill formation systems is all the more surprising given that the micro-foundations of one of the most prominent research agendas in contemporary CPE – the Varieties of Capitalism (VoC) framework – builds precisely on the relationship between (types of) skills and demand for social protection (Estevez-Abe, Iversen and Soskice, 2001; Iversen and Soskice, 2001). Here the central tenet is again formulated along the lines of a "risk increases demand for social protection" relationship where, however, risk is not automation but rather skill specificity. The argument is famously formalized in Iversen and Soskice (2001) and holds in essence that there is a direct relationship between investment in specific skills and the risk that this investment carries due to the lower probability for specific-skilled individuals relative to individuals holding general skills to find an equally remunerating job in case of unemployment. Therefore, individuals who were to invest in highly specific skills - typically provided according to this view by dual VET system(Estevez-Abe, Iversen and Soskice, 2001; Iversen and Soskice, 2001; Iversen and Stephens, 2008) - would also demand some form of insurance against this risk, most notably unemployment and employment protection (for a critical discussion, see Busemeyer 2009 and Emmenegger 2009).

This brief review of the literature presents us with a stark theoretical puzzle: (i) if type of skills (not just - or not even primarily - levels of education) is an important predictor of individual social policy preferences; (ii) if automation risk is an important factor shaping such preferences; and (iii) if automation risk is moderated by skill types, why do we lack systematic theorization and empirical scrutiny of the role that different types of education and skill systems play in shaping preferences for social protection in the age of automation? One plausible answer that one might put forward is simply that "we do not need one." This is because education and skill systems might be hypothesized - if all that has been discussed thus far holds true - as simply pushing in the same direction as automation. We refer to this as the *doubling-down hypothesis*, which would roughly run as follows: If technology-induced automation wipes out jobs in the middle of the skill distribution according to the prominent "hollowing out" thesis,[2] and if these jobs were already underpinned by "risky" investments in specific skills even before these new technologies had been adopted at large, then we must conclude that automation risk and skill specificity reinforce each other and jointly contribute to increasing demand for insurance against these risks via increased social protection in the age of automation.

Is that it, then? Not so soon. We argue that there are reasons to advance an alternative argument around the role of education and training systems - and in particular on the role of dual VET systems - in moderating the relationship between automation risk and preferences for compensatory social policies in the opposite direction compared to the doubling-down hypothesis that received wisdom would steer us towards. We submit, in other words, that dual VET systems dampen - rather than magnify - support for compensatory social policies in the age of automation. Formulating this argument requires reconceptualizing dual VET systems by going beyond the specificity of the skills that they create and by focusing on other crucial dimensions of dual VET systems.

Theory: Reconceptualizing skills in the age of automation

We identify three crucial characteristics of dual VET systems that allow us to posit (i) that they matter in moderating the relationship between automation risk and social policy preferences; and (ii) that they

[2] Although this narrative is not undisputed, especially in European countries, see for example Haslberger (2021b), Oesch and Piccitto (2019), and Fernández-Macías and Hurley (2017).

do so by dampening – not magnifying - support for compensatory social policies. We refer to this as the *dual advantage hypothesis*, which works through three non-mutually exclusive mechanisms. Firstly, dual VET has a unique system that authoritatively certifies the skills acquired. Secondly, dual VET facilitates school-to-work transitions and allows individuals to command above average salaries at the beginning of their professional careers. Thirdly, dual VET socializes young people mostly at the workplace rather than in schools, thus instilling comparatively workfarist attitudes. We discuss each of these three features in the remainder of this section, highlighting how they allow us to hypothesize three (non-mutually exclusive) mechanisms that can theoretically account for dual VET moderating the relationship between technological change and social policy preferences by dampening support for social protection in the age of automation.

It is important to note at the outset that the three mechanisms that we outline in the remainder of this section are expected to be just as relevant in the context of technological change as they would be in the absence of it. That is, an important corollary of our argument is that the three mechanisms that we identify imply that dual VET systems make their graduates less supportive of compensatory social policy in general *and* they dampen the demand for compensatory social policy in the face of automation risk. By implication, dual VET can be thought of as both a predictor of social policy preferences and a moderator in the relationship between automation risk and demand for compensatory social policy. Indeed, in the empirical analysis, we examine both the direct effect of dual VET and its role as moderator. However, given our ambition to advance the debate on technological change and social policy preferences, we emphasise relatively more the moderating function of dual VET, as we seek to draw attention to and make theoretical sense of the hitherto neglected triangular relationship between skills, technological change, and social policy preferences. Moreover, focusing on the moderating role of dual VET is warranted on research design grounds. As discussed in outlining the "doubling down" hypothesis in the previous section, received wisdom from VoC associates the skills produced by dual VET systems with (industrial) occupations in the middle of the skill distribution (Culpepper and Thelen, 2008) – which are in turn most amenable to automation according to the labor economics literature (Autor, Levy and Murnane, 2003; Acemoglu and Autor, 2011). Taken together, these prominent theories imply therefore that dual VET should make its graduates respond to technological change by *increasing* demand for compensatory social policy. Given that our argument predicts that the opposite holds true, focusing on the moderating role of dual VET in the context of technological change allows us to effectively stack the cards against our own argument and test it in a "least likely" setting.

Skill certification mechanism

We first develop a skill certification mechanism building on the uniqueness of dual VET's authoritative certification of skills, inspired at a theoretical level by Streeck's (2011) encompassing critique of Iversen and Soskice's (2001) "asset theory of social policy preferences." Streeck's critique is wide-ranging. For our purposes, we note two aspects. Firstly, skills produced by dual VET systems are in fact "broader" than asset theory would predict, as they feature a consolidated curriculum in the first two years of an apprenticeship for "adjacent occupations" as well as an "academic part of vocational training" that "was upgraded to a point where a growing segment of youth were no longer able to meet the ever higher academic demands" (Streeck 2011, 23). In most dual VET systems, general skills are a key part of the mandatory training content (e.g., literacy and numeracy). For this reason, Schulz, Solga and Pollak (2023, 15) argue that "skill-use differentials between vocationally and tertiary-educated workers are rather small overall" and that these "observed differences in skill use remain rather stable across career stages." Similarly, Adda and Dustmann (2023, 458) demonstrate that vocationally-educated workers accumulate experience in cognitive-abstract tasks throughout their labor market careers, which helps sustain wage growth later in the life cycle.

Secondly, these (broad rather than "just specific") skills are authoritatively certified by governments, business, and unions consisting of a "system of occupations and occupational training profiles that, through publicly supervised examination and certification of acquired skills, allowed for, in principle, unlimited mobility of workers in nationwide sectoral labor markets" (Streeck 2011, 5; see also Busemeyer 2009). The equation of dual VET with few general skills, a focus on routine manual tasks, and the absence of mobility between occupations, inspired by classic formulations of human capital theory and promulgated by the Varieties of Capitalism literature, thus reflects an outdated conception of dual VET (e.g., Gathmann and Schönberg, 2010; Adda and Dustmann, 2023; Schulz, Solga and Pollak, 2023; Mayer, Grunow and Nitsche, 2010; Streeck, 2011; Emmenegger and Haslberger, 2023).

These features become ever more salient in the transition to the knowledge economy. Given employers' central in the definition of training content and the provision of training, dual VET systems are particularly responsive to labor market needs and constantly adapted to employers' demands, which, in the transition to the knowledge economy, means incorporating in the curricula the skills needed to cope with technological change (Emmenegger and Bonoli, 2022; Weiss, 2015; Emmenegger and Haslberger, 2023). For this reason, VET educated workers have at their disposal portable - because broad and authoritatively certified - skills that are perceived as being developed in close correspondence with labor market needs and with firm employers' buy-in. Therefore, these skills might be perceived as cushioning rather than amplifying the "threat" of automation, thereby lowering their support for compensatory policies by means of social protection.

Material self-interest mechanism

We now turn to the second key feature of dual VET systems, i.e. their ability to promote smooth school-to-work transitions and high salaries at the beginning of workers' careers. We refer to this as the material self-interest mechanism, which builds at a theoretical level on recent work in political science (Gelepithis and Giani, 2022; Bullock, 2021; Marshall, 2016). The core channel through which education shapes social policy preferences according to this body of work is via the wages that workers command at different educational levels. Here the typical finding is that higher levels of education attract higher wages, which in turn decrease demand for compensatory social policies. This has been found to be the case for higher education, which Gelepithis and Giani (2022, 45) argue "to foster norms of cultural inclusion, while simultaneously eroding norms of economic solidarity." Similar findings apply to studies analyzing reforms increasing compulsory schooling age in Great Britain and the USA. Such reforms turned individuals who stayed longer in secondary school against generous compensatory social policies by virtue of the higher wages accrued to them as a result of additional years of schooling (Bullock, 2021; Marshall, 2016).

This line of reasoning is highly relevant for dual VET from a life-course perspective. It is a well-established fact that dual VET systems are (and continue to be) associated with low youth unemployment rates (e.g., Breen, 2005; Tomić, 2018; Zimmermann et al., 2013). Furthermore, dual VET-trained individuals have higher relative incomes at the beginning of their career (compared to graduates of other educational tracks within their age cohort) due to the greater proximity of their qualifications to labor market needs, even as this advantage gradually decreases and flattens out over time (e.g., Hanushek et al., 2017; Korber and Oesch, 2019; Chuan and Ibsen, 2022; Schulz, Solga and Pollak, 2023). It has also been noted that dual VET systems have kept adapting to the needs of the knowledge economy (Bonoli and Emmenegger, 2022).

Following this line of reasoning, we hypothesize that dual VET dampens demand for compensatory social protection from individuals *at the beginning* of their careers by granting them an economically advantageous position (compared to graduates of other educational pathways) in the form of higher employment rates and higher relative incomes. However, we expect this effect to disappear over time as the dual VET wage premium flattens.[3] As this relative income advantage disappears over time, we expect the dampening effect of dual VET background on demand for compensatory social policies to weaken over time as well (compared to graduates of other educational pathways in the same age cohort).

[3]Young workers have generally been more exposed to the newest technologies, which might make them less concerned about automation. However, VET trained individuals benefit from the additional advantage of smooth school-to-work transitions and comparatively high salaries early in their labor market careers.

Workplace socialization mechanism

Lastly, the workplace socialization mechanism focuses on the role of the education and workplace environment in shaping individuals' worldviews (Sears, 1975). As argued by Kitschelt and Rehm (2014, 1670), adults spend most of their waking time doing their job. Should we not expect these long hours spent at the workplace to influence their social policy preferences? The same argument can be made about the period before people become economically active. In these years, individuals spend most of their time in education and training. Socialization theory argues that institutions such as education systems or workplaces serve as "inferential spaces" that shape how individuals come to think about cause-effect relationships and the desirability of certain policies (Mijs, 2018). Importantly, experiences made in secondary schooling and first years in employment have been found to be particularly influential because attitudes and beliefs developed at a relatively young age - the so-called "impressionable years" (Schuman and Scott, 1989) - tend to have lasting effects on policy preferences (Emmenegger, Marx and Schraff, 2017; Jennings and Niemi, 1974; Sears and Funk, 1999). The different experiences individuals made during their training years and the first years of employment are thus likely to shape their social policy preferences.

Again, there are strong theoretical reasons to expect dual VET to be different compared to any other form of education and training from a workplace socialization standpoint. Most notably, dual VET students conduct a significant proportion - often a majority - of their training within a company, not in a school. And as famously put by Van Maanen and Schein (1979, 209), "[w]ork organizations offer a person far more than merely a job." According to the OECD definition, combined school- and work-based programmes are considered examples of dual VET when "less than 75 percent of the curriculum is presented in the school environment or through distance education, [whereas] programs that are more than 90 percent work-based are excluded" (OECD, 2001, 401). Put differently, following the OECD definition of dual VET systems, which we also follow in this analysis, dual VET students spend between 25% and 90% of their time in a company. Most work-based training is offered by small- and medium-sized companies.[4] Moreover, in dual VET systems, firms and their intermediary associations are typically involved in the definition of training content, which, we argue, provides another important lever to influence the socialization of dual VET students (Busemeyer and Trampusch, 2011, 14-15).

We hypothesize in particular that technology-induced automation can be connoted negatively – as job destruction – or positively - as opening up new employment and profit opportunities. Similarly, we hypothesize that compensatory social policies can be framed positively - as necessary insurance against automation

[4]We do not know any specifics about the time spent at the training firms and the training firms themselves. However, all VET trainees spend at least a *significant* amount of time at the company. Moreover, in the analysis, we explore the effect of dual VET on workplace socialization effect by gender. Due to gender segregation in the labor market, women (men) are more likely to receive training from public (private) sector companies. However, the inclusion of gender does not affect our findings.

risks - or negatively - as a burden on companies facing technological challenges. In both cases, we expect the latter to be the framing that young adults are more likely to encounter in dual VET systems relative to entirely school-based education systems, because such framing is a correlate of managerial and business discourse and because firms play a key role in training provision and content definition in dual VET systems. If this is the dominant discourse, then dual VET trainees are expected to develop more workfarist attitude, where excessive government intervention (e.g. through unemployment protection) in the face of technological change is considered harmful disruption to the "natural" course of events. Recent research indeed lends strong support to the hypothesized relationship between vocational training and workfarist attitudes. For instance, Busemeyer and Guillaud (2023) show that individuals with no higher education background privilege a view of education as providing "marketable skills" (as opposed to "knowledge," which is emphasized by graduates of higher education institutions), which comes in turn with a strong preference for workfare policies and against compensatory social spending.[5]

Table 1 summarizes our expectations and the observable implications. The conventional perspective holds that the risk deriving from skill specificity (cf. Iversen and Soskice, 2001) adds on to the risk of automation (*doubling down hypothesis*). For this reason, a dual VET background should be associated with higher levels of support for compensatory social policies. For the same reason, a dual VET background should magnify the effect of automation risk on demand for compensatory social policies. In contrast to this conventional perspective, the *dual advantage hypothesis* holds that a dual VET background decreases support for compensatory social policies in the age of automation. It does so through three non-mutually exclusive mechanisms: skill certification, material self-interest, and workplace socialization. For these reasons, a dual VET background also dampens - not magnifies - the effect of automation risk on demand for compensatory social policies. In the next section, we will discuss the research design and data that we use to put these hypotheses to an empirical test.

Data and Methods

Data

Our main data source is the 2016 wave of the European Social Survey (ESS). The ESS is a biennial survey of demographic and attitudinal characteristics of European populations, with changing special modules. The 2016 wave includes a battery of questions about welfare attitudes, from which our dependent variable, unemployment support, is taken. The question captures support for passive labor market policies and reads

[5] In companies, VET trainees might also get in contact with unions or work councils. However, companies are responsible for training provision and content definition, which suggests that their framing is more likely to prevail.

Table 1: Hypotheses and Mechanisms

Hypotheses	Hypothesized mechanism	Observable implication
Doubling down	Skill specificity mechanism: Risk deriving from skill specificity adds on to the risk of automation	VET background leads to higher demand for compensatory social policies and magnifies the effect of automation risk on demand for compensatory social policies
Dual advantage	Three mechanisms:	VET background leads to lower demand for compensatory social policies and dampens the effect of automation risk on demand for compensatory social policies
	(1) Skill certification mechanism: Authoritative certification makes dual VET widely portable, increasing labor market security of individuals holding such certifications	Dual VET background leads to lower concerns about ability to find new employment
	(2) Material self-interest mechanism: Dual VET facilitates school-to-work transition and allows workers to command above-average salaries early on in their careers	The negative effect of dual VET background on demand for compensatory social policies becomes smaller as respondents grow older
	(3) Workplace socialization mechanism: Dual VET socializes individuals in a profit-seeking logic, portraying compensatory social policies as inhibiting economic performance	Dual VET background leads to more workfarist attitudes

as follows:

- "Is it the government's responsibility to ensure a reasonable standard of living for the unemployed?" (0 = not government's responsibility at all; 10 = entirely government's responsibility)

Scholars interested in the political responses to automation risk have looked at a variety of outcomes, including support for activation policies, early retirement schemes, or a universal basic income. We focus on unemployment support because an increase in demand for compensatory policies, and especially for unemployment support, has been the closest to a consistent finding in this literature (Kurer and Häusermann, 2022; Busemeyer et al., 2022; Gallego and Kurer, 2022). It is also conceptually most closely related to unemployment risk, as unemployment benefits are likely the most immediate concern of people who lose their job due to automation. Thus, we expect to find a negative effect of dual VET on demand for unemployment support, and a moderating effect of dual VET on the relationship between automation risk and demand for unemployment support, but not necessarily on other social policy fields.[6]

Our main explanatory variables span the individual and country levels. To capture people's highest level of education, we create a 3-category variable distinguishing between general secondary education (henceforth simply "general secondary"), vocational education up to short-cycle tertiary education at vocational colleges ("VET degree"), and a bachelor degree or higher at higher education institutions ("general tertiary").[7] The precise coding procedure is described in Appendix A. Unfortunately, the cross-country ESS data do not allow us to distinguish between school-based and dual (school- and work-based) VET. According to our theoretical argument, it is mainly in the latter where the skill certification, material self-interest, and workplace socialization effects should be visible. To alleviate this limitation of the ESS data, we have collected country-level information on the shares of upper-secondary students who were enrolled in work-based/all VET programs in 2010 and 2016 (from OECD.stat and country-specific sources, see Emmenegger and Haslberger 2023). If the VET effect is indeed primarily driven by graduates of dual programs, this carries several implications: First, we should find a more pronounced effect of the dual VET share than of the overall VET share. Second, there should be an interaction between the dual VET share and individual VET status. And finally, we expect an interaction between the dual VET share and automation risk. We test all three implications to substantiate our argument.

To further strengthen our case, we conduct separate analyses on the German ESS sample, which contains fine-grained data on the type of people's vocational education. We construct an approximate mapping onto

[6] Below, we discuss some evidence that the relationship is particular to demand for unemployment support.

[7] Some countries have a binary or diversified system of higher education with different tertiary education institutions providing more selective academic or research-oriented programs on the one hand and less selective vocational or application-oriented programs on the other (such as the distinction between universities and universities of applied science in Germany) (European Social Survey, 2016). We include all degrees at bachelor level or higher in the "general tertiary" category. However, the results are unaffected if we code lower tier bachelor and master degrees as VET (see Table D2).

dual and school-based VET at the individual level, which allows us to test our hypothesis in the illustrative case of Germany (see Appendix A for details). With this alternative indicator of dual VET status at the individual level, we are able to show that dual VET is indeed distinct from school-based VET in its effect on social policy preferences.

Our other independent variable is objective automation risk. This reflects the argument, common in the literature, that workers in more routine-intensive occupations are at greater risk of unemployment and hence should demand more generous unemployment benefits. To operationalize automation risk, we calculate routine task intensity (RTI) scores using 2-digit ISCO-08 task content data from the European Working Conditions Survey (EWCS) following the procedure of Haslberger (2021a).[8] This measure is similar to the widely used RTI scores of Goos, Manning and Salomons (2014) but contains important improvements such as a better matching of concepts and empirical measures and the use of up-to-date European task data. Thus, for an analysis of ESS data it is superior to the Goos, Manning and Salomons (2014) measures. However, since they are widely used in the literature, we replicate our analyses using the Goos, Manning and Salomons (2014) measures.[9]

Our main coefficient of interest is the interaction between VET and automation risk, but we also explore the direct effect of VET on demand for compensatory social policies. We argue that individuals who have received a vocational education – especially if it involved firm-based training – show a muted increase in their demand for social protection in response to automation risk, reflecting three possible mechanisms: skill certification, material self-interest, and workplace socialization. Therefore, we expect the interaction coefficient to be negative. The main effect of VET status or dual VET share should also be negative, while the coefficient on RTI should be positive.

As control variables, we include a number of individual-level characteristics (age, age squared, gender, household income decile, union membership, left-right placement, subjective unemployment risk), and the average unemployment rate in the survey year and the two preceding years (from ILOSTAT) to account for national labor market performance.

Mechanisms

In trying to parse out the mechanisms through which dual VET attenuates the relationship between automation risk and demand for passive labor market policies, we moreover look at the following variables:

- Skill certification mechanism: Authoritative certification makes dual VET skills portable beyond firms

[8] In the 2010 wave of the ESS, occupations are still classified according to ISCO-88, hence we calculate ISCO-88 RTI scores for the analyses of the skill certification hypothesis.

[9] Using these measures requires translating the ISCO-08 codes back into ISCO-88. We do so using Ben Jann's *iscogen* package in Stata.

and sectors, increasing labor market security of individuals holding such certifications. For the analysis of the certification hypothesis, we rely on the 2010 wave of the ESS, as the relevant items were not included in the 2016 wave.[10]

  - Difficulty of finding a new job: “How difficult or easy would it be for you to get a similar or better job with another employer if you had to leave your current job?” (0 = extremely difficult; 10 = extremely easy)
  - Value of skills to other employers: “Do you know of any other employers who would have good use for what you have learned in your present job?” (0 = “I have not learned anything in my present job”/“No, none”; 1 = “Yes, one or two”/“Yes, some”/“Yes, many”)

- Material self-interest mechanism: Dual VET fosters anti-compensatory preferences by allowing workers to command above average salaries early on in their careers.

  - Split samples by age cohort

- Workplace socialization mechanism: Dual VET socializes trainees in a profit-seeking logic, where state intervention is seen as inhibiting economic performance.

  - Mediation analysis using the ESS 8 variable on “workfarist” attitudes: “To what extent [do] you agree or disagree that social benefits and services in [country] place too great a strain on the economy?” (1 = “disagree strongly”; 5 = “agree strongly”)

Analytical Strategy

We estimate multilevel models combining individual, occupation, and country level data. Our models include a random country intercept. Observations are weighted using the analytical survey weights provided by the ESS. The model thus takes the following form:

$$y_{ioc} = \alpha_c + \beta_1 VET_{ioc} \times RTI_{oc} + \beta_2 VET_{ioc} + \beta_3 RTI_{oc} + \hat{\beta}_4 X_{ioc} + \hat{\beta}_5 X_c + e_{ioc} \tag{1}$$

α_c is a random country intercept, $\beta_1 VET_{ioc}$ is the indicator of VET status which is interacted with $\beta_2 RTI_{oc}$, the occupation-level measure of automation risk. $\hat{\beta}_3 X_{ioc}$ is a vector of individual-level control variables and $\hat{\beta}_4 X_c$ a vector of country-level covariates, and finally e_{ioc} is the residual error term. In some

[10] Ideally, we would perform a mediation analysis like for the workplace socialization mechanism below. However, the 2010 ESS wave does not include the unemployment support question. Hence, we can only test the effect of VET background on the skill portability questions.

specifications we use variations of this model, for example by including different interaction structures. In the analysis for Germany, we estimate linear probability models.

By including subjective unemployment risk in our vector of control variables, we set a high bar for the models to find a significant effect of RTI, which after all also predicts subjective unemployment risk.[11] Thus, our estimate captures only the direct effect of objective automation risk, not the portion that is mediated by subjective unemployment risk. The substantive results are the same when we opt for a less conservative specification and exclude subjective unemployment risk.

After establishing that dual VET indeed dampens the link between automation risk and support for compensatory social policies, we study the mechanisms behind this relationship. We use the same basic model as above, with the dependent variables listed above in case of the skill certification and workplace socialization mechanisms, and an additional interaction and split samples in case of the material self-interest mechanism.

Results

VET attenuates the effect of automation risk, driven by dual VET

In this section, we present models which show that a VET background is associated with lower support for generous unemployment benefits and attenuates the positive effect of automation risk on support for unemployment benefits. Since this finding pertains to all forms of VET (school-based and dual), but we argue that the relationship is driven by dual VET in particular, we include additional analyses that provide evidence to this effect. For clarity, we make explicit when we refer to dual VET (combining school-based and firm-based training); where we refer to VET without further qualification, the data include school-based and dual VET.

Additive models

Before investigating whether a VET background moderates the relationship between RTI and passive labor market policy preferences, we show the results from additive models in Table D1. We find that people with a vocational education are less likely to consider it a government responsibility to ensure a decent living standard for the unemployed than both higher educated respondents (general tertiary) and respondents with a general secondary (usually meaning lower) education. This confirms the first building block of our argument. RTI, on the other hand, is positively associated with attitudes towards unemployment support. It

[11]The subjective unemployment risk indicator is not available in ESS 5, which we use to test the skill certification hypothesis.

is highly statistically significant in models 1 and 3, but the coefficient is smaller and less precisely estimated when we control for subjective unemployment risk in models 2 and 4. Subjective unemployment risk, in turn, is highly significant in those models. This echoes the mixed findings of previous research, which has investigated the impact of automation risk on social policy demand with similar setups (Gallego and Kurer, 2022).[12] The other variables in the model behave as expected, and also do so in the subsequent analyses. Female, older respondents with higher subjective unemployment risk, as well as union members, exhibit higher approval of unemployment support, whereas individuals with higher household income and right-leaning political views are opposed. The country-level variables in models 3 and 4, including the dual VET share, are not statistically significant. To account for possible heterogeneous effects of dual training in the public and private sectors, we leverage the fact that females tend to be strongly overrepresented in the public sector, while males are overrepresented in the private sector (REFERENCE). Interacting educational attainment and sex, we find no evidence that the sex of VET-educated individuals affects their support for UE benefits (see Figure D1).

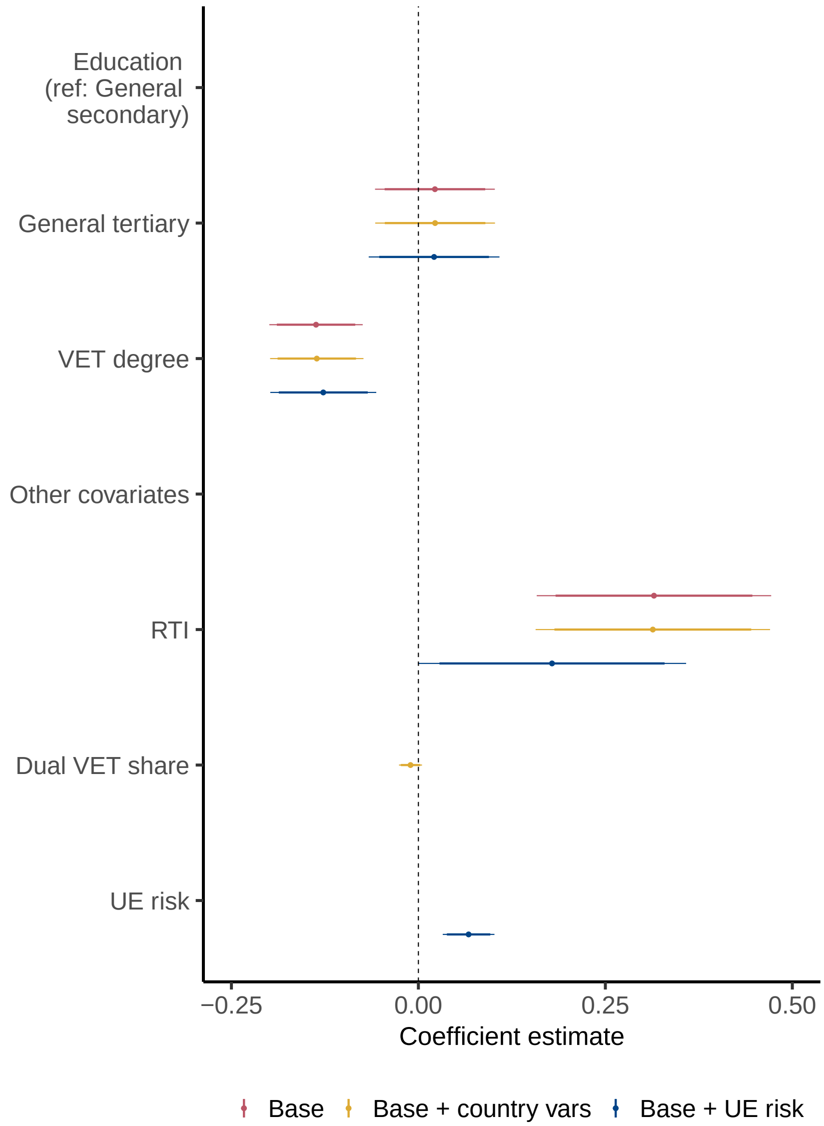
Since individuals with a vocational education often work in occupations that are considered at relatively high risk of automation, the negative effect of having a VET degree suggests that VET systems may moderate the relationship between technological risk and support for compensatory social policies. So far we have only considered automation risk (operationalized as routine task intensity) in an additive model, with mixed findings: RTI is positively associated with support for unemployment benefits, but the relationship is not consistently statistically significant. This is in line with the previous literature which has found positive or null effects of automation risk on preferences for passive labor market policies (Gallego et al., 2022; Kurer and Häusermann, 2022; Busemeyer and Tober, 2022). This research has not theorized or studied the impact that skill formation systems may have on this relationship. However, in a recent paper, Weisstanner (2023) shows that the effect of RTI on policy preferences is stronger in countries with higher enrollment in dual VET programs (although overall enrollment in VET has no effect). Hence, we hypothesized that the effect of RTI on demand for compensatory social policies is dampened in respondents who have a vocational education, that is, a negative interaction between VET status and RTI. Furthermore, we expect this relationship to be driven by countries with a high dual VET share.

VET attenuates the effect of automation risk, driven by dual VET

To test our main hypothesis that (dual) VET moderates the relationship between automation risk and support for unemployment benefits, we estimate a set of interaction models in Table D2. Model 1 indicates

[12] It should also be noted that subjective unemployment risk is conceptually very similar to the subjective automation risk indicators used in research such as Gallego and Kurer (2022).

Figure 1: The VET-educated are less positive towards unemployment support



Note: The figure shows estimates from multilevel model including a random country intercept and ESS survey weights, with 90% and 95% confidence intervals (thick and thin lines). The base model controls for sex, age, income decile, union membership, and political orientation. The model with country variables additionally controls for the unemployment rate. N = 28,407 (Base model and country model) and 22,901 (UE risk model). For the full set of results, see Appendix B.

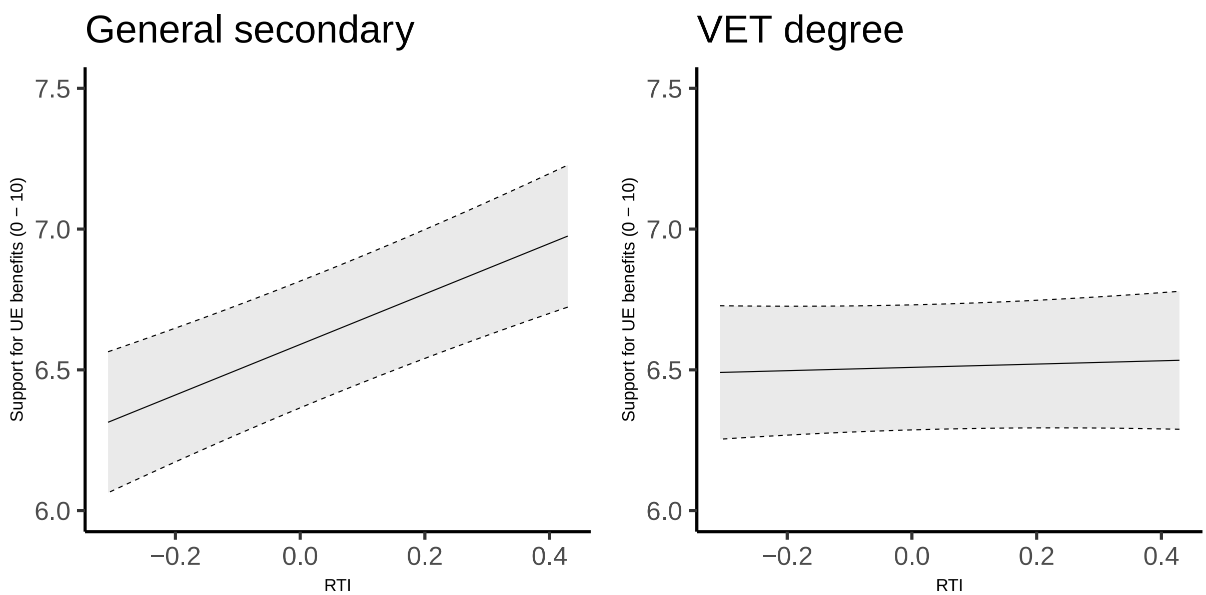
that a VET background moderates the relationship, and model 2 suggests that dual VET is indeed the driving force behind this finding. VET is negatively and RTI positively associated with demand for unemployment support in the reference group (general secondary education). In model 1, we find a highly significant negative interaction coefficient between VET and RTI, according to which having a VET degree all but cancels out the positive effect of RTI on demand for unemployment benefits among VET degree holders. The dual VET share (as a share of all upper secondary students) is not statistically significant by itself. The same is true for model 2; however, the interaction between the dual VET share and RTI is negative and highly statistically significant. The coefficients imply that where the dual VET share exceeds 25%, the effect of RTI on unemployment support turns negative, all while having a VET degree also exerts a sizeable negative effect.

Figures 2 and 3 illustrate these complex relationships. Figure 2 shows the different relationship between RTI and support for unemployment benefits in individuals with general secondary education and those with a VET degree, based on model 1. Whereas routine workers with a general secondary education exhibit higher support for unemployment benefits, in line with the predominant theory, this relationship is entirely absent in VET-educated individuals. Figure 3 displays the relationship between RTI and support for unemployment support conditional on the dual VET share. It shows that in countries with zero dual VET or the median level of dual VET in our sample (7.9%), there is a slight positive relationship between RTI and UE support. However, in high-dual VET countries such as Germany (40.3% dual VET share in 2016), the relationship is negative. Even though the confidence intervals overlap for most levels of RTI, this interaction is statistically significant and substantively meaningful according to Table D2. This constitutes strong support for our dual advantage hypothesis over the doubling down hypothesis.[13]

Since we cannot observe dual VET status at the individual level in the cross-country data, we perform additional tests to substantiate our claim that dual VET is driving the relationship. Models 3 and 4 in Table D2 constitute a placebo test where we use the total (school- and work-based) VET share instead of the dual VET share. Model 3 shows essentially the same results as model 1, but model 4 differs from model 2 since it shows no evidence for an interaction between the total VET share and the impact of occupational routine intensity on unemployment support. Moreover, the main effect of RTI (interpretable as the estimated effect of RTI in a country with 0% VET share) is substantially smaller and not statistically significant. This placebo test strongly suggests that the individual-level VET effect is primarily due to individuals who have a dual VET background. This is further reinforced by models 5 and 6, where we express the dual VET

[13]In Tables D3 and D4 in Appendix C, we show results for two other outcomes that have attracted the interest of scholars: demand for active labor market policy (ALMP) and support for a universal basic income. Our results for ALMP echo the findings of Busemeyer et al. (2022) who find that workers at risk of automation favour compensation over activation, with little evidence for an effect of VET background. We also replicate the finding of Weisstanner (2020) who finds no increase in support for UBI in response to automation risk, and again find no evidence that a VET background moderates this non-relationship.

Figure 2: Vocational education nullifies the effect of RTI on support for UE benefits



Note: The figure shows estimates from multilevel model including a random country intercept and ESS survey weights, with 95% confidence bands. The model controls for sex, age, income decile, union membership, political orientation, unemployment risk, unemployment rate, and dual VET share. N = 22,901. For the full set of results, see model 1 in Table D1.

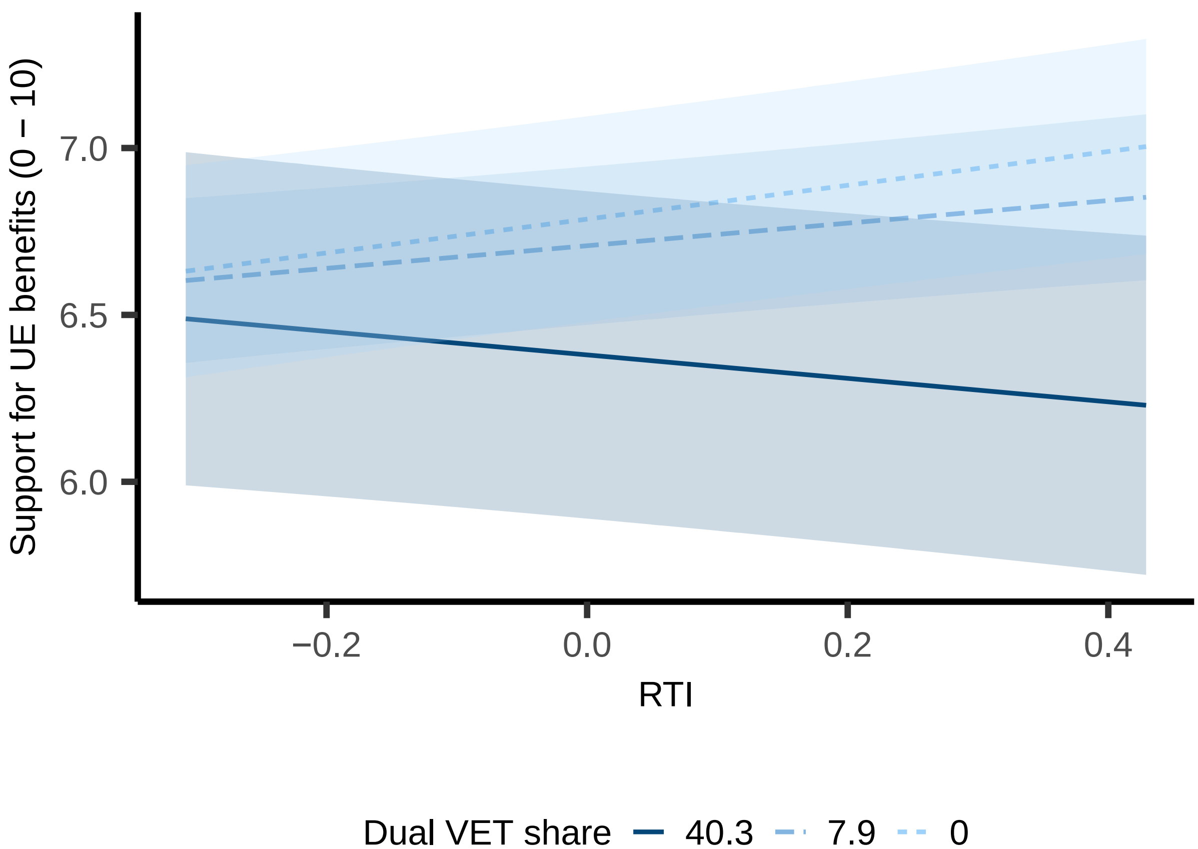
share in relation to the overall VET share, not as a proportion of all upper secondary students. In model 5, the ratio itself has a negative coefficient that is significant at a 10% level and in model 6 we find a significant interaction coefficient, which implies that the effect of RTI is significant and positive where all VET is school-based, and significant and negative where all VET is dual. The difference in support for unemployment benefits between individuals with a VET degree and individuals with general secondary or tertiary education remains statistically significant throughout the models.

Overall, we find strong evidence for the argument that skill formation systems shape individuals' social policy preferences. VET-educated individuals express lower approval of government support for the unemployed and, crucially for the debate about the policy implications of technology-induced automation, the link between routine task intensity and demand for compensatory social policies such as unemployment support is severed in people with a VET background. Moreover, we find that this pattern is driven by countries where dual VET predominates. The evidence thus firmly supports the dual advantage hypothesis.

The effect of individual dual VET status in Germany

Yet, our analysis is still limited by the fact that the harmonized education data in the ESS do not allow us to distinguish between school-based and dual VET. We now use the case of Germany, where the national coding scheme is sufficiently detailed to determine whether individuals have obtained a dual VET qualification,

Figure 3: High dual VET share reduces the effect of RTI on support for UE benefits



Note: The figure displays the relationship between RTI and support for UE benefits at different dual VET shares. The levels correspond to the share in Germany in 2016 (40.3%), the sample median (7.9%) and countries without dual VET (0%). The estimates are based on a multilevel model including a random country intercept and ESS survey weights, with 95% confidence bands. The model controls for educational attainment, sex, age, income decile, union membership, political orientation, unemployment risk, and the unemployment rate. N = 22,901. For the full set of results, see model 2 in Table D2.

Table 2: Dual VET-educated in Germany are particularly opposed to unemployment support...

	Model 1	Model 2	Model 3	Model 4
Dual VET dummy	−0.279**		−0.294**	
	(0.091)		(0.100)	
Dual VET (Ref.: no VET)		−0.383***		−0.355**
		(0.107)		(0.118)
Other VET (Ref.: no VET)		−0.263+		−0.149
		(0.141)		(0.153)
RTI	−0.145	−0.193	−0.431	−0.450
	(0.257)	(0.259)	(0.288)	(0.289)
Covariates				
Female	−0.465***	−0.446***	−0.458***	−0.445***
	(0.090)	(0.091)	(0.099)	(0.100)
Age	−0.0004	0.0004	−0.002	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Income decile	−0.067***	−0.064***	−0.072***	−0.071***
	(0.017)	(0.018)	(0.019)	(0.019)
Union member	0.142	0.161	0.223+	0.233+
	(0.125)	(0.126)	(0.130)	(0.131)
Left-right scale	−0.166***	−0.164***	−0.161***	−0.160***
	(0.024)	(0.024)	(0.027)	(0.027)
UE risk			0.166*	0.163*
			(0.068)	(0.068)
(Intercept)	7.493***	7.526***	7.277***	7.305***
	(0.217)	(0.218)	(0.283)	(0.284)
Num.Obs.	2214	2214	1836	1836
R2	0.041	0.042	0.047	0.047
R2 Adj.	0.038	0.039	0.043	0.043
AIC	9809.5	9808.0	8112.3	8113.3
BIC	9860.8	9865.0	8167.4	8174.0
Log.Lik.	−4895.761	−4894.011	−4046.136	−4045.662
RMSE	2.06	2.06	2.05	2.05

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Linear probability models with survey weights.

school-based VET, or no VET at all.[14] Based on this coding, approximately 57% of Germans in 2016 had a dual VET background, 16% had other forms of VET, and 27% had no VET background at all (higher education or no qualifications).[15] Using this indicator of individual-level dual VET status, we provide further evidence that dual VET drives the relationships we discuss in this paper. For the analyses in this section, we use linear probability models since the data have neither a cross-country nor a multilevel structure.

We first replicate models 1 and 2 from Table D1. We see in models 1 and 3 of Table 2 that the dual VET

[14] There are of course some uncertainties, but the coding scheme allows us to identify dual VET-educated individuals with a fairly high degree of precision. Details about the coding scheme can be found in Appendix A. In later iterations of the paper, we will construct such individual-level indicators for all countries where the national coding scheme allows for it.

[15] We currently code whether people have a dual VET qualification, not whether this is their highest qualification. Thus, some of the people in our dual VET category will also have a tertiary degree.

Table 3: ...but there is no interaction with RTI

	Model 1	Model 2	Model 3	Model 4
Dual VET dummy	−0.289**		−0.299**	
	(0.091)		(0.101)	
Dual VET (Ref.: no VET)		−0.380***		−0.356**
		(0.107)		(0.118)
Other VET (Ref.: no VET)		−0.259+		−0.148
		(0.148)		(0.161)
RTI	0.232	0.249	−0.312	−0.341
	(0.369)	(0.446)	(0.417)	(0.507)
Dual VET dummy × RTI	−0.697		−0.217	
	(0.490)		(0.551)	
Other VET × RTI		−0.427		−0.080
		(0.796)		(0.886)
Dual VET × RTI		−0.699		−0.177
		(0.551)		(0.622)
Covariates				
Female	−0.473***	−0.453***	−0.461***	−0.448***
	(0.090)	(0.091)	(0.099)	(0.100)
Age	−0.0004	0.0003	−0.002	−0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Income decile	−0.065***	−0.063***	−0.071***	−0.071***
	(0.017)	(0.018)	(0.019)	(0.019)
Union member	0.143	0.157	0.223+	0.232+
	(0.125)	(0.126)	(0.130)	(0.131)
Left-right scale	−0.167***	−0.166***	−0.161***	−0.160***
	(0.024)	(0.024)	(0.027)	(0.027)
UE risk			0.167*	0.164*
			(0.068)	(0.069)
(Intercept)	7.507***	7.537***	7.282***	7.307***
	(0.217)	(0.218)	(0.283)	(0.284)
Num.Obs.	2214	2214	1836	1836
R2	0.042	0.043	0.047	0.047
R2 Adj.	0.038	0.039	0.042	0.042
AIC	9809.5	9810.4	8114.1	8117.2
BIC	9866.5	9878.8	8174.8	8188.9
Log.Lik.	−4894.747	−4893.202	−4046.057	−4045.620
RMSE	2.06	2.06	2.05	2.05

Note: + p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001. Linear probability models with survey weights.

effect is more than two times the size of the overall VET effect in the earlier models.[16] In models 2 and 4, we disaggregate the data further to show that individuals with dual VET background differ from those with school-based VET. We find that, while people with school-based VET are also somewhat less supportive of unemployment benefits than Germans without VET background (at least when we do not control for subjective unemployment risk), the effect for dual VET graduates is much larger and robustly significant. This clearly highlights the difference between dual VET and not just non-VET tracks, but also school-based VET. Although the difference between dual VET and school-based VET is not itself statistically significant, it is apparent that school-based VET in Germany is qualitatively different from dual VET and occupies an intermediate position between dual VET and non-vocational education. In contrast to the cross-country sample, in the models for Germany the coefficient on objective automation risk is negative (albeit imprecisely estimated), especially when also controlling for subjective unemployment risk. This result once again brings to mind the existing literature on automation risk and social policy preferences, where other single-country studies such as Gallego et al. (2022) for Spain also find no effect of RTI. A further difference is that being female is robustly negatively associated with support for unemployment benefits in Germany, whereas in the cross-country sample the coefficient is mostly positive and insignificant. These differences render Germany a less-than-ideal example. Nevertheless, the available data dictate that we use Germany to illustrate the effect of dual VET on the relationship between automation risk and social policy preferences.

In Table 3 we test whether the interaction between dual VET and RTI also shows up in Germany. We therefore replicate model 1 from Table D2 without the country-level variables, first without and then with controlling for subjective unemployment risk. We find that dual VET is significantly associated with less support for unemployment support in models 1 and 3, but neither RTI nor the interaction of dual VET and RTI are statistically significant. Including subjective unemployment risk in model 3 once again reduces the size of the coefficient on RTI, causing it to flip from positive to negative. The same pattern is repeated in models 2 and 4, where we again distinguish between dual and other VET. Thus, at least in Germany, objective automation risk does not appear to affect social policy preferences in the first place. This, and the much smaller sample than in the cross-country analyses, undoubtedly contributes to the fact that the interaction coefficients, even though large, are not statistically significant, preventing us from declaring resounding support for this element of our argument.

The evidence from Germany thus falls short of a "smoking gun" in favor of our argument regarding the moderating role of dual VET. However, it adds to the weight of the evidence that we have presented thus far and which in its totality strongly suggests that a dual VET background has a distinct negative effect on

[16]The reference category in Table 2 also includes degree holders and school-based VET, whereas in Table D1 only non-degree, non-VET holders constitute the reference category.

compensatory social policies and – to the extent to which such a relationship really exists – moderates the impact of automation risk on social policy preferences. In future versions of the paper, we intend to develop further country-specific coding schemes for individual-level dual VET status and integrate the data into the analysis in this section to hopefully address any lingering doubts.

Potential mechanisms

After demonstrating that skill formation systems may influence the formulation of policy demands in response to automation risk, we now delve into the mechanisms through which this might be affected. Our theoretical discussion identified three such mechanisms, which we termed the skill certification, material self-interest, and workplace socialization mechanisms. According to the skill certification hypothesis, the VET-educated may be optimistic regarding their chances of finding a new job if necessary, owing to the quality of their training and their certified and portable occupational skills. This would mean that they consider themselves still less likely to have to rely on government support for extended periods of time, making their high objective automation risk less relevant as a determinant of policy preferences. On the other hand, their material self-interest may turn young VET-educated workers against unemployment support in light of their (initially) superior employment and wage outcomes. Finally, workplace training and socialization may have inculcated the (dual) VET-educated with a work ethic and a set of values that is opposed to generous unemployment support. In this case, independent of their level of automation risk, their values would prompt them to oppose dependency on the government. We present the evidence for these – non-mutually exclusive – mechanisms in turn.

Skill Certification mechanism

The skill certification hypothesis holds that authoritative certification makes dual VET skills widely portable, increasing labor market security of individuals holding such certifications. This is because even if holders of a dual VET qualification were to become unemployed, they would feel confident that other employers would have good use for their skills, and that they could quickly find a new job of similar quality. We test this mechanism by estimating the impact of having a VET background on answers to the following two questions:

- "How difficult or easy would it be for you to get a similar or better job with another employer if you had to leave your current job?"
- "Do you know of any other employers who would have good use for what you have learned in your present job?"

Since these questions were not asked in ESS 8, we rely on ESS 5 (2010) for this analysis.[17] Our certification argument stipulates that authoritative certification makes dual VET qualifications widely portable. This should increase the likelihood that other employers would have use for the skills of a dual VET graduate, and make it easier for such an individual to find a new job if necessary. In short, we expect VET holders to look rather like degree holders, and less like non-degree, non-VET holders.

Our analyses provide mixed evidence for this mechanism. Models 1 - 3 in 4 show that VET graduates are closer to non-degree, non-VET graduates than to degree holders when it comes to the ease of finding a new job of similar or better quality. Model 2 furthermore indicates that whatever small advantage VET graduates enjoy over non-degree, non-VET graduates, erodes slightly in countries with a high dual VET share. Model 3 shows that the effect of RTI is strongly negative for individuals without a degree or VET, essentially zero for individuals with a vocational qualification, and positive for degree holders. We therefore do not find strong evidence that individuals with a vocational qualification are more confident that they could find a similar or better job if they had to leave their current job.

In contrast, models 4 - 6 show that VET graduates are just as likely to say that they know other employers who would value their skills as degree holders, and significantly more likely to say so than individuals with neither a degree nor VET background. According to model 5, the effect of a higher dual VET share is positive on individuals with a degree or VET background, but negative and insignificant in the reference group. Model 6 shows that the effect of RTI does not differ between educational groups but is significantly negative for all groups. With regard to skill portability, the certification hypothesis is therefore supported.

Overall, however, the evidence that VET-trained individuals view their skills as highly portable and therefore express lower demand for social protection is ambiguous. When asked about the transferability of their skills – which speaks most directly to the hypothesis – VET holders are indeed as optimistic as degree holders with high general skills. However, to firmly conclude that the certification of VET skills reduces graduates' anxiety about unemployment and therefore their willingness to support the unemployed by means of government transfers, we should also find them more positive about their prospects of finding a new job if necessary – which we do not. The skill certification hypothesis is therefore only partially supported.

Material Self-Interest

We have further argued with reference to the literature on the education-wage-social-policy nexus that VET may dampen demand for compensatory social policies by allowing VET-graduates to command higher wages

[17] The fact that the data for this analysis were collected in 2010 is potentially problematic for two reasons. First of all, being at the height of the Global Financial Crisis, it is possible that idiosyncratic factors drive people's expectations to a greater extent than during more "normal" times. Furthermore, the data were collected at a time when automation risk to routine jobs, rightly or wrongly, was much less salient than even just 6 years later. The ESS 5 data thus constitute a tough test for the certification hypothesis.

Table 4: VET graduates are optimistic about skill portability, but less so about finding a new job

	DV: Find job			DV: Skill transfer		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Educational attainment (Ref.: non-degree, non-VET)						
Degree	0.309***	0.321***	0.394***	0.046***	0.007	0.050***
	(0.072)	(0.096)	(0.084)	(0.008)	(0.011)	(0.010)
Non-degree VET	0.073	0.184*	0.038	0.041***	0.015	0.042***
	(0.061)	(0.087)	(0.064)	(0.007)	(0.010)	(0.007)
Interaction variables						
RTI	−0.260+	−0.301+	−0.891**	−0.137***	−0.120***	−0.122***
	(0.158)	(0.182)	(0.304)	(0.018)	(0.020)	(0.035)
Dual VET share		−0.004			−0.001	
		(0.012)			(0.001)	
Degree x dual VET		−0.004			0.003***	
		(0.005)			(0.0005)	
Non-degree VET x dual VET		−0.012**			0.002***	
		(0.004)			(0.0005)	
Degree x RTI			1.466***			0.008
			(0.442)			(0.052)
Non-degree VET x RTI			0.624+			−0.031
			(0.369)			(0.043)
Covariates						
Female	−0.046	−0.101+	−0.047	−0.015**	−0.015*	−0.015**
	(0.047)	(0.054)	(0.049)	(0.005)	(0.006)	(0.006)
Age	−0.037***	−0.039***	−0.037***	−0.001***	−0.002***	−0.001***
	(0.002)	(0.002)	(0.002)	(0.0002)	(0.0003)	(0.0002)
Income decile	0.086***	0.086***	0.084***	0.012***	0.011***	0.012***
	(0.010)	(0.011)	(0.010)	(0.001)	(0.001)	(0.001)
Union member	−0.536***	−0.527***	−0.536***	−0.019**	−0.023**	−0.019**
	(0.058)	(0.068)	(0.060)	(0.007)	(0.008)	(0.007)
Left-right scale	0.021+	0.018	0.019	0.002+	0.001	0.002+
	(0.012)	(0.013)	(0.012)	(0.001)	(0.001)	(0.001)
UE rate		−0.180**	−0.134*		−0.009	−0.010
		(0.060)	(0.054)		(0.007)	(0.006)
(Intercept)	5.450***	7.251***	6.571***	0.804***	0.933***	0.881***
	(0.215)	(0.615)	(0.492)	(0.024)	(0.072)	(0.059)
SD (Intercept cntry)	0.833	0.714	0.737	0.091	0.084	0.090
SD (Observations)	2.786	2.841	2.834	0.317	0.316	0.324
Num.Obs.	13 909	10 953	13 257	13 731	10 852	13 070
R2 Marg.	0.040	0.066	0.052	0.026	0.036	0.033
R2 Cond.	0.119	0.121	0.112	0.101	0.101	0.101
AIC	77 477.5	60 832.4	73 856.4	16 839.5	12 713.7	16 150.9
BIC	77 560.4	60 941.9	73 961.3	16 922.3	12 823.1	16 255.5
ICC	0.08	0.06	0.06	0.08	0.07	0.07
RMSE	2.64	2.63	2.63	0.32	0.32	0.33

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Multilevel models with random country intercepts and survey weights. This analysis uses ESS 5 data from 2010.

at the beginning of their career and fostering long-lasting social policy preferences as a way to safeguard their material self-interest. In a way, this argument mirrors the literature on the scarring effects of unemployment. Analogous to a long-lasting effect of early unemployment experience, for example on political interest and turnout (Emmenegger, Marx and Schraff, 2017), we posit that early experience of gainful employment and paying taxes, while much of their age cohort still relies on parental or state support, may induce sustained opposition to compensatory social policies among (dual) VET-educated individuals. To test this mechanism, we perform analyses for different age cohorts. To see the self-interest hypothesis supported, we would need to find that the interaction effects in Table D2 are driven by younger workers.

Indeed, this is what Table 5 shows. Mirroring the analysis above, we first show the interaction between individual VET background and RTI (model 1 in Table D2). To substantiate our claim that this relationship is driven by dual VET, we then interact the dual VET share with RTI and finally with the individual VET background dummy. Among employed individuals under 35 years of age, having a vocational degree reduces the (otherwise positive and significant) effect of RTI on unemployment support. Among prime-age workers aged 35-49, there is no significant interaction effect, although a VET background by itself is negatively associated with unemployment support. Finally, among older workers, no relationship between unemployment support and either RTI or VET background, or the interaction of the two, can be discerned, despite a larger sample size than in the other age groups.

This pattern is repeated for the other interactions. In young workers, a higher dual VET share is associated with a reduced positive effect of RTI on unemployment support. The relationship is less pronounced in both size and statistical significance for prime age and older workers. Since a higher dual VET share means that it is more likely that a worker has received firm-based vocational training, this indicates that the interaction between individual VET background and RTI is really driven by high-dual VET countries. Interacting the dual VET share with the individual VET dummy serves to further substantiate this interpretation. The significant interaction for young workers and the smaller and less precisely estimated coefficients for prime-age and older workers show that the impact of dual VET is strongest early in one's career and recedes over time.

An interesting secondary observation is that subjective unemployment risk increases in importance with age. Young workers exhibit no significant relationship between subjective unemployment risk and support for compensatory social policies, but for prime-age and especially older workers, subjective unemployment risk is a highly significant predictor. This is all the more remarkable as youth unemployment exceeds overall unemployment in most countries (Emmenegger and Haslberger, 2023; Breen, 2005).

Thus, we can conclude that younger workers who have obtained a VET degree fairly recently are less likely to respond to automation risk by increasing their demand for unemployment support. This is in line with their material self-interest as they tend to be relatively well-earning compared to others in their age group (Hanushek et al., 2017; Korber and Oesch, 2019). Moreover, since this is mainly true of graduates of dual VET systems, which are known to facilitate school-to-work transitions, we can show that this age gradient is indeed driven by countries with strong dual VET systems. A higher dual VET share reduces the impact of RTI on unemployment support even when controlling for individual VET status, and accentuates the negative effect of individual VET status.

Given the rapid pace of change in the labor market, a further advantage of younger VET-educated workers might be their more recent training which should have better prepared them for current and future challenges than training received several decades ago. This might further insulate them from fears of automation and thereby reduce their demand for compensatory social policies. Overall, our analysis suggests that the material self-interest of younger VET-educated workers is one of the driving factors behind the pattern which we have established and attempt to explain in this paper.

Table 5: Young workers drive the interaction between VET and RTI

	Worker age			*Worker age*			*Worker age*		
	Under 35	35 - 49	50+	Under 35	35 - 49	50+	Under 35	35 - 49	50+
Educational attainment (Ref.: non-degree, non-VET)									
Degree	0.069	−0.231*	−0.023	0.085	−0.165*	0.197**	−0.220+	−0.398***	0.040
	(0.096)	(0.093)	(0.086)	(0.090)	(0.082)	(0.070)	(0.115)	(0.102)	(0.094)
Non-degree VET	0.039	−0.378***	0.106+	−0.055	−0.408***	0.073	0.105	−0.361***	0.077
	(0.079)	(0.071)	(0.055)	(0.076)	(0.069)	(0.054)	(0.103)	(0.089)	(0.073)
Interaction variables									
RTI	1.565***	0.365	0.895***	1.221***	0.040	0.461**	0.409*	−0.205	0.338*
	(0.330)	(0.326)	(0.208)	(0.256)	(0.220)	(0.173)	(0.188)	(0.171)	(0.131)
Dual VET share	−0.011	−0.012	−0.007	−0.011	−0.012	−0.007	−0.012	−0.016+	−0.010
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
Degree x RTI	−1.919***	−1.242*	−2.185***						
	(0.507)	(0.485)	(0.411)						
Non-degree VET x RTI	−1.654***	−0.609	−0.585*						
	(0.428)	(0.395)	(0.277)						
Dual VET x RTI				−0.052***	−0.018+	−0.009			
				(0.011)	(0.010)	(0.007)			
Dual VET x Degree							0.022***	0.017**	0.010*
							(0.005)	(0.005)	(0.004)
Dual VET x Non-degree VET							−0.010*	−0.0008	0.001
							(0.005)	(0.005)	(0.004)
Covariates									
Female	0.111+	0.064	0.055	0.116+	0.061	0.062	0.128*	0.077	0.068
	(0.060)	(0.053)	(0.043)	(0.060)	(0.053)	(0.043)	(0.060)	(0.053)	(0.043)
Age	0.004	0.041***	0.006*	0.004	0.042***	0.007*	0.005	0.041***	0.007*
	(0.007)	(0.006)	(0.003)	(0.007)	(0.006)	(0.003)	(0.007)	(0.006)	(0.003)
Income decile	−0.021+	−0.073***	−0.054***	−0.021+	−0.075***	−0.055***	−0.023+	−0.074***	−0.055***
	(0.012)	(0.012)	(0.009)	(0.012)	(0.012)	(0.009)	(0.012)	(0.012)	(0.009)
Union member	0.361***	0.122+	0.245***	0.376***	0.122+	0.258***	0.379***	0.115+	0.259***
	(0.091)	(0.068)	(0.060)	(0.091)	(0.068)	(0.060)	(0.091)	(0.068)	(0.060)
Left-right scale	−0.184***	−0.167***	−0.143***	−0.183***	−0.166***	−0.143***	−0.179***	−0.165***	−0.143***
	(0.015)	(0.013)	(0.010)	(0.015)	(0.013)	(0.010)	(0.015)	(0.013)	(0.010)
UE risk	0.046	0.075*	0.079**	0.052	0.073*	0.076**	0.051	0.071*	0.076**
	(0.035)	(0.033)	(0.027)	(0.035)	(0.033)	(0.027)	(0.035)	(0.032)	(0.027)
UE rate	0.027	0.019	0.065+	0.028	0.020	0.066*	0.032	0.022	0.067*
	(0.033)	(0.032)	(0.033)	(0.033)	(0.032)	(0.033)	(0.033)	(0.032)	(0.033)
(Intercept)	7.107***	6.099***	6.585***	7.134***	6.127***	6.592***	7.089***	6.143***	6.610***
	(0.419)	(0.447)	(0.419)	(0.415)	(0.446)	(0.417)	(0.424)	(0.450)	(0.420)
SD (Intercept cntry)	0.518	0.509	0.534	0.511	0.508	0.530	0.514	0.509	0.532
SD (Observations)	2.333	2.238	2.077	2.332	2.239	2.080	2.328	2.236	2.080
Num.Obs.	5605	6985	10 311	5605	6985	10 311	5605	6985	10 311
R2 Marg.	0.044	0.054	0.054	0.045	0.053	0.051	0.048	0.055	0.051
R2 Cond.	0.089	0.100	0.112	0.089	0.100	0.109	0.092	0.102	0.109
AIC	29 377.9	36 287.4	53 971.2	29 379.4	36 296.0	54 003.3	29 370.8	36 290.3	54 010.3

Workplace Socialization

The workplace socialization hypothesis holds that workplace training inculcates workfarist attitudes. Where students are socialized in the workplace, the reasoning goes, they are likely, in their "impressionable years" (Schuman and Scott, 1989), to be more exposed to discourses framing government intervention as burdensome than in general schooling. To assess this mechanism, we look at agreement with the statement that "social benefits and services place too great a strain on the economy" and perform a mediation analysis. We expect a positive effect of individual VET status on the likelihood of viewing social benefits as a strain on the economy, and a weakened negative effect of VET status in models of unemployment support that include "benefits strain economy" as a control variable.

We find solid support for this conjecture. In model 1 of Table 6, having a VET background substantially increases agreement with the statement that benefits place too great a strain on the economy. Comparing models 2 and 3, we see that the size of the coefficient on VET status is reduced when the benefits variable is included as a predictor. While the size of the coefficient is noticeably reduced, the difference is not itself statistically significant. Still, the models indicate at least partial mediation of the VET effect through people's socialization into workfarist views. These conclusions are reinforced by the results of models 4 - 6, which find essentially the same pattern in the interaction model from column 1 of Table D2. Interestingly, survey participants in more automatable occupations are also more likely to agree that social benefits place too great a strain on the economy, at least if they do not hold a vocational qualification (see model 4). This may at first seem surprising, but since we are looking only at employed individuals, the mechanism uncovered by Jacques and Weisstanner (2022) may be at play, by which workers facing the threat of economic decline become *less* supportive of taxation, lest their already precarious consumption levels be reduced.

All in all, this analysis provides strong evidence that individuals with a vocational education view social benefits in general more critically than individuals with either higher or lower education, and that this is part of the reason why find them to be less supportive of unemployment benefits. Evidence from Germany, in the appendix, furthermore establishes that it is once again individuals with a dual VET background who are most opposed to unemployment support. This strongly suggests that workplace socialization is one of the mechanisms through which the negative relationship between VET background and support for social policy comes about.

Table 6: Workfarist attitudes partially mediate the effect of VET

	DV: Strain	DV: UE support		DV: Strain	DV: UE support	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Educational attainment (Ref.: non-degree, non-VET)						
Degree	−0.115***	0.021	−0.016	−0.031	−0.075	−0.108*
	(0.014)	(0.045)	(0.045)	(0.019)	(0.051)	(0.051)
Non-degree VET	0.059***	−0.126***	−0.094**	0.066***	−0.081*	−0.052
	(0.012)	(0.036)	(0.036)	(0.013)	(0.037)	(0.037)
RTI		0.177+	0.229*	0.224***	0.897***	0.919***
		(0.091)	(0.092)	(0.051)	(0.156)	(0.157)
Degree x RTI				0.390***	−1.717***	−1.649***
				(0.098)	(0.260)	(0.261)
Non-degree VET x RTI				−0.139*	−0.839***	−0.799***
				(0.070)	(0.201)	(0.202)
Benefits strain economy			−0.314***			−0.312***
			(0.014)			(0.014)
Covariates						
Female		0.074*	0.080**		0.074*	0.079**
		(0.029)	(0.029)		(0.029)	(0.029)
Age		0.005***	0.005***		0.005***	0.005***
		(0.001)	(0.001)		(0.001)	(0.001)
Income decile		−0.045***	−0.044***		−0.045***	−0.044***
		(0.006)	(0.006)		(0.006)	(0.006)
Union member		0.246***	0.225***		0.238***	0.217***
		(0.040)	(0.040)		(0.040)	(0.040)
Left-right scale		−0.158***	−0.132***		−0.158***	−0.132***
		(0.007)	(0.007)		(0.007)	(0.007)
UE risk		0.066***	0.054**		0.065***	0.053**
		(0.018)	(0.018)		(0.018)	(0.018)
UE rate		0.036	0.050+		0.035	0.049+
		(0.031)	(0.029)		(0.031)	(0.029)
Dual VET share		−0.010	−0.008		−0.010	−0.008
		(0.008)	(0.008)		(0.008)	(0.008)
(Intercept)	2.993***	7.120***	7.785***	2.986***	7.111***	7.774***
	(0.054)	(0.341)	(0.320)	(0.055)	(0.341)	(0.321)
SD (Intercept cntry)	0.250	0.507	0.470	0.254	0.508	0.471
SD (Observations)	1.091	2.205	2.183	1.079	2.203	2.181
Num.Obs.	39 617	22 901	22 449	36 021	22 901	22 449
R2 Marg.	0.004	0.043	0.062	0.007	0.045	0.064
R2 Cond.	0.053	0.091	0.104	0.059	0.093	0.106
AIC	147 319.6	119 790.2	116 958.9	134 335.3	119 751.6	116 924.2
BIC	147 362.6	119 902.7	117 079.2	134 403.2	119 880.3	117 060.5
ICC	0.05	0.05	0.04	0.05	0.05	0.04
RMSE	1.02	2.12	2.09	1.02	2.12	2.09

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Multilevel models with random country intercepts and survey weights.

Discussion and conclusions

In this paper, we sought to advance the literature on the political consequences of technological change by analyzing the moderating effect of education and training institutions on preferences for compensatory social policies in the context of automation. As such, we concur with recent contributions that highlight the need to place "preferences in context" (Busemeyer and Tober 2022, see also Gingrich and Ansell 2012). More specifically, we developed a theoretical argument centered on the impact of dual VET systems in two steps. Firstly, we hypothesized that dual VET systems dampen demand for compensatory social policies in the age of automation and, secondly, we identified three non-mutually exclusive mechanisms through which this might happen, namely: (i) skill certification; (ii) material self-interest, and (iii) workplace socialization.

Accordingly, the empirical analysis also proceeded in two main steps. In a first step, we mobilized cross-country ESS data to ascertain the impact of dual VET systems on preferences for generous unemployment benefits. In strong support of our "dual advantage" hypothesis, we found that indeed the relationship between risk of automation and demand for compensatory social policies drops significantly among workers with a VET background in high dual VET countries. Ancillary evidence from Germany exploited more fine-grained information on individuals' educational background to lend additional support to the expectation that dual VET reduces demand for compensatory social policies.

The second step of the empirical analysis went back to cross-national ESS data to test the three mechanisms by which we hypothesized that dual VET dampens demand for unemployment support. We found some evidence in support of the skill certification mechanism and strong evidence in support of the material self-interest and workplace socialization mechanisms. Given that the three mechanisms are not mutually exclusive, we interpret the results as overall providing strong support to our theoretical propositions. In other words, in the age of automation, dual VET systems reduce support for compensatory social policies (i) by making dual VET graduates somewhat more confident of their skills in fast-changing labor markets; (ii) by turning them "against" public spending on social policy to "protect" their above-average salaries, particularly at the beginning of their professional careers; and (iii) by socializing them in a workfarist environment that comes with a negative view of government intervention. Our paper, therefore, provides theoretical and empirical insights to fully integrate the role of education and training systems in the study of the political consequences of technological change.

Yet, our findings also go beyond the debate on social policy preferences in the age of automation. Indeed, the evidence presented in this paper challenges the "asset theory of social policy preferences," which posits a positive relationship between skill specificity and support for compensatory social policies such as generous unemployment benefits (Iversen and Soskice, 2001; Estevez-Abe, Iversen and Soskice, 2001). A long tradition of CPE research has portrayed the skills produced in dual VET systems as "specific" and therefore inherently "risky" due to low portability, fostering support for non-market mechanisms (e.g., employment and unemployment protection) that provide insurance against the risk carried by investing in specific skills. While this argument has been already subject to critiques on both theoretical and empirical grounds (see e.g. Streeck 2011; Emmenegger 2009; Busemeyer 2009), it has come to characterize contemporary CPE research as a core element of the micro-foundations of one of its most successful research paradigms, namely VoC (Hall and Soskice, 2001b).

We believe that the context of technological change provides a critical case to reassess the "asset theory of social policy preferences." Indeed, dual VET systems have traditionally fed occupations in the middle of the skill distribution, i.e. those very occupations that labor economists see as most threatened by automation. According to the asset theory, therefore, we should expect dual VET systems to further increase demand for compensatory social policies given that workers with a dual VET background are now subject to a double risk: alongside the traditional risk of holding specific skills, they are also employed in occupations that might be replaced by technology. We referred to this as the "doubling down" hypothesis.

Yet, we find strong evidence suggesting that the opposite holds true: dual VET systems decrease support for compensatory social policies, as predicted by our alternative, "dual advantage" hypothesis. This finding has two important implications. Firstly, in line with the wide-ranging critique formulated by (Streeck, 2011), depicting dual VET systems as primarily providing specific skills in the sense of having low portability might be misleading: a system of skill certification supported by all the major actors across the labor market appears to facilitate skill portability and to work therefore as an in-built insurance system for individuals who hold those skills. Moreover, the emphasis on skill specificity might overshadow other features of dual VET systems that are of no less importance, as illustrated by strong evidence in support of our material self-interest and workplace socialization mechanisms. Secondly, and relatedly, the strong evidence in favor of "dual advantage" over "doubling down" questions the assumption of a causal relationship between large (dual) VET systems and generous welfare states (see also Emmenegger 2009; Emmenegger and Marx 2011) suggesting that these two variables might stand in a relationship best characterized by co-evolution rather than complementarity (Boyer, 2005).

This article also suggests at least two avenues for future research to substantiate our findings further. Firstly, our individual-level information drawn from cross-national ESS data does not distinguish between firm-based and school-based VET. We dealt with this issue by combining national-level data on the size of the dual VET system with an individual-level VET dummy. Moreover, we used data from the German ESS module that do allow to distinguish between firm-based and school-based VET at the individual level. It would be however worthwhile exploring this relationship further via surveys that in the future will hopefully collect cross-national individual-level data on the type of VET background. Secondly, while we go beyond much existing research in our attempt to open up the black box and tease out the mechanisms that drive our main finding, the ESS data do not allow us to make truly causal claims. This paper should therefore serve as a starting point for further efforts to pinpoint exactly how dual VET (or other aspects of skill formation systems) shape the relationship between technology and social policy preferences. Detailed single-country studies as well as experimental research will help to properly establish causal mechanisms. We hope that our paper will motivate further research into this issue.

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Appendix: For Online Publication

Contents

A Coding of Education Variables

The ESS allows researchers to come up with their own purpose-built educational variables based on the 3-digit variable EDULVLB. The first digit represents the 8 ISCED-11 levels. "The second digit reflects program orientation (1: general and 2: vocational) at ISCED levels 2 to 5 programs (programs below the degree level). A similar kind of differentiation is more difficult to achieve within higher education above level 5. EDULVLB thus contains an additional distinction: in countries with a binary or diversified system of higher education with different tertiary education institutions providing more selective academic or research oriented programs on the one hand and less selective vocational or application oriented programs on the other, code 1 on the second digit is used to denote vocationally oriented or applied programs and degrees/qualifications ('lower tier'), and code 2 to denote academically oriented degrees/qualifications ('upper tier'). In countries with a unified system of higher education, all programs are coded 2 on the second digit ('single tier'); code 1 is irrelevant in those countries" (ESS 2016). The third digit is irrelevant for our purposes. Based on these codes, we devise four education variables for our analyses.

For the main analyses, we rely on the *edu3* variable which is a categorical variable which takes the value 1 for general secondary education, 2 for vocational education up to short-cycle tertiary education at vocational colleges, and 3 for a bachelor degree or higher at higher education institutions ("general tertiary"). We perform sensitivity analyses with several alternative formulations of the VET variable. For the *vocational* dummy, up until ISCED level 5 all codes where the second digit is 2 are coded as vocational, as are codes 610 and 710; all other codes are subsumed under general education. In this coding, bachelor and even master degrees from a university of applied science or dual/cooperative universities are considered vocational education. To ensure that our findings are not driven by these two groups (which are quite sizeable in some countries: 17% in group 610 in Belgium and Norway and 9% in group 710 in the Netherlands), we create a second variable (*vocational_ s*) which only includes VET up to ISCED-11 level 5, thus coding all bachelor degrees and higher as general education, regardless of the institution where they were obtained. Finally, *degree* captures whether respondents have a university degree (including universities of applied science). The precise allocation can be seen in the color-coded Table A2.

Figure A1 shows the prevalence of vocational education by country, with familiar patterns of variation. The German-speaking countries have high VET shares, as do some Eastern European countries. Southern Europe and the Anglo countries, on the other hand, have very low VET shares. When higher-level VET is excluded in figure A2, this pattern is accentuated. However, the ESS data do not allow us to distinguish between school-based and work-based VET at the individual level, hence why we additionally collected dual VET shares data for 2010 and 2016 from the OECD Education at a Glance reports and country-specific sources, as specified in the Appendix to Emmenegger and Haslberger (2023).

Table A1: Education codes in the ESS

Code	**Label**
0	Not completed ISCED level 1
113	ISCED 1, completed primary education
129	Vocational ISCED 2C < 2 years, no access ISCED 3
212	General/pre-vocational ISCED 2A/2B, access ISCED 3 vocational
213	General ISCED 2A, access ISCED 3A general/all 3
221	Vocational ISCED 2C >= 2 years, no access ISCED 3
222	Vocational ISCED 2A/2B, access ISCED 3 vocational
223	Vocational ISCED 2, access ISCED 3 general/all
229	Vocational ISCED 3C < 2 years, no access ISCED 5
311	General ISCED 3 >= 2 years, no access ISCED 5
312	General ISCED 3A/3B, access ISCED 5B/lower tier 5A
313	General ISCED 3A, access upper tier ISCED 5A/all 5
321	Vocational ISCED 3C >= 2 years, no access ISCED 5
322	Vocational ISCED 3A/3B, access 5B/lower tier 5A
323	Vocational ISCED 3A, access upper tier ISCED 5A/all 5
412	General ISCED 4A/4B, access ISCED 5B/lower tier 5A
413	General ISCED 4A, access upper tier ISCED 5A/all 5
421	ISCED 4 programs without access ISCED 5
422	Vocational ISCED 4A/4B, access ISCED 5B/lower tier 5A
423	Vocational ISCED 4A, access upper tier ISCED 5A/all 5
510	SCED 5A short, intermediate/academic/general tertiary below
520	ISCED 5B short, advanced vocational qualifications
610	SCED 5A medium, bachelor/equivalent from lower tier tertiary
620	ISCED 5A medium, bachelor/equivalent from upper/single tier
710	ISCED 5A long, master/equivalent from lower tier tertiary
720	ISCED 5A long, master/equivalent from upper/single tier tertiary
800	ISCED 6, doctoral degree
5555	Other

Note: Cyan: vocational = 0; `vocational_s` = 0; degree = 0; edu3 = 1
Yellow: vocational = 1; `vocational_s` = 1; degree = 0; edu3 = 2
Orange: vocational = 1; `vocational_s` = 0; degree = 1; edu3 = 3
Lime: vocational = 0; `vocational_s` = 0; degree = 1; edu3 = 3.

Figure A1: Share with vocational training as highest educational attainment

label	variable	cntry																						
		AT	BE	CH	CZ	DE	EE	ES	FI	FR	GB	HU	IE	IL	IS	IT	LT	NL	NO	PL	PT	RU	SE	SI
vocational	0	602 (30.0%)	816 (46.2%)	527 (34.6%)	978 (43.1%)	945 (33.1%)	1150 (57.0%)	1577 (80.5%)	861 (44.7%)	1088 (52.6%)	1276 (65.1%)	609 (37.7%)	1773 (64.3%)	1728 (67.6%)	596 (67.7%)	1746 (66.5%)	1007 (47.5%)	868 (51.6%)	844 (54.6%)	754 (44.5%)	1049 (82.6%)	1337 (55.0%)	714 (46.0%)	586 (44.8%)
	1	1408 (70.0%)	950 (53.8%)	998 (65.4%)	1291 (56.9%)	1907 (66.9%)	869 (43.0%)	381 (19.5%)	1064 (55.3%)	982 (47.4%)	683 (34.9%)	1005 (62.3%)	984 (35.7%)	829 (32.4%)	284 (32.3%)	880 (33.5%)	1115 (52.5%)	813 (48.4%)	701 (45.4%)	940 (55.5%)	221 (17.4%)	1093 (45.0%)	837 (54.0%)	721 (55.2%)

Figure A2: Share with vocational training as highest educational attainment (excluding ISCED levels 6 - 8)

label	variable	cntry																						
		AT	BE	CH	CZ	DE	EE	ES	FI	FR	GB	HU	IE	IL	IS	IT	LT	NL	NO	PL	PT	RU	SE	SI
vocational_s	0	710 (35.3%)	1197 (67.8%)	668 (43.8%)	978 (43.1%)	1200 (42.1%)	1273 (63.1%)	1577 (80.5%)	1081 (56.2%)	1187 (57.3%)	1276 (65.1%)	761 (47.1%)	1773 (64.3%)	1978 (77.4%)	596 (67.7%)	1776 (67.6%)	1179 (55.6%)	1179 (70.1%)	1170 (75.7%)	875 (51.7%)	1115 (87.8%)	1337 (55.0%)	900 (58.0%)	650 (49.7%)
	1	1300 (64.7%)	569 (32.2%)	857 (56.2%)	1291 (56.9%)	1652 (57.9%)	746 (36.9%)	381 (19.5%)	844 (43.8%)	883 (42.7%)	683 (34.9%)	853 (52.9%)	984 (35.7%)	579 (22.6%)	284 (32.3%)	850 (32.4%)	943 (44.4%)	502 (29.9%)	375 (24.3%)	819 (48.3%)	155 (12.2%)	1093 (45.0%)	651 (42.0%)	657 (50.3%)

For Germany, it is furthermore possible to create an approximate indicator of individual dual VET background, based on the national-level ESS variable *edumade3*. This is still tricky since for some occupations there are no unified rules and in some states the training is school-based while it happens in the dual system in others.[18] We apply the OECD definition which considers *combined school- and work-based programs* those in which "less than 75 per cent of the curriculum is presented in the school environment or through distance education. Programs that are more than 90 per cent work-based are excluded" (OECD, 2001, p.401). Thus, for example, training to become a kindergarten teacher, which in most states combines two years of school-based education with a year of practical training, is considered dual VET. Another ambiguous case is category 10 (Fachschule) which in most cases is a school-based extension of previous dual training, for example in the trades. Due to its close link to the dual system and the practical orientation of the courses, coding it as dual VET would seem justifiable. Even though it strictly speaking is not, it requires a previous dual apprenticeship in most cases. To assess the robustness of our results, we work with both definitions. With this coding, approximately 47% to 57% of Germans have a dual VET background, which is in line with existing estimates (based on the tables above, between 58% and 67% of Germans have any kind of VET background).

Table A2: Education codes and shares in Germany

Code	**Label**	**Share (%)**
0	Kein beruflicher Ausbildungsabschluss	26.93
1	Betriebliche Anlernzeit mit Abschlusszeugnis; Teilfacharbeiterabschluss	1.26
2	Berufsgrundbildungsjahr, Berufsfachschule (Grundkenntnisse), med. Hilfsberufe	0.88
3	2- bis 3-jähriger Ausbildung an Schule d. Gesundheitswesens (z.B. Pflege)	4.38
4	Berufsqual. Abschluss Berufsfachschule/ Kolleg (schul. Berufsausbildung)	3.19
5	Abschluss einer Ausbildung zum Erzieher/zur Erzieherin	1.51
6	Gewerbliche Lehre/duale Ausbildung in Industrie, Handwerk oder Landwirtschaft	25.28
7	Abgeschlossene kaufmännische Lehre/duale Ausbildung (Kaufmannsgehilfenbrief)	17.15
8	Laufbahnprüfung für den mittleren Dienst	1.40
9	Abschluss einer 2. Berufsausbildung (berufliche Zweitausbildung)	1.44
10	Meister-/Techniker-/gleichwertiger Fachschulabschluss; VWA; Fachakademie (BY)	10.24
11	Laufbahnprüfung für den gehobenen Dienst	1.40
12	Staatsexamen	4.45
7777	Refusal	0.25
8888	Don't know	0.25

Note: Cyan: school-based VET; yellow: dual VET; lime: no VET; orange: varied coding.

[18] See here for occupations in the health sector and here for pedagogical occupations.

B Full Model Outputs

C Sensitivity Analyses

Figure D1: Support for UE benefits by educational attainment and sex

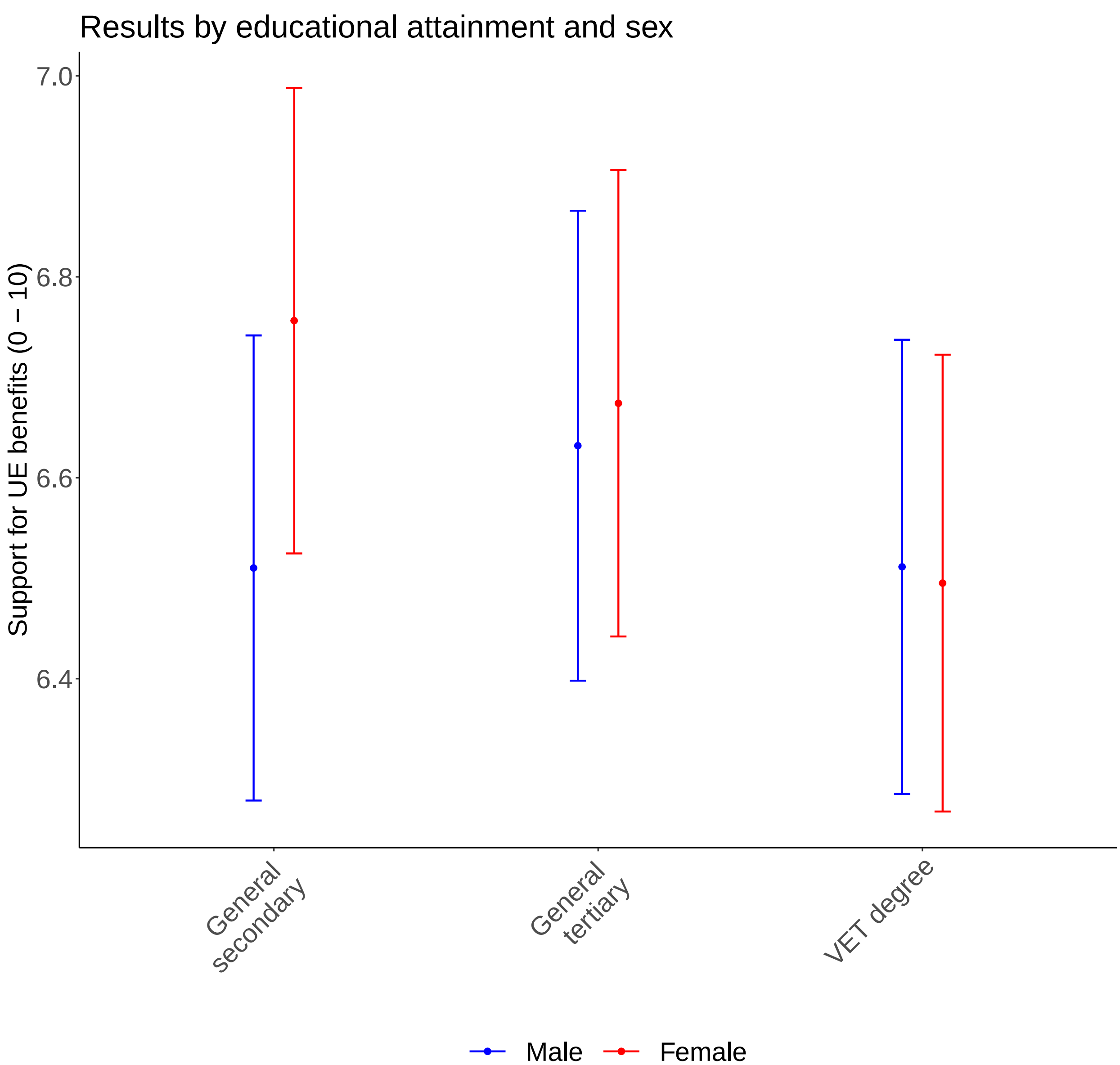

Table D1: Vocationally educated are less positive towards unemployment support

	Model 1	Model 2	Model 3	Model 4
Educational attainment (Ref.: non-degree, non-VET)				
Degree	0.022	0.021	0.022	0.021
	(0.041)	(0.045)	(0.041)	(0.045)
Non-degree VET	−0.137***	−0.127***	−0.136***	−0.126***
	(0.032)	(0.036)	(0.032)	(0.036)
Individual covariates				
RTI	0.315***	0.179+	0.313***	0.177+
	(0.080)	(0.091)	(0.080)	(0.091)
Female	0.079**	0.074*	0.079**	0.074*
	(0.027)	(0.029)	(0.027)	(0.029)
Age	0.007***	0.005***	0.007***	0.005***
	(0.0008)	(0.001)	(0.0008)	(0.001)
Income decile	−0.049***	−0.045***	−0.049***	−0.045***
	(0.005)	(0.006)	(0.005)	(0.006)
Union member	0.221***	0.245***	0.223***	0.246***
	(0.039)	(0.040)	(0.039)	(0.040)
Left-right scale	−0.144***	−0.158***	−0.144***	−0.158***
	(0.006)	(0.007)	(0.006)	(0.007)
UE risk		0.067***		0.066***
		(0.018)		(0.018)
Country-level covariates				
UE rate			0.037	0.036
			(0.029)	(0.031)
Dual VET share			−0.011	−0.010
			(0.008)	(0.008)
(Intercept)	7.300***	7.283***	7.136***	7.120***
	(0.132)	(0.146)	(0.320)	(0.341)
SD (Intercept cntry)	0.530	0.544	0.481	0.507
SD (Observations)	2.249	2.205	2.249	2.205
Num.Obs.	28 407	22 901	28 407	22 901
R2 Marg.	0.029	0.032	0.041	0.043
R2 Cond.	0.080	0.087	0.083	0.091
AIC	148 941.6	119 777.6	148 953.3	119 790.2
BIC	149 032.4	119 874.0	149 060.6	119 902.7
ICC	0.05	0.06	0.04	0.05
RMSE	2.13	2.12	2.14	2.12

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Multilevel models with random country intercepts and survey weights.

Table D2: Dual VET reduces the effect of RTI

	DV: Support for unemployment benefits					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Educational attainment (Ref.: non-degree, non-VET)						
Degree	−0.075	0.021	−0.011	0.068	−0.010	0.074+
	(0.051)	(0.045)	(0.050)	(0.043)	(0.050)	(0.043)
Non-degree VET	−0.081*	−0.124***	−0.147***	−0.176***	−0.147***	−0.170***
	(0.037)	(0.036)	(0.036)	(0.035)	(0.036)	(0.035)
Interaction variables						
RTI	0.897***	0.507***	0.562***	0.115	0.562***	0.459***
	(0.156)	(0.121)	(0.150)	(0.340)	(0.150)	(0.126)
Degree x RTI	−1.717***		−1.188***		−1.189***	
	(0.260)		(0.251)		(0.251)	
Non-degree VET x RTI	−0.839***		−0.494*		−0.495*	
	(0.201)		(0.192)		(0.192)	
Dual VET share	−0.010	−0.010				
	(0.008)	(0.008)				
All VET share			0.0007	0.0008		
			(0.007)	(0.007)		
Dual/all VET ratio					−0.634+	−0.636+
					(0.358)	(0.357)
Dual VET x RTI		−0.021***				
		(0.005)				
All VET x RTI				−0.0002		
				(0.007)		
VET ratio x RTI						−0.898***
						(0.231)
Covariates						
Female	0.074*	0.076**	0.016	0.014	0.016	0.014
	(0.029)	(0.029)	(0.028)	(0.028)	(0.028)	(0.028)
Age	0.005***	0.005***	0.008***	0.008***	0.008***	0.008***
	(0.001)	(0.001)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Income decile	−0.045***	−0.045***	−0.051***	−0.051***	−0.051***	−0.052***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Union member	0.238***	0.248***	0.231***	0.236***	0.230***	0.237***
	(0.040)	(0.040)	(0.038)	(0.038)	(0.038)	(0.038)
Left-right scale	−0.158***	−0.157***	−0.160***	−0.160***	−0.160***	−0.159***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
UE risk	0.065***	0.065***	0.117***	0.117***	0.116***	0.115***
	(0.018)	(0.018)	(0.017)	(0.017)	(0.017)	(0.017)
UE rate	0.035	0.036	0.047	0.047	0.028	0.028
	(0.031)	(0.031)	(0.031)	(0.031)	(0.030)	(0.030)
(Intercept)	7.111***	7.130***	6.734***	6.747***	7.125***	7.142***
	(0.341)	(0.340)	(0.491)	(0.489)	(0.333)	(0.333)
SD (Intercept cntry)	0.508	0.507	0.541	0.539	0.499	0.498
SD (Observations)	2.203	2.204	1.946	1.947	1.946	1.946
Num.Obs.	22 901	22 901	22 134	22 134	22 134	22 134
R2 Marg.	0.045	0.043	0.055	0.054	0.064	0.063
R2 Cond.	0.093	0.091	0.123	0.121	0.122	0.121
AIC	119 751.6	119 783.4	111 671.4	111 697.5	111 660.5	111 664.6
BIC	119 880.3	119 904.0	111 799.5	111 817.6	111 788.6	111 784.6
ICC	0.05	0.05	0.07	0.07	0.06	0.06
RMSE	2.12	2.12	2.09	2.09	2.09	2.09

Note: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Multilevel models with random country intercepts and survey weights.

Table D1: Table 1 including the unemployed

	Model 1	Model 2	Model 3	Model 4
(Intercept)	7.206***	7.153***	7.002***	7.512***
	(0.129)	(0.142)	(0.334)	(0.513)
fedu3Degree	0.149***	0.152***	0.151***	0.158***
	(0.036)	(0.038)	(0.038)	(0.039)
fedu3Non-degree, non-VET	0.135***	0.131***	0.130***	0.135***
	(0.031)	(0.035)	(0.035)	(0.035)
r08_EU27	0.293***	0.156+	0.155+	0.166
	(0.077)	(0.088)	(0.088)	(0.166)
female	0.059*	0.065*	0.065*	0.069*
	(0.026)	(0.028)	(0.028)	(0.028)
age	0.007***	0.005***	0.005***	0.005***
	(0.0008)	(0.001)	(0.001)	(0.001)
inc_decile	−0.058***	−0.053***	−0.054***	−0.055***
	(0.005)	(0.006)	(0.006)	(0.006)
union	0.225***	0.244***	0.245***	0.243***
	(0.038)	(0.040)	(0.040)	(0.040)
lrscale	−0.139***	−0.152***	−0.152***	−0.151***
	(0.006)	(0.007)	(0.007)	(0.007)
ue_now	0.486***	0.398***	0.397***	0.388***
	(0.054)	(0.062)	(0.062)	(0.062)
ue_risk		0.073***	0.072***	0.071***
		(0.017)	(0.017)	(0.017)
ue15.3y			0.035	−0.048
			(0.030)	(0.065)
vetshare			−0.010	−0.010
			(0.008)	(0.009)
SD (Intercept cntry)	0.522	0.536	0.499	1.644
SD (ue15.3y cntry)				0.236
SD (vetshare cntry)				0.022
SD (r08_EU27 cntry)				0.572
SD (Observations)	2.257	2.211	2.211	2.209
Num.Obs.	30 002	24 270	24 270	24 270
R2 Marg.	0.032	0.035	0.048	0.034
R2 Cond.	0.081	0.089	0.094	0.196
AIC	157 218.9	126 767.2	126 779.7	126 765.7
BIC	157 318.6	126 872.4	126 901.2	126 960.0
ICC	0.05	0.06	0.05	0.2
RMSE	2.13	2.11	2.11	2.11

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D2: Table 1 with lower-tier tertiary coded as VET

	Model 1	Model 2	Model 3	Model 4
(Intercept)	7.305***	7.289***	7.142***	7.125***
	(0.132)	(0.146)	(0.321)	(0.342)
fedu3_2University Degree	−0.006	−0.017	−0.006	−0.018
	(0.043)	(0.047)	(0.043)	(0.047)
fedu3_2VET	−0.119***	−0.106**	−0.118***	−0.105**
	(0.031)	(0.036)	(0.031)	(0.036)
r08_EU27	0.269***	0.120	0.267***	0.119
	(0.079)	(0.090)	(0.079)	(0.090)
female	0.081**	0.076*	0.081**	0.076*
	(0.027)	(0.029)	(0.027)	(0.029)
age	0.007***	0.005***	0.007***	0.005***
	(0.0008)	(0.001)	(0.0008)	(0.001)
inc_decile	−0.047***	−0.043***	−0.047***	−0.043***
	(0.005)	(0.006)	(0.005)	(0.006)
union	0.222***	0.245***	0.223***	0.246***
	(0.039)	(0.040)	(0.039)	(0.040)
lrscale	−0.144***	−0.159***	−0.144***	−0.159***
	(0.006)	(0.007)	(0.006)	(0.007)
ue_risk		0.067***		0.067***
		(0.018)		(0.018)
ue15.3y			0.037	0.036
			(0.030)	(0.031)
vetshare			−0.011	−0.010
			(0.008)	(0.008)
SD (Intercept cntry)	0.531	0.546	0.483	0.509
SD (Observations)	2.250	2.205	2.250	2.205
Num.Obs.	28 407	22 901	28 407	22 901
R2 Marg.	0.029	0.031	0.041	0.042
R2 Cond.	0.080	0.087	0.083	0.091
AIC	148 951.3	119 787.0	148 963.1	119 799.6
BIC	149 042.1	119 883.5	149 070.4	119 912.1
ICC	0.05	0.06	0.04	0.05
RMSE	2.13	2.12	2.14	2.12

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D3: Alternative outcome: support for ALMP over PLMP

	By dual VET share:		*All countries*			
	High	Low	Model 3	Model 4	Model 5	Model 6
(Intercept)	2.828***	2.679***	2.762***	2.849***	2.846***	2.840***
	(0.071)	(0.053)	(0.042)	(0.099)	(0.100)	(0.100)
vocational	0.016	0.009	0.007	0.006	0.008	0.015
	(0.016)	(0.013)	(0.010)	(0.010)	(0.010)	(0.014)
r08_EU27	−0.081+	−0.192***	−0.092*	−0.092*	−0.149***	−0.139***
	(0.044)	(0.036)	(0.038)	(0.038)	(0.038)	(0.028)
female	−0.001	−0.045***	−0.027**	−0.027**	−0.026**	−0.026**
	(0.015)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)
age	−0.004***	0.0004	−0.002***	−0.002***	−0.002***	−0.002***
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
inc_decile	0.012***	0.011***	0.011***	0.011***	0.011***	0.011***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
union	0.051*	−0.082***	−0.021	−0.021	−0.022+	−0.022+
	(0.020)	(0.018)	(0.013)	(0.013)	(0.013)	(0.013)
lrscale	0.019***	0.010***	0.012***	0.012***	0.012***	0.013***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
ue_risk	−0.041***	−0.029***	−0.035***	−0.035***	−0.035***	−0.035***
	(0.010)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)
vocationalr08_EU27			−0.099+	−0.099+		
			(0.053)	(0.053)		
vetshare				−0.0009	−0.0009	−0.0005
				(0.002)	(0.002)	(0.002)
ue15.3y				−0.009	−0.009	−0.009
				(0.009)	(0.009)	(0.009)
vetsharer08_EU27					0.0007	
					(0.002)	
vocationalvetshare						−0.0005
						(0.0006)
SD (Intercept cntry)	0.153	0.141	0.142	0.146	0.146	0.146
SD (Observations)	0.736	0.694	0.710	0.710	0.710	0.710
Num.Obs.	8074	14 081	22 155	22 155	22 155	22 155
R2 Marg.	0.015	0.010	0.009	0.011	0.011	0.011
R2 Cond.	0.056	0.049	0.047	0.051	0.051	0.051
AIC	21 096.7	44 575.8	65 712.2	65 733.1	65 743.3	65 744.8
BIC	21 173.6	44 658.9	65 808.2	65 845.2	65 855.4	65 856.9
ICC	0.04	0.04	0.04	0.04	0.04	0.04
RMSE	0.69	0.73	0.71	0.71	0.71	0.71

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D4: Alternative outcome: support for UBI

	By dual VET share:		*All countries*			
	High	Low	Model 3	Model 4	Model 5	Model 6
(Intercept)	3.014***	2.867***	2.923***	3.024***	3.022***	3.004***
	(0.100)	(0.065)	(0.054)	(0.137)	(0.137)	(0.137)
vocational	−0.010	0.004	−0.004	−0.004	−0.003	0.019
	(0.018)	(0.014)	(0.011)	(0.011)	(0.011)	(0.016)
r08_EU27	0.029	−0.025	−0.006	−0.006	−0.086*	−0.012
	(0.051)	(0.039)	(0.042)	(0.042)	(0.043)	(0.031)
female	−0.020	0.039**	0.013	0.013	0.013	0.014
	(0.018)	(0.014)	(0.011)	(0.011)	(0.011)	(0.011)
age	−0.002***	−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
	(0.0006)	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
inc_decile	−0.027***	−0.015***	−0.021***	−0.021***	−0.021***	−0.021***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
union	−0.040+	−0.036+	−0.033*	−0.033*	−0.034*	−0.034*
	(0.023)	(0.019)	(0.015)	(0.015)	(0.015)	(0.015)
lrscale	−0.065***	−0.025***	−0.039***	−0.039***	−0.039***	−0.039***
	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ue_risk	0.046***	0.036***	0.040***	0.040***	0.040***	0.040***
	(0.012)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)
vocationalr08_EU27			−0.012	−0.012		
			(0.059)	(0.059)		
vetshare				−0.004	−0.004	−0.004
				(0.003)	(0.003)	(0.003)
ue15.3y				−0.005	−0.005	−0.005
				(0.013)	(0.013)	(0.013)
vetsharer08_EU27					0.005*	
					(0.002)	
vocationalvetshare						−0.001*
						(0.0007)
SD (Intercept cntry)	0.239	0.192	0.205	0.206	0.206	0.206
SD (Observations)	0.849	0.742	0.784	0.784	0.784	0.784
Num.Obs.	8090	13 943	22 033	22 033	22 033	22 033
R2 Marg.	0.035	0.021	0.024	0.029	0.029	0.029
R2 Cond.	0.105	0.082	0.087	0.092	0.092	0.092
AIC	23 491.2	45 999.9	69 690.1	69 709.0	69 709.6	69 713.7
BIC	23 568.2	46 082.9	69 786.1	69 821.0	69 821.6	69 825.7
ICC	0.07	0.06	0.06	0.06	0.06	0.06
RMSE	0.79	0.79	0.79	0.79	0.79	0.79

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table D5: Alternative outcome: support for redistribution

	By dual VET share:		*All countries*			
	High	Low	Model 3	Model 4	Model 5	Model 6
(Intercept)	4.410***	4.126***	4.252***	4.002***	4.004***	3.991***
	(0.119)	(0.087)	(0.068)	(0.167)	(0.167)	(0.168)
vocational	0.003	0.053**	0.030*	0.030*	0.029*	0.047*
	(0.023)	(0.017)	(0.014)	(0.014)	(0.014)	(0.019)
r08_EU27	0.338***	0.299***	0.212***	0.211***	0.229***	0.314***
	(0.063)	(0.048)	(0.051)	(0.051)	(0.052)	(0.038)
female	0.077***	0.104***	0.096***	0.096***	0.094***	0.094***
	(0.021)	(0.017)	(0.013)	(0.013)	(0.013)	(0.013)
age	0.002**	0.004***	0.003***	0.003***	0.003***	0.003***
	(0.0007)	(0.0006)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
inc_decile	−0.042***	−0.035***	−0.039***	−0.039***	−0.038***	−0.038***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
union	0.151***	0.138***	0.143***	0.143***	0.145***	0.145***
	(0.028)	(0.024)	(0.018)	(0.018)	(0.018)	(0.018)
lrscale	−0.105***	−0.081***	−0.090***	−0.090***	−0.090***	−0.090***
	(0.006)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
ue_risk	0.033*	0.037***	0.036***	0.036***	0.036***	0.035***
	(0.014)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
vocationalr08_EU27			0.218**	0.219**		
			(0.073)	(0.073)		
vetshare				0.001	0.001	0.002
				(0.004)	(0.004)	(0.004)
ue15.3y				0.029+	0.029+	0.029+
				(0.015)	(0.015)	(0.015)
vetsharer08_EU27					0.005*	
					(0.002)	
vocationalvetshare						−0.001
						(0.0009)
SD (Intercept cntry)	0.281	0.269	0.264	0.252	0.252	0.253
SD (Observations)	1.056	0.943	0.986	0.986	0.986	0.986
Num.Obs.	8324	14 628	22 952	22 952	22 952	22 952
R2 Marg.	0.060	0.062	0.061	0.072	0.071	0.071
R2 Cond.	0.122	0.133	0.124	0.129	0.128	0.128
AIC	27 828.2	55 130.9	83 046.0	83 062.1	83 072.2	83 077.8
BIC	27 905.5	55 214.4	83 142.5	83 174.6	83 184.8	83 190.4
ICC	0.07	0.08	0.07	0.06	0.06	0.06
RMSE	0.95	0.95	0.95	0.95	0.95	0.95

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001