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Political and Social Consequences of Qualification Mismatches: A Bounding Approach to Status Inconsistency

Social Forces

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Appendix to Political and Social Consequences of Qualification Mismatches: A bounding approach to status inconsistency

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September 13th, 2021

A. Deriving restrictions on education and occupation parameters

To derive the uniquely identified parameters θ_1 and θ_2 from the underidentified equation $Y = \beta_E X_E + \beta_O X_O + \beta_{MM} X_{MM}$, I replace X_O with the expression $(X_E - X_{MM})$:

$$Y = \beta_E X_E + \beta_O (X_E - X_{MM}) + \beta_{MM} X_{MM} = \beta_E X_E + \beta_O X_E - \beta_O X_{MM} + \beta_{MM} X_{MM}$$

, which by rearranging eventually yields the equation

$$Y = \underbrace{(\beta_E + \beta_O)}_{\theta_1} X_E + \underbrace{(\beta_{MM} - \beta_O)}_{\theta_2} X_{MM}$$

, where the two combined parameters $\theta_1 = (\beta_E + \beta_O)$ and $\theta_2 = (\beta_{MM} - \beta_O)$ are uniquely identified, and estimated from X_E and X_{MM} , respectively. To then derive restrictions for β_{MM} , I first solve Eq. 4 ($\theta_2 = \beta_{MM} - \beta_O$) for β_{MM} , which gives the first restriction:

$$\beta_{MM} = \theta_2 + \beta_O$$

In a second step, I replace β_O in Eq. 3 ($\theta_1 = \beta_E + \beta_O$) with the expression $\beta_O = \beta_{MM} - \theta_2$ (also from rearranging Eq. 4), which yields

$$\theta_1 = \beta_E + \beta_{MM} - \theta_2$$

I then solve this expression for β_{MM} to arrive at the second restriction

$$\beta_{MM} = \theta_1 + \theta_2 - \beta_E$$

B. Details on the measurement of variables

Coding of virtual years of education

I use information on the detailed highest qualification attained to construct a metric variable of years of education. I consider elementary, secondary, tertiary, and vocational education, in so far it results in nationally recognized qualifications. Further education programs that are company specific, or not certified, do not enter the estimation of formal education requirements. Importantly, my measure is based on the typically required time for the completion of qualification as opposed to the actual time spent on attaining it (Schneider 2010). The conversion took place using the translation keys displayed in Tables B-1 and B-2, which are based on background information on countries' education systems (DoE 2013; 2018; Jones 2016; KMK 2017a; 2017b; Ofqual 2009; Schneider 2008). In cases where these background sources did not provide guidance on how to treat British vocational qualifications, I use the observed median duration needed by respondents to attain the respective qualifications to calculate its contribution to respondents' years of education.

To, then, derive the typical years of schooling in each occupation, I calculate the mean years of schooling and their standard deviation in 3-digit ISCO-groups from the data. To increase precision, I pool education information within a 11-year window to form a moving average of an occupation's observed years of education. By dropping repeated observations of respondent-occupation combinations within that window, I make sure that each respondent contributed to the calculated mean and standard deviation of any occupation in a given year only once. I further distinguish between East/West Germany and (non-)/London, respectively, and employ the appropriate cross-sectional poststratification weights. In each country, this leaves me with around 100 different occupations, for which I possess information on typical education profiles.

Table B-1 Virtual years of education, United Kingdom

Years of education assigned	Qualification/certificate
8	none
10	school leaving certificate, standard/ordinary grade, cse, gcse/o-level
12	a-levels and equivalents
14	Diploma in higher education
15	1st degree level including foundation degree, graduate of professional institute, pgce
17	university higher degree (e.g. Msc, PhD)
to which we added a maximum of one of the following further education qualifications if respondents did not report tertiary education (values based on median duration times)	
3	hnc/hnd, onc/ond
2	modern/trade apprenticeship, scotvec, scotec, scotbec, other vocational, technical or professional qualification, city and guilds certificate, gnvq/gsvq, nvq/svq-level 1-2, btec/bec/tec/edexcel/lq, rsa/ocr, clerical/commercial qualification, youth training certificate, key/basic skills, entry level qualifications (wales)
1	
Foreign qualifications of respondents	
3	none
5	completed primary school
10	completed secondary school
11	post-secondary vocational training (up to 1 year)
12	post-secondary vocational training (2 and more years)
14	post-secondary academic below-degree level qualification
15	Bachelors or equivalent first degree qualification
16	postgraduate academic below-masters level qualification
17	Masters or equivalent higher degree level qualification
20	PhD
Qualifications of respondents' parents	
4	no schooling reported
9	left school with no qualifications or certificates
10	left school with some qualifications or certificates
12	post-school qualifications or certificates (e.g. City & Guilds)
16	university degree or higher degree

Table B-2 Virtual years of education, Germany

Years of education assigned	Qualification/certificate
7	none
9	general secondary school (Hauptschule)
10	intermediate secondary school (Realschule)
10.5	general secondary school + other vocational training
11.5	intermediate secondary school + other vocational training
12	general secondary school + apprenticeship or equivalent, vocational maturity certificate (Fachabitur)
13	general maturity certificate (Abitur), intermediate secondary school + apprenticeship or equivalent
14.5	vocational maturity certificate + other vocational training
15	vocational maturity certificate + apprenticeship or equivalent
16	Bachelors or equivalent, general maturity certificate + apprenticeship or equivalent
18	Masters/PhD or equivalent
Qualifications of respondents' parents	
3	none
5	general secondary school (Hauptschule)
10	intermediate secondary school (Realschule)
12	vocational maturity certificate (Fachabitur)
13	general maturity certificate (Abitur)
to which we added the following vocational qualifications if applicable	
1	unspecified vocational training
3	apprenticeship or equivalent
5	crafts-master (Meister), technician-degree, technical tertiary degree (FH) or equivalent
6	university degree

Immigrants were assigned the closest German equivalent.

C. Measurement of control variables

In all analyses, I control for respondents' cognitive and non-cognitive skills. A rarity in population studies, both the UKHLS and SOEP contain direct measures of cognitive ability, although the tests are somewhat different and hence not directly comparable. UKHLS respondents solved logical puzzles, subtraction exercises, and tests of their everyday numeracy skills (McFall 2013). SOEP respondents had to match a range of symbols to numbers according to a predefined key (Schupp et al. 2008). Unfortunately, only a random 25% sub-sample of the SOEP was assessed each time. Because the other 75% are missing completely at random (MCAR) I impute their cognitive ability scores using a chained equation approach as explained in the main article.

The measures of non-cognitive skills are directly comparable across the UKHLS and SOEP. To assess the Big-5 personality dimensions, both surveys rely on identical short versions of the FFM personality inventory (Dehne and Schupp 2007). For each survey year, I perform a varimax rotated principal-component analysis of the 15 items, which are measured on 7-point scales. As predictors in our analysis I use factor scores based on a five-component solution reflecting the Big-5 personality dimensions. Two other measures of personality I take into account, risk aversion and locus of control, were measured using standard single item scales in both survey (Risk aversion: 'Are you generally a person who is fully prepared to take risks or do you try to avoid taking risks?' with an eleven-point scale ranging from 'avoid taking risks' to 'fully prepared'). Locus of control: 'I feel that what happens in life is often determined by factors beyond my control' with a six-point scale ranging from 'strongly disagree' to 'strongly agree').

I measure parental SES by using respondents' recollection of their parents' occupation when they were 14/15 years old. In particular, I use the average of parents' international socio-economic index (ISEI) to measure socio-economic origin. For the UKHLS, I obtain ISEI-values through a translation routine provided by the CAMSIS project (Lambert and Prandy 2008). Parental education is also inferred from respondents' reports. I use a metric variable that was derived from survey respondents according to the key in Appendix B. Like for SES, I use the average virtual years of education of respondents' parents as an indicator of parental education.

D. Measurement of dependent variables

In the following, I list the questions from the two surveys I use to measure the dependent variables:

Table D-1 Dependent variable items

Variable	Item UKLHS	Response categories UKLHS	Item SOEP	Response categories SOEP
Trust	Are you generally a person who is fully prepared to take risks in trusting strangers or do you try to avoid taking such risks?	0 Avoid taking risks in trusting strangers – 10 Fully prepared to take risks in trusting strangers	How do you evaluate your attitude towards risk regarding the following areas? How is it about confidence regarding foreign people?	0 risk averse -- 10 fully prepared to take risks
Satisfaction with democracy	On the whole, are you very satisfied, fairly satisfied, a little dissatisfied or very dissatisfied with the way democracy works in this country?	Very satisfied, Fairly satisfied, A little dissatisfied, Very dissatisfied	How satisfied are you today with the following areas of your life: - With democracy as it exists in Germany?	
Job satisfaction	Please look at this card and tell me, all things considered, which number best describes how satisfied or dissatisfied you are with your present job overall?	1 completely dissatisfied – 7 completely satisfied	- With your job?	Completely dissatisfied 0 – 10 Completely satisfied
Life Satisfaction	Please tick the number which you feel best describes how dissatisfied or satisfied you are with the following aspects of your current situation: - Your life overall		How satisfied are you currently with your life in general?	
Importance politics	Please think about each of the following and tick the box that indicates whether you think it is very important, fairly important, not very important or not at all important to your sense of who you are: - Your political beliefs?	very important, fairly important, not very important, not at all important	Different things are important to different people. How important are the following things to you? - Being politically and/or socially involved	Very important, important, less important, not at all important?
Importance profession	- Your profession?		- Being successful in my career	

Two other dependent variables of our analyses are voting intentions for left-wing parties and voting intentions for far-right parties. In the UK party support was coded in three steps: In a first step, I used information from an item that asked, which party the respondent would vote for if there was a general election tomorrow. However, about 16% of respondents answered “None”, yielding a total of just 53% of usable party nominations. Thus, if information on that variable was missing, I relied on an item that

asked which party a respondent “felt closest to”. If again no information was recorded, I coded party-support using information on which party a respondent had voted for during the last election. In the end, 62% of respondents in the sample could be assigned a party affiliation. In Germany, I was able to carry out only the second step, yielding just over 40% of usable nominations. I here list the parties I counted as left and far-right, respectively:

Variable	UK	Germany
Left-wing voting intention	Labour, SNP, Plaid Cymru, Green Party, SDLP, Sinn Fein	SPD, Greens, and Die Linke
Far-right voting intention	Ulster Unionists, UKIP, BNP	DVU, Republikaner, NPD, AfD

Table D-Fehler! Kein Text mit angegebener Formatvorlage im Dokument.-2 Left-wing and Right-wing parties in the UK and in GermanyResults for Different Specifications

E. Comparison to the ORU and OEU models

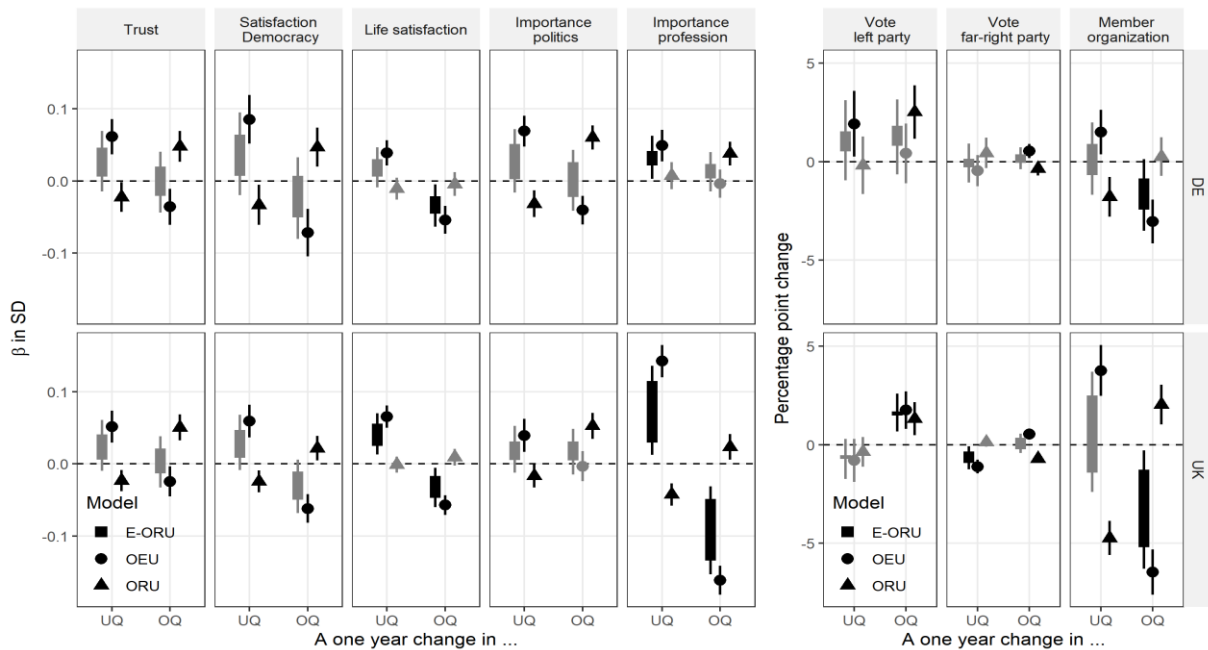
Figure E-1 present the results of the analysis of pooled data using three different specifications: the E-ORU model described in the main text, the classic ORU decomposition, and the OEU model, where instead of acquired education, E , (as in ORU) the effect of occupation-typical education, O , is assumed to be zero. In the OEU model the comparison is between matched and mismatched workers in occupations with the same occupation-typical education. In ORU, it is between matched and mismatched workers with the same education. E-ORU, finally, aims to isolate the mismatch-effect net of education and occupation. All of the differences reported are net of control variables, but essentially cross-sectional.

The first take-away from Figure E-1 is that in general both education and occupation have sizeable true main effects on the outcomes. This is indicated by the fact that for virtually all dependent variables the mismatch parameters obtained from the OEU and the ORU specifications have different signs. This is because matched and mismatched workers differ not only in their mismatch-status, they also differ in their education, or, depending on the model, their occupation. This pattern underlines that the main effects of occupation and of education cannot simply be assumed to be zero. Had we naively assumed that OEU and ORU returned the effects of mismatches proper, the conclusions would have differed starkly between specifications. This fact illustrates the importance of gaining a theoretical understanding of the assumptions implied by empirical approaches.

Underqualified workers are more trusting, more satisfied with politics, their lives, identify more with their profession, put a larger emphasis on political involvement, are more likely to be members of an organization, and less likely to intent to vote for a party of the far-right, *compared to matched workers with the same education*. However, if I compare mismatched workers with matched workers in a similar occupation, I tend to find the opposite. Now underqualified workers appear as less trusting, less satisfied with politics, their lives (n.s. in the UK), attach less importance to politics and their profession, and are

less likely to be members of an organization. For overqualified workers the picture is again generally the inverse.

Figure E-1 Social and political attitudes and behaviors among mismatched workers, results for different specifications

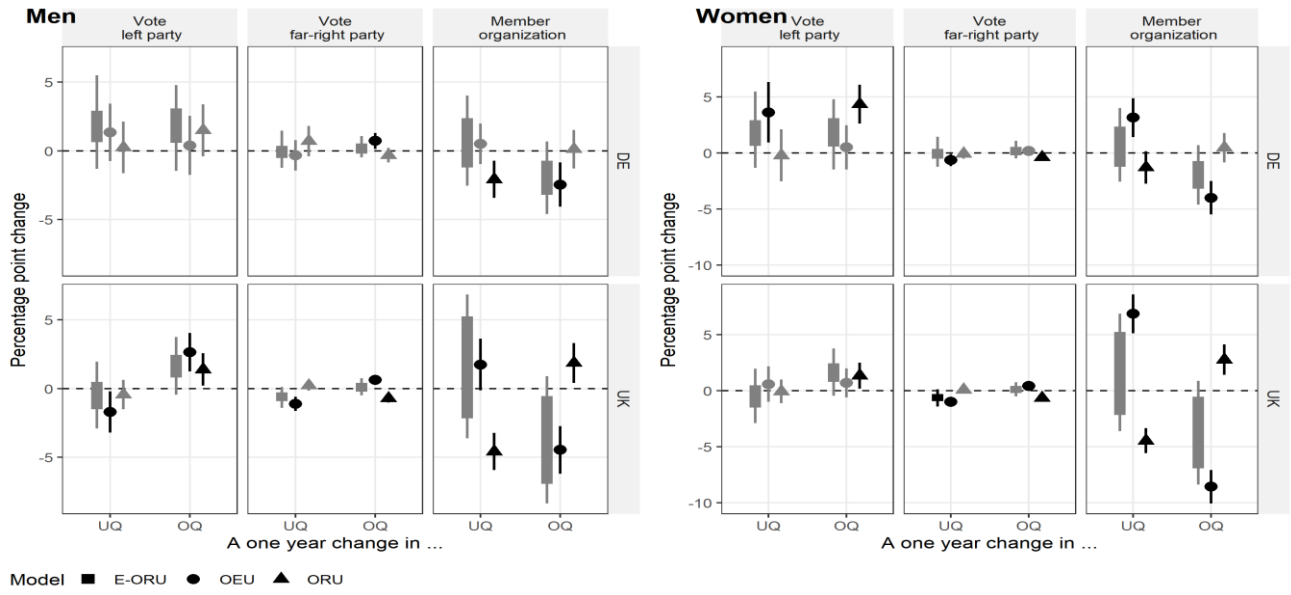


Note: Constrained least squares models estimated on pooled data. 95%-Confidence intervals based on cluster-robust standard errors and ten imputations. Results controlled for personal characteristics.

F. Gender specific results

Figures F-1 and F-2 replicate the analyses of the main text separately for men and women. As can be seen, the results are largely identical for both genders. However, due to the reduced sample size, some of the results that were clearly significant in the combined analysis only border conventional levels of significance, when estimated separately.

Figure F-2 Social and political behaviors among mismatched workers, by gender



Note: Constrained linear probability models estimated on pooled data. Confidence intervals based on cluster-robust standard errors and ten imputations. Results controlled for personal characteristics.

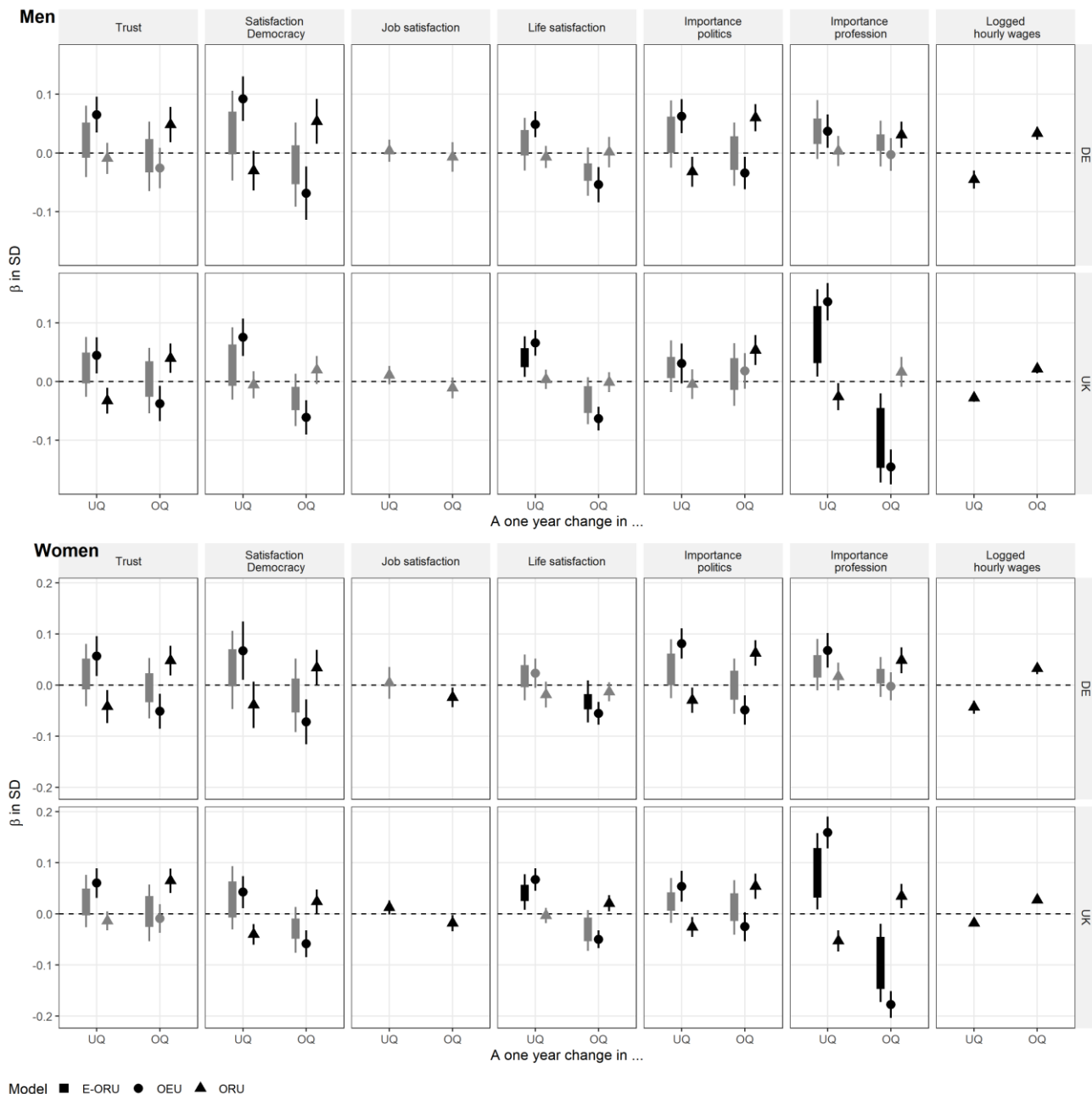


Table E-1 Social and political attitudes, and wages among mismatched workers, by gender

Note: Constrained least squares models estimated on pooled data. Confidence intervals based on cluster-robust standard errors and ten imputations. Logged hourly wages: effects given in log-points. Results controlled for personal characteristics.

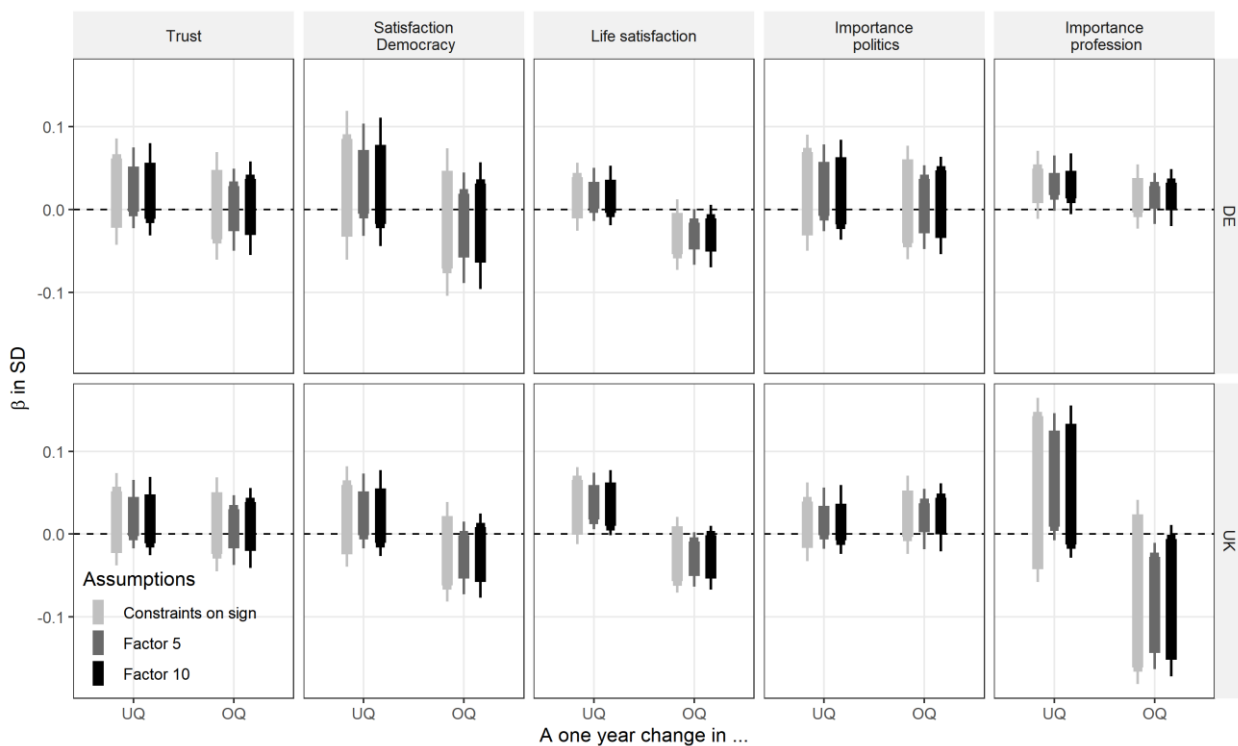
G. Sensitivity analysis for alternative identifying restrictions

Figures G-1 and G-2 replicate the main analysis employing different assumptions about the relative importance of education and occupation for our outcomes of interest. In the analyses reported in the main text, mismatch-effects are identified using the constraint $\frac{\beta_E}{3} < \beta_O^{\min} < 3\beta_E$, i.e. I assume that the effect of education is not three times larger or three times smaller than that of occupational status. Here I report results for using the factors five or ten instead, which imply weaker constraints on the relative

weight of education and occupation. In a final specification, I merely constrain β_E and β_O to have the same sign. This excludes the possibility, for instance, that education has a positive effect on life satisfaction, but that working in a job that requires more education has a negative one. This is a very weak constraint and hence produces likely overly conservative bounds on the true effect size.

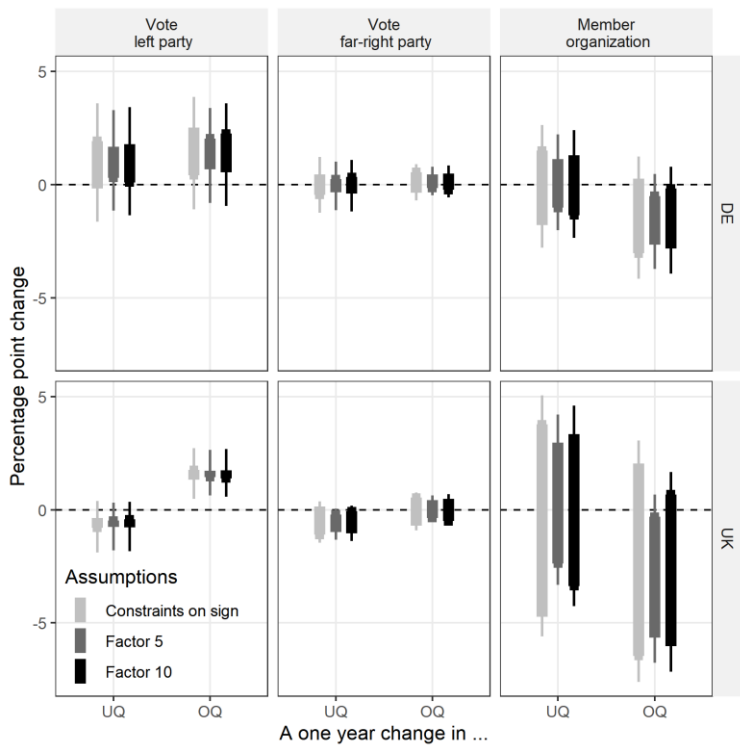
As can be seen, the picture that emerges using these alternative values is strikingly similar to the results reported in the main text. However, in some instances, making weaker assumptions results in identification-bounds crossing zero. This is true for trust, life satisfaction, the satisfaction with democracy, the importance of politics, and organizational membership. Note however, that in these cases, extreme conditions are necessary to rule out mismatch effects. For instance, a zero or negative impact of underqualification on life-satisfaction is only compatible with our data, if the direct effect of education is regarded as close to zero. As soon as some effect of education is granted, the estimates for underqualification effects turn positive. Not all estimates within the identification bounds are equally likely.

Figure G-1 Social and political attitudes, and wages among mismatched workers, under different identifying assumptions



Note: Constrained least squares models estimated on pooled data. Confidence intervals based on cluster-robust standard errors and ten imputations. Logged hourly wages: effects given in log-points. Results controlled for personal characteristics.

Figure G-2 Social and political behaviors among mismatched workers under different identifying assumptions



Note: Constrained linear probability models estimated on pooled data. Confidence intervals based on cluster-robust standard errors and ten imputations. Results controlled for personal characteristics.

H. Fixed-effects specification and result

The pooled-data E-ORU specification addresses the linear dependency of O, E and MM. However, as a cross-sectional model, it is susceptible to confounding from unobserved variables. I address this problem in an additional robustness check using a person-fixed-effects (FE) approach. This design eliminates all person-level time-constant confounders. However, a fixed effects approach cannot rule out selection into and out of mismatch based on trends in outcomes, reverse causality (e.g. changes in political attitudes causing people to become mismatched), or confounding by time variant unobservables (Brüderl and Ludwig 2014).

For this additional step, I make use of all the survey years available in which the respective dependent variable was measured, i.e. I use all waves of the GSOEP since 1984. Table H-1 lists the number of gap years between measurements for the dependent variables, and the mean number of observations per respondent that I draw on to estimate the FE models. I only use data from respondents, whose education has remained constant throughout the observation period and use only mismatch-changes that I can relate to job-changes as indicated by changes in the 3-digit ISCO occupational title, ignoring periods of unemployment and inactivity. In these models, I only adjust for age, the tenure in the current position, and survey year. If the E-ORU specification is applied in a FE context, the E-term, as a time-constant variable, is absorbed by α_i , the person FE, yielding the ORU-FE specification

$$Y_{it} = \alpha_i + \beta_{O_{it}} O_{it} + \beta_{OQ_{it}} OQ_{it} + \beta_{UQ_{it}} UQ_{it} + \sum \beta_{X_{jit}} X_{jit} + \epsilon_{it}$$

where i indexes individuals, j control variables and t survey waves. Again, assuming only linear effects, both β_O and β_{MM} , the shared linear component of β_{OQ} and β_{UQ} , have to be estimated from the same changes of occupation—which is always both an equal change in O and in linear mismatch, X_{MM} . There is hence again an identification problem. As in the cross-sectional case, the combination of both parameters is identified as $\theta_3 = \beta_O - \beta_{MM}$. In order to learn something about, β_{MM} we therefore must make assumptions about β_O . Unfortunately, β_{MM} and β_O may take the same direction, so that merely constraining the sign of β_O is not informative about the range of values β_{MM} can take. Instead, we must specify a maximal effect size for β_O relative to θ_3 , π^{\max} , in order to infer β_{MM} . I define π as $\pi = \frac{\beta_O}{\theta_2}$, which here can take values between 0 and 1.

Since it is impossible to know such a maximal effect size a priori, I gauge the potential for mismatch effects due to occupation changes by resorting to bounded estimates. The endpoints of the bounds are comprised of the two extreme cases: that the linear effect of changing occupation is entirely due to the linear mismatch-component, $\pi^{\max} = 0$, and that there is no linear effect of mismatch at all, $\pi^{\max} = 1$. To the resultant bounds I add the non-linear components of mismatches. Concretely, I allow different coefficients for moving deeper into overqualification, relative to individuals' multi-year average, $\beta_{OQ_{it}}$, and vice versa for moving deeper into underqualification, $\beta_{UQ_{it}}$. This procedure results in conservative bounds on the effects of under- and overqualification. In many cases, it allows demonstrating or ruling out mismatch-effects, even when the relative size of the linear component is unclear.

Figure H-1 gives bounded estimates of mismatch-effects. As explained above, the bars represent results for assuming that between all ($\pi=0$) and none ($\pi=1$) of the linear portion of the combined occupation/mismatch effects, θ_3 , are due to the mismatch component β_{MM} . Because these assumptions are weak, estimates remain relatively imprecise. Such concerns notwithstanding, the patterns confirm the interpretation of the cross-sectional analysis. I find that outcomes close to the employment relationship change with mismatch changes. Increases in overqualification go together with decreases in job satisfaction and a falling subjective importance of one's profession, as shown by identification bounds consistently in the negative for these outcomes. Safe for values of π towards the extreme of $\pi=1$, these patterns are also statistically significant (effects on job satisfaction in Germany are always significant). Changes in outcomes upon increasing undereducation are present in the cases of organizational membership, the importance of professional identity and of job satisfaction the UK. Again, however, they are statistically significant only if we are willing to assume that some of the linear effects of job-changes are due to mismatches. Once we move towards attitudes and behaviors relating to politics, there is hardly any evidence for an effect of mismatch-changes, or, for that matter, of occupation changes, at all and either identification bounds or confidence intervals clearly overlap with zero. Similar to the pooled regressions, differences between countries, finally, appear to be negligible in the ORU-FE specification.

	Trust	Satisfaction democracy	Job satisfaction	Life satisfaction	Importance politics	Importance profession	Vote left party	Vote far-right party	Member organization	
UKHLS	N _{Obs}	14 789	22 112	84 428	77 446	20 528	21 599	59 687	59 687	11 838
	N _{Resp}	14 789	14 964	25 955	24 334	14 631	15 227	20 749	20 749	11 838
	Mean number of waves/person	1	1.47	3.25	3.18	1.40	1.41	2.87	2.87	1
	Longest gap	-	2	0	0	2	2	0	0	-
SOEP	N _{Obs}	14 977	22 112	202 729	205 849	45 387	45 387	83 225	83 225	34 436
	N _{Resp}	11 825	14 964	36 625	37 491	23 358	23 358	20 707	20 707	18 040
	Mean number of waves/person	1.26	1.47	5.53	5.49	1.94	1.94	4.01	4.01	1.90
	Longest gap	4	4	0	0	4	4	0	0	4

Table H-1: Sizes and measurement frequencies of the longitudinal samples

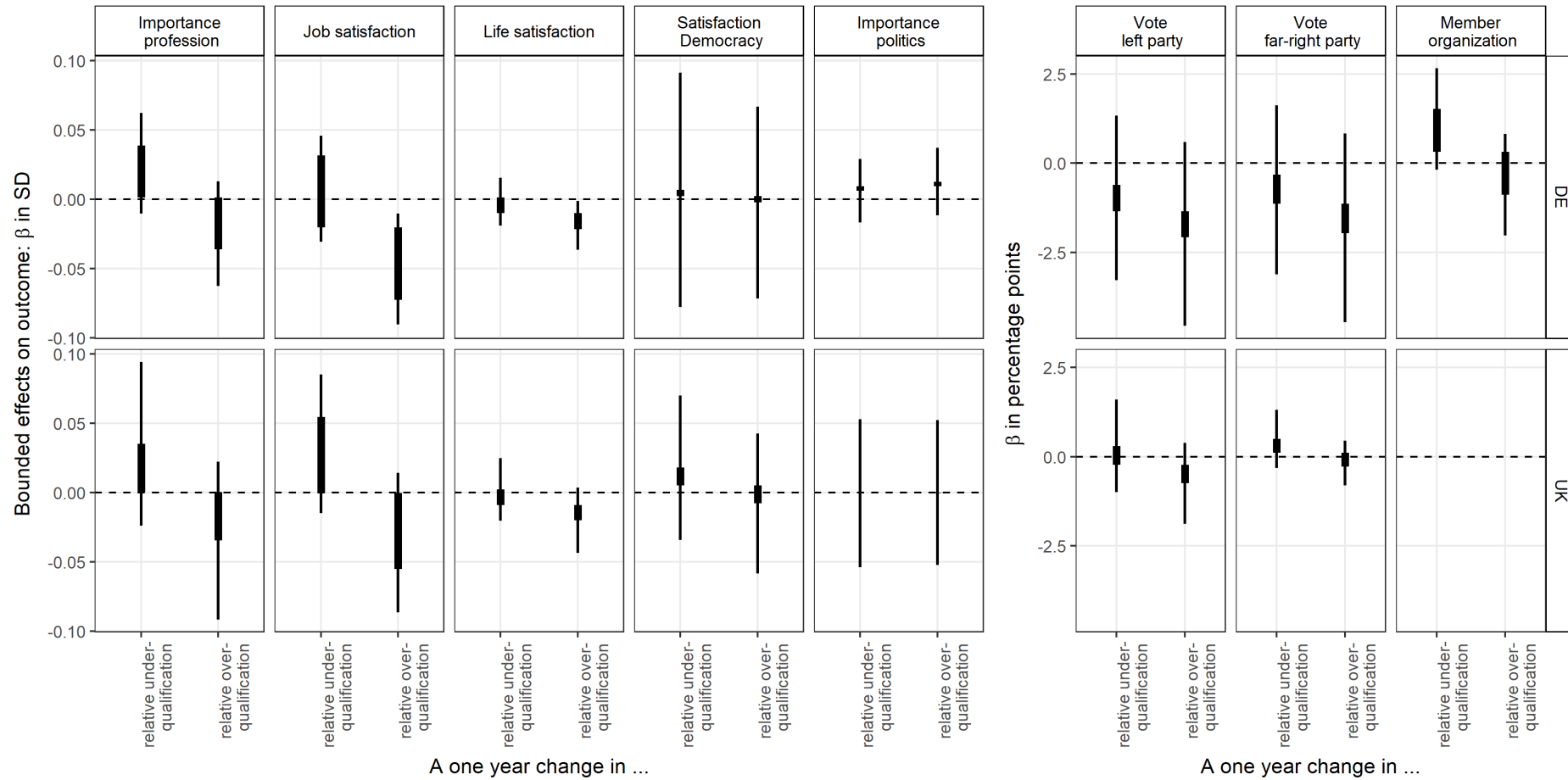


Figure H-1 Changes in social and political attitudes with changes of occupation/mismatch status

Note: Constrained least squares fixed effects models. 95% confidence intervals based on cluster-robust standard errors and ten imputations. Controls for age, tenure, and survey year.

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