This research report aims to predict job satisfaction across Europe, with examination of the variability of individual and country-level observations. Job satisfaction (JS) will refer to someone's personal contentment and fulfilment of their job, and such factors predicting JS will be indicated and analysed. Data in this study is extracted from round 10 of the European Social Survey 2021 (ESS), offering the quantitative analysis of 16,010 observations. The key data analysis techniques to be used in this study include K-means clustering and multilevel modelling.

Literature Review

A cross-national study by Sousa-Poza and Sousa-Poza (2000) analysed the International Social Survey Program (ISSP) from 1997, to find that European workers were generally satisfied in their jobs, particularly in Denmark and Switzerland. Lower rankings of JS were found in Hungary, Slovenia, Bulgaria and Czech Republic. A bottom-up approach analysed the balance of inputs (such as education and working time) with outputs (wages, management and colleague relationships). Greater outputs, relative to inputs, indicated higher JS. Management relations, working independently and income were found to explain JS. However, Easterlin (1974) considered that workers' satisfaction of their income is based on comparison to others, rather than the actual value. Having an exhausting job was found to have the largest negative effect JS (Sousa-Poza and Sousa-Poza, 2000). Countries scoring highly in masculinity, such as Hungary and Italy, are more satisfied in jobs with attractive economic factors, including retention bonuses and financial stability (Gu et al., 2021).

A more recent multilevel analysis of the ISSP from 2015 was conducted by Gu et al. (2021). Hofstede's cultural model was applied to analyse how culture moderates the relationship between job characteristics and JS. Individualistically cultured countries, such as the Netherlands, rated higher JS if their job was perceived as exciting, than those in collectivist countries. This was alongside the job offering personal growth and career development. Moreover, a significant interaction between uncertainty avoidance and income was found. This interaction had been previously explained by Hauff, Richter and Tressin (2015), as high-income nations often have safeguards in place which protect against unemployment and poverty. Thus, greater JS is found in countries where income is higher, as there is less anxiety for the consequences of unemployment.

Across Europe, women generally report higher JS than men, despite the disparities faced by women in the workplace (Perugini and Vladisavljević, 2019). Gu et al. (2021) expressed that women's subordinate position has meant they disproportionately struggle in the workplace in comparison to men. Moreover, women are often disadvantaged in career progression by caregiving duties. Across Europe, societal differences in gender equality have created a gender-gap in both the labour force and JS (Perugini and Vladisavljević, 2019). A suggested explanation for this is the lower expectations held by women of their position in the labour force, thus they are more easily satisfied with their position. Perugini and Vladisavljević (2019) found that early-life exposure to equal-gender settings corresponded to higher JS across Europe. Women's participation in the labour market was higher in Central and Eastern Europe (CEE) compared to Western Europe (WE). This aligned with greater equal-gender settings in early life, thus higher JS. This finding was explained by CEE maintaining more progressive attitudes towards gender equality after transitioning to a free-market economy. Similarly, Clark et al. (2021) found higher wellbeing in workers whose jobs had greater gender diversity.

Gender differences in JS are found to vary with age. Clark et al. (1996) established the effect of age on JS across Europe is typically U-shaped, where younger and older workers rate higher satisfaction than those in-between; this relationship is stronger for males. Despite this, positive linear relationships where JS increases with age have also been found (Ng and

Feldman, 2010). Besen et al. (2013) argued that depending on age, workers have different needs impacting JS. The researchers found that the positive relationship between autonomy and JS weakens as age increases. However, JS remains stable as age increases when considering emotional characteristics. These findings contribute to the idea that life priorities change, and JS varies with age. Cavanagh et al. (2019) conducted a longitudinal study of 2,593 Americans aged 18-95, adding that JS and its relationship with autonomy and income increases with age. Despite studies often including education as a predictor of JS, research has found it to be insignificant (Perugini and Vladisavljević, 2019; Fialová, 2023).

The COVID-19 pandemic is relevant to consider in JS studies, as the circumstances of many jobs were impacted, and consequently worker satisfaction (Fialová, 2023). Fialová (2023) found that during the pandemic, CEE reported considerably lower JS compared to WE. Explanations included relocation during lockdowns, working from home, and income changes which affected how people considered their jobs. In line with previous studies, socio-demographic characteristics were less important predictors than job characteristics, however Fialová (2023) investigated the relationship between JS and life satisfaction. Based on the literature reviewed, the present study will examine JS at the individual and country level. As such, the research question of this study is:

How can job satisfaction be predicted across Europe, and is variability larger between countries or individuals?

<u>Methodology</u>

This study analyses round 10 of the ESS, which was conducted in 2021 (ESS ERIC, 2023). This is a cross-national survey which gathers data on a broad range of social topics. Included in this range are questions which ask participants to report characteristics of their jobs, including their satisfaction, and their socio-demographic factors. Hence, the ESS provides an appropriate dataset for analysis in this study. Participants are sampled by random probability methods, to represent those aged over 15 who reside in private households in each country. Prior to data cleaning, the sample size of the ESS was 37,611. 22 countries are included in this analysis (Appendix A).

JS is the outcome being predicted in this analysis (measured on a scale from 0=Extremely Dissatisfied to 10=Extremely Satisfied). Predictors of *JS* were determined by the literature review and include: *Manager Supports in Work* (1=Very likely, 4=Not likely at all)*; Manager supports balancing work/life* (0= Not at all, 10=Completely); *Too tired after work* (1=Never, 5=Always); *Can Decide Place of Work* (1=Every day, 6 =Never); *Can decide start and finish time* (1=Not at all, 3=Completely). *Total hours worked per week* is recorded in hours; and *Household income* is recorded in deciles. *Gender* is dichotomous (1=Male, 2=Female). *Age* is recorded in years. The code label of each variable is in Appendix B.

It was determined that for variables with 'Not Applicable' as a possible response, the data was Missing Not At Random. Imputing these cases would have been inappropriate, because for someone without a manager, for example, may rate their *JS* differently if they did have a manager. Therefore, these responses were dropped from the dataset. This unavoidably decreased the sample size, but it remained sufficient for analyses. Responses of 'Don't know', 'Refusal' and 'No Answer' were determined as Missing At Random, and multiple imputation was performed where over 5% of data were missing, using predictive mean matching (van Buuren and Groothuis-Oudshoorn, 2011). This applied to *Total hours worked per week* where 9.61% of data was imputed. This variable was capped at the 99th percentile (84 hours), as values ranged to 168 hours. For *Household income,* 28.4% of data was Missing At Random, and imputed*.* After data cleaning and multiple imputation, the dataset contained 16,010 fully productive cases. Univariate analysis was conducted to understand the distribution of each variable to ensure they were appropriate. Bivariate analyses explored the relationship between the predictors with *JS*, and each other, with a covariate heatmap.

The data reduction technique of K-means clustering was used, to reduce the large number of observations in the ESS into typologies. This technique separates populations into groups where each datapoint is similar to those in the same group, and dissimilar to those in other groups (Davidson, 2002). The *Country* column was dropped because K-means clustering requires numerical data. The dataset was also standardised to the same scale, so the mean of each variable was 0 and the standard deviation was 1. The silhouette coefficient was calculated and plotted to determine the ideal number of clusters, by considering the mean intra-cluster distance and the mean nearest-cluster distance for each data point (Shahapure and Nicholas, 2020). The silhouette score was calculated as 2 (Appendix C). Observations were then reduced into 2 clusters, and the characteristics of each cluster were analysed through calculating the mean values of all predictors. After retaining the *Country* column, analyses of which cluster the majority of observations in each country were conducted. K-means clustering therefore aided the predicted of *JS* across Europe answering the first part of the research question.

The second part of the research question, investigating variability, was investigated as follows. Due to the hierarchical structure of the ESS, where individual observations are nested within countries, the assumption of independence is violated. As this research aims to analyse the variance of *JS* at both the individual and country level, multilevel modelling was essential to capture the different levels of analysis (Nezlek, 2010). Thus, multilevel modelling was used to determine whether variability of *JS* is larger on the individual or country level. Due to the limited scope of this research and the exploration of predictor variables, one predictor was chosen to assess individual and country level variability, through statistical means. The findings of this analytical process are detailed next.

Findings

Figure 1 displays the mean national *JS* across Europe, ranging from 6.97 to 8.01, with absent countries of the ESS in grey. Highest averages are reported in Norway, Iceland and Finland and the lowest means are found in Czechia, Greece and Italy. Appendix D presents the mean value of each country in descending order. Appendix E displays the bivariate distribution of *JS* and *Country*. Scores range from 0 to 10, with a mean of 7.48 and a median of 8. The standard deviation of scores is 1.89; skewness is -1.04, representing a negative skew to the left. The lower quartile is 7, the upper quartile is 9 and the inter-quartile range is 2 indicating that half of the data falls within these two points on the scale.

Figure 1

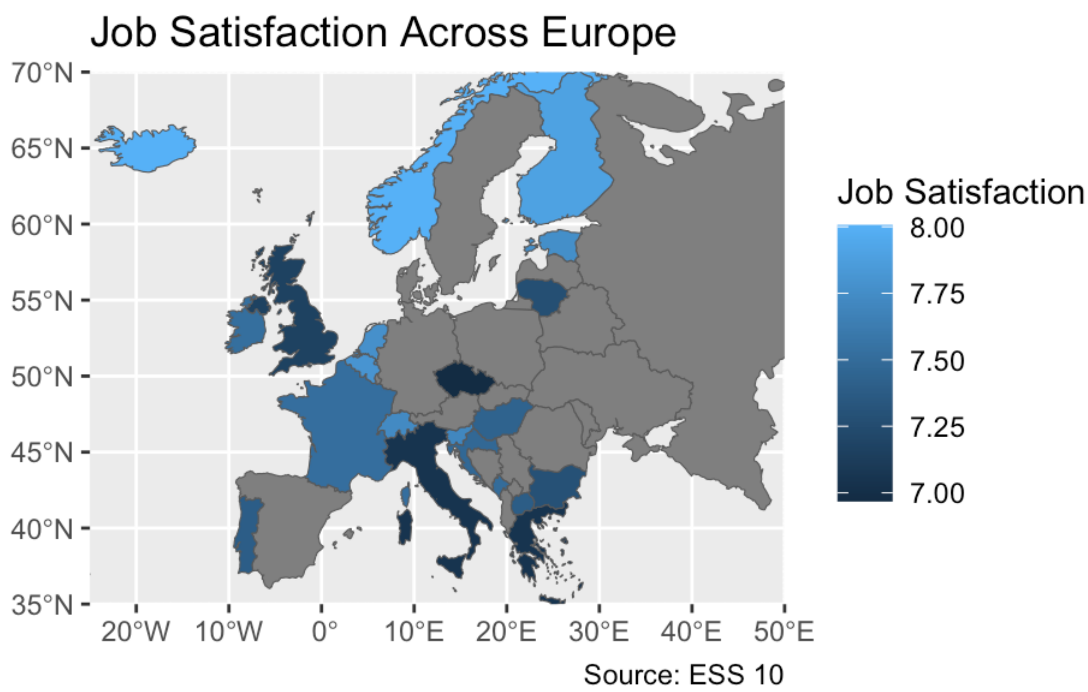


Figure 2 presents a covariate heatmap of the variables in this study. A relatively weak positive covariance is found between *JS* and *Manager supports balancing work/life*. This aligns with the literature, where positive relationships with managers predict higher JS

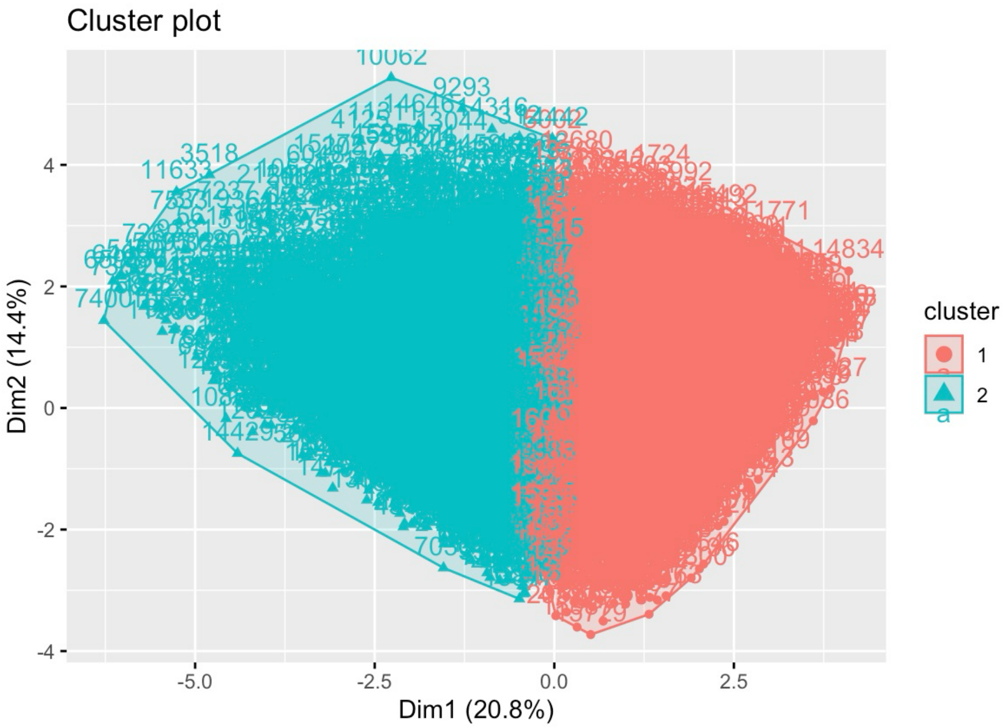
(Sousa-Poza and Sousa-Poza, 2000). Also worth mentioning is the negative covariance between *JS* and *Manager supports in work*. Due to the coding of this variable, the higher value represents a manager not being supportive in work and is therefore associated with lower JS, again aligning with previous findings. *Gender* and *Age* appear to be independent of *JS*, and other predictors. Notable relationships also include a strong negative covariance between *Manager supports in work* and *Manager supports balancing work/life,* which is again susceptible to the reverse coding of *Manager supports in work*. Another strong negative covariance is found between *Can decide place of work* and *Can decide start and finish time*.

Figure 2

Figure 3 presents the K-means clustering results, where there is little overlap of the 2 clusters. The characteristics of cluster 1 (8858 observations) and cluster 2 (7152) are as follows. Mean *JS* in cluster 1 is 8.35, which is greater than the overall mean of all observations (7.48). *Household income* was on average, in the 7th decile. *Total hours worked per week* was 38.9. The mean of *Manager supports in work* is 1.35 and *Manager supports balancing work/life* is 8.27. The average of being *Too tired after work* is 2.72. Job autonomy was indicated by the two variables *Can decide place of work* and *Can decide start and finish time.* The average of the former is 4.23 and the latter is 1.92. Average *Age* in cluster 1 is 47.06 years. *Gender* averages at 1.49 for cluster 1.

Comparatively, mean *JS* in cluster 2 is 6.40, considerably less than cluster 1. *Household income* was on average lower, in the 5th decile. There is marginal difference between clusters in *Total hours worked per week* (38.8). Being *Too tired after work* is 3.35 in cluster 2, indicating more exhaustion on average in this cluster. The mean of *Manager supports in work* is increases to 2.10 and *Manager supports balancing work/life* decreases to 5.50. *Can decide place of work* increases to 5.49, and the average score for *Can decide start and finish time* decreases to 1.35 in cluster 2. The average *Age* in cluster 2 is slightly older, at 53.66 years. *Gender,* whilst marginally different to cluster 1, is an average of 1.54 for cluster 2, indicating slightly more female observations.

Figure 3



The distribution of observations, by country and cluster is presented in Appendix F. Cluster 1 includes more observations in Belgium, Switzerland, Estonia, Finland, France, Great Britain, Ireland, Iceland, and Slovenia. Considerably more observations are in cluster 1 for the Netherlands and Norway. More cluster 2 observations were in Greece, Hungary, Italy, Lithuania, North Macedonia, Portugal, and Slovakia. Countries with marginal difference in the distribution of observations between clusters are: Bulgaria, Czechia, Croatia, and Montenegro.

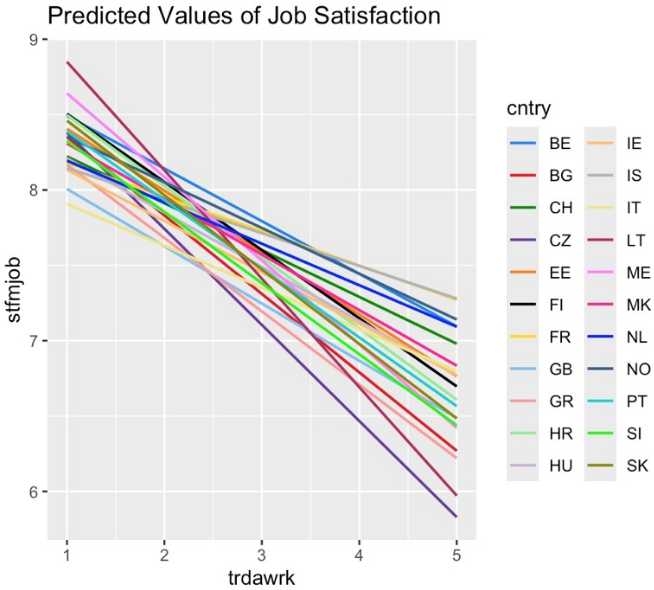
A simple linear regression model was fitted with *JS* as the outcome variable and all other variables as significant predictors other than *Age*, which is dropped from analysis henceforth (Appendix G). Negative coefficients of each country demonstrate decreased *JS*, while controlling for predictors, compared to the reference category (Belgium) which is evidenced as reporting higher *JS*. The adjusted R-squared indicates a predictive value of around 21%.

The fixed effects were plotted (Appendix H), demonstrating substantial variability between countries. A random intercepts model (Appendix I) analyses the hierarchical structure of the data. The random effects demonstrate larger variability for individual than country observations, as the estimated standard deviation of country residuals are 0.20, and 1.68 for individual. The intracluster coefficient indicates only 1.4% of the unobserved variability is from country differences, and therefore individual characteristics have greater importance at predicting JS.

Due to the exploratory, predictive nature of this research, and the absence of a main predictor variable but rather multiple independent variables predicting JS, the variability between countries was assessed with a predictor with a statistically significant, large effect size, as well as theoretical reasoning. *Too tired after work* had the largest effect size (-0.42) on *JS* and thus was utilised for multilevel modelling.

The standard deviation for the random slope representing the between country variability in the association between *JS* and *Too tired after work* is 0.44, with a strong negative correlation of -0.99. Therefore, in countries where average *JS* is higher, the positive association between being *Too tired after work* and *JS* is weaker, and in countries where *JS* is lower, the association between being *Too tired after work* and *JS* is stronger. This is statistically significant and concludes that the association is not uniform across countries (Figure 4).

Figure 4



After considering the country specific random slopes, the average association between *JS* and *Too tired after work* is 0.08. The weakest association is found with Italy (6.16) and the strongest with Lithuania (7.54). Thus, it can be confirmed that there is a meaningful, statistically significant variability in the association between *Job Satisfaction* and *Too tired after work.*

Discussion

This study aimed to answer to the research question:

How can job satisfaction be predicted across Europe, and is variability larger between countries or individuals?

The research has determined that job and socio-demographic characteristics are found to predict JS. As found by Fialová (2023), job characteristics were of greater importance. A predominant factor in predicting JS was tiredness after work, which aligns with research by Sousa-Poza and Sousa-Poza (2000). Multilevel modelling found greater variability at the individual level than at the country level.

Other variables were found to predict JS, as displayed in Figure 2. Due to the cross-sectional research design of the ESS, the direction of causality cannot be determined which has implications for predicting JS. For example, the positive covariance between *Manager supports balancing work/life* and JS can be explained in both directions. A manager may support a healthy balance, so the employee is therefore satisfied with their job. Alternatively, someone may be generally satisfied in their job but has a good work/life balance which happens to be supported by their manager. Being unable to identify causality is therefore a limitation of this research. Income was measured by *Household income*, which requires care when interpreting as general 'household income' does not specify who receives this income, and so its prediction of JS may be misleading. Gu et al. (2021) noted how the ESS is limited by the job characteristics which are covered by the survey; possible predictors of JS which are not measured include day to day tasks and job location, but despite these restrictions, insightful analyses of JS was achieved.

K-means clustering separated observations into 2 clusters. Although the results of the clustering aligned with previous literature, data variance was reduced considerably, as the individuality of each observation was removed. While aggregated averages offered insight into cluster characteristics, assumptions cannot be made for entire countries based on which cluster a country had more observations assigned to. Countries in cluster 1 (typically rating higher JS), are mostly WE countries. Cluster 2 contained a mixture of WE and CEE countries and demonstrated considerably lower averages for the predictor variables. Management support was lower in cluster 2, which Sousa-Poza and Sousa-Poza (2000) found to be explanative of JS, hence its lower rating. Autonomy, which was indicated by being able to decide location, and start and finish time, was also less evident in cluster 2. Cavanagh et al. (2019) found the relationship between autonomy and JS to increase with age, but age was insignificant in this analysis.

Cluster 1 observations were on average, in the 7th decile, 2 above cluster 2. Hauff, Richter and Tressin (2015) indicated that higher income countries have more unemployment and poverty safeguards, and so people may be satisfied with their jobs if there is a safety net in the case of job loss. With mention to a few specific countries' JS and their alignment to the literature, Czechia were the least job-satisfied country, emulating Sousa-Poza and Sousa-Poza (2000). However, their observations were almost evenly split between clusters. Bulgaria also remained as low rankers of JS. Slovenia were on the higher end of the scale, with many more observations in cluster 1 (68.1%) compared to cluster 2 (31.9%). Switzerland's high ranking of JS remained consistent.

Multilevel modelling examined the difference between individual and country-level variability of JS, with the predictor variable representing after-work tiredness on JS. A meaningful, statistically significant association was found, which was not uniform across countries, indicating variability. Larger variability between countries, than individuals, was identified, answering the second part of the research question. Beyond this research, future studies would benefit from modelling more potential predictors to examine the individual and country-level variability, rather than just after-work tiredness. Specifically, analysis of post-pandemic job satisfaction would provide interesting research and would be ideal to conduct with the next version of the ESS as the settling of consequential circumstances offers insightful findings.

To conclude this research, multiple statistically significant predictors of job satisfaction across Europe have been found, through analysis of round 10 of the European Social Survey. Such predictors include, but are not limited to, relationships with management, work/life balance, job autonomy and income. K-means clustering was utilised for the assignment of observations into 2 clusters; while it reduced some variance, the mean values of clusters offered insight of the data. Linear regression was then modelled with after-work tiredness as a theoretically proven and statistically significant predictor of job satisfaction. Multilevel modelling found greater variance in between-country observations, than individual observations. While this study presents a broad understanding of job satisfaction, future research should take a more detailed analysis of factors predicting job satisfaction.

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Appendices

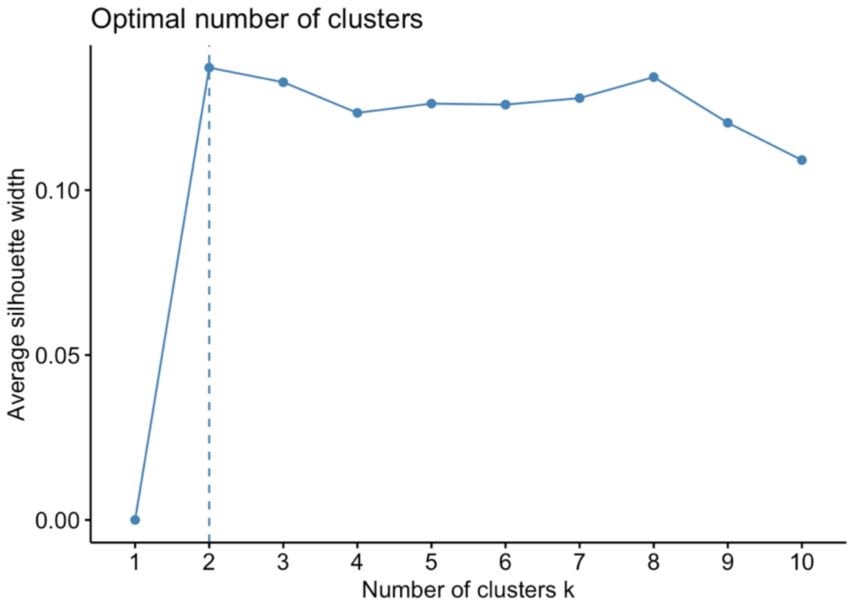
Appendix A

BE	Belgium
BG	Bulgaria
HR	Croatia
CZ	Czechia
EE	Estonia
FI	Finland
FR	France
GR	Greece
HU	Hungary
IS	Iceland
IE	Ireland
IT	Italy
LT	Lithuania
ME	Montenegro
NL	Netherlands
MK	North Macedonia
NO	Norway
PT	Portugal
SK	Slovak Republic
SI	Slovenia
CH	Switzerland
GB	United Kingdom

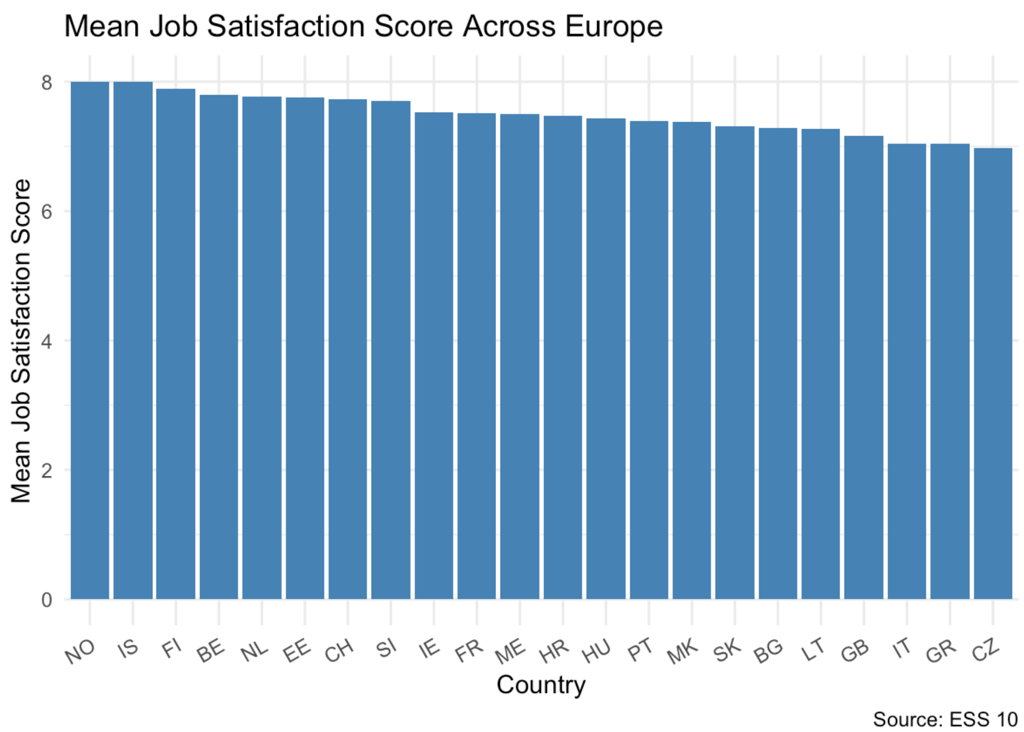
Appendix B

cntry	Country
agea	Age
gndr	Gender
stfmjob	Job satisfaction
hinctnta	Household's total net income, all sources
wkhtot	Total hours normally worked per week in main job overtime included
dcsfwrka	Current job: can decide time start/finish work
wrkhome	Work from home or place of choice, how often
trdawrk	Too tired after work to enjoy things like doing at home, how often
mansupp	Line manager supports employees in balancing work, how much
manhlp	Line manager gives work-related help, how likely

Appendix C



Appendix D



Appendix E

Job Satisfaction Across Europe

Job Satisfaction	BE	BG	CH	CZ	EE	FI	FR	GB	GR	HR	HU	IE	IS	IT	LT	ME	MK	NL	NO	PT	SI	SK	***Total***
	Country																						
0	2	16	5	6	4	0	11	4	2	8	2	2	0	11	2	4	4	2	1	4	4	7	101
1	2	7	3	8	3	1	1	3	2	4	2	0	1	3	3	0	1	2	0	4	3	2	55
2	4	24	10	14	3	9	10	8	7	6	8	7	3	14	11	4	3	4	1	4	10	8	172
3	9	19	20	32	11	12	18	24	15	7	9	13	6	23	24	17	14	12	9	10	9	18	331
4	18	30	15	30	17	14	27	16	28	16	24	15	7	32	22	13	13	22	19	21	11	28	438
5	14	120	31	143	50	16	63	24	68	69	88	38	20	61	87	41	50	16	29	76	39	59	1202
6	30	115	55	144	51	30	81	60	122	61	113	44	29	142	59	26	49	52	44	77	44	54	1482
7	108	206	138	244	152	107	171	90	199	87	179	132	61	265	113	58	74	154	142	138	98	113	3029
8	227	235	275	241	256	255	246	117	236	171	229	164	176	286	158	58	95	329	285	170	155	111	4475
9	138	104	166	127	156	190	149	77	91	81	117	90	114	94	98	32	37	179	243	93	111	54	2541
10	61	224	115	93	123	65	142	48	27	115	129	75	75	63	104	107	97	68	107	107	109	130	2184
Total	613	1100	833	1082	826	699	919	471	797	625	900	580	492	994	681	360	437	840	880	704	593	584	16010

Appendix F

Job Satisfaction by Cluster

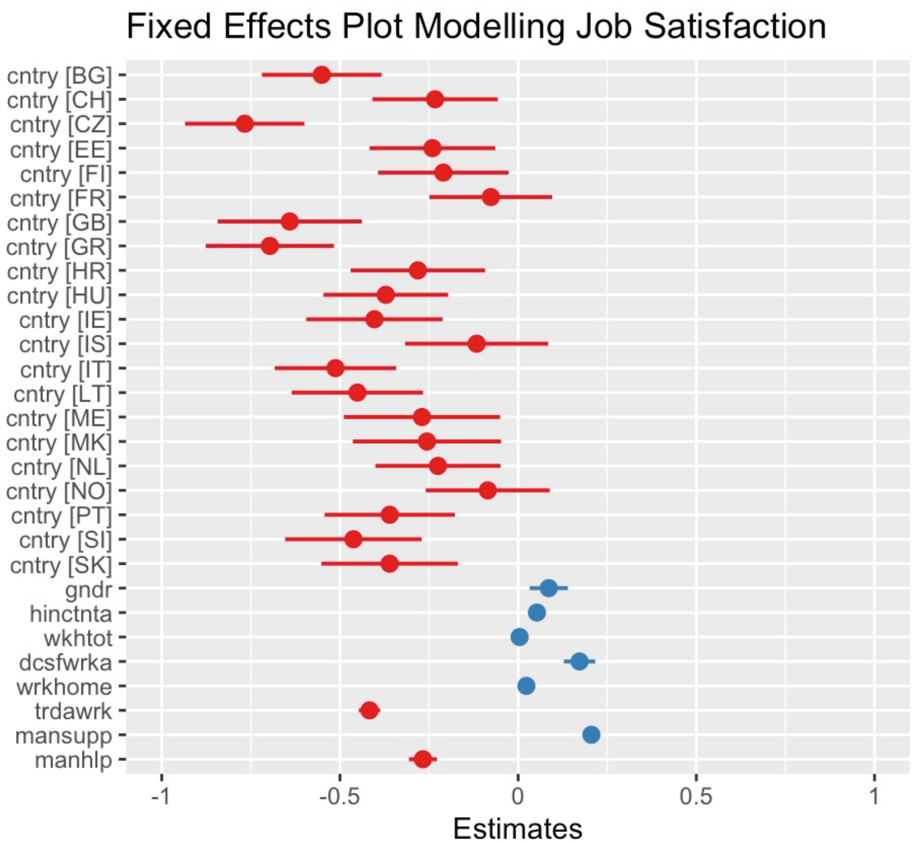
Country	*Cluster* 1	2	***Total***
BE	367 (59.9 %)	246 (40.1 %)	613 (100 %)
BG	533 (48.5 %)	567 (51.5 %)	1100 (100 %)
CH	550 (66 %)	283 (34 %)	833 (100 %)
CZ	523 (48.3 %)	559 (51.7 %)	1082 (100 %)
EE	561 (67.9 %)	265 (32.1 %)	826 (100 %)
FI	531 (76 %)	168 (24 %)	699 (100 %)
FR	484 (52.7 %)	435 (47.3 %)	919 (100 %)
GB	292 (62 %)	179 (38 %)	471 (100 %)
GR	293 (36.8 %)	504 (63.2 %)	797 (100 %)
HR	322 (51.5 %)	303 (48.5 %)	625 (100 %)
HU	398 (44.2 %)	502 (55.8 %)	900 (100 %)
IE	355 (61.2 %)	225 (38.8 %)	580 (100 %)
IS	370 (75.2 %)	122 (24.8 %)	492 (100 %)
IT	339 (34.1 %)	655 (65.9 %)	994 (100 %)
LT	321 (47.1 %)	360 (52.9 %)	681 (100 %)
ME	186 (51.7 %)	174 (48.3 %)	360 (100 %)
MK	179 (41 %)	258 (59 %)	437 (100 %)
NL	595 (70.8 %)	245 (29.2 %)	840 (100 %)
NO	669 (76 %)	211 (24 %)	880 (100 %)
PT	335 (47.6 %)	369 (52.4 %)	704 (100 %)
SI	404 (68.1 %)	189 (31.9 %)	593 (100 %)
SK	251 (43 %)	333 (57 %)	584 (100 %)
Total	8858 (55.3 %)	7152 (44.7 %)	16010 (100 %)

Appendix G

	Job Satisfaction			
Predictors	*Estimates*	*std. Error*	*CI*	*p*
(Intercept)	7.07	0.15	6.78 – 7.35	**<0.001**
Bulgaria	-0.55	0.09	-0.72 – -0.39	**<0.001**
Switzerland	-0.23	0.09	-0.41 – -0.06	**0.009**
Czechia	-0.77	0.09	-0.93 – -0.60	**<0.001**
Estonia	-0.24	0.09	-0.42 – -0.06	**0.007**
Finland	-0.21	0.09	-0.39 – -0.03	**0.025**
France	-0.08	0.09	-0.25 – 0.10	0.384
United Kingdom	-0.64	0.10	-0.84 – -0.44	**<0.001**
Greece	-0.70	0.09	-0.88 – -0.52	**<0.001**
Croatia	-0.28	0.10	-0.47 – -0.10	**0.003**
Hungary	-0.37	0.09	-0.55 – -0.20	**<0.001**
Ireland	-0.41	0.10	-0.60 – -0.21	**<0.001**
Iceland	-0.12	0.10	-0.32 – 0.08	0.255
Italy	-0.52	0.09	-0.69 – -0.35	**<0.001**
Lithuania	-0.45	0.09	-0.64 – -0.27	**<0.001**
Montenegro	-0.27	0.11	-0.49 – -0.05	**0.015**
North Macedonia	-0.26	0.11	-0.47 – -0.05	**0.015**
Netherlands	-0.23	0.09	-0.40 – -0.05	**0.012**
Norway	-0.09	0.09	-0.26 – 0.09	0.337
Portugal	-0.36	0.09	-0.54 – -0.18	**<0.001**
Slovenia	-0.46	0.10	-0.65 – -0.27	**<0.001**
Slovak Republic	-0.37	0.10	-0.56 – -0.17	**<0.001**
Age	0.00	0.00	-0.00 – 0.00	0.249
Gender	0.09	0.03	0.03 – 0.14	**0.002**

Household Income	0.05	0.01	0.04 – 0.06	**<0.001**
Total Hours Worked Per Week	0.00	0.00	0.00 – 0.01	**<0.001**
Can Decide Start and Finish Time	0.17	0.02	0.13 – 0.22	**<0.001**
Can Decide Place of Work	0.02	0.01	0.01 – 0.04	**0.008**
Too Tired After Work	-0.42	0.02	-0.45 – -0.39	**<0.001**
Manager Supports Balancing Work/Life	0.21	0.01	0.19 – 0.22	**<0.001**
Manager Supports in Work	-0.27	0.02	-0.31 – -0.23	**<0.001**
Observations	16010			
R^2 / R^2 adjusted	0.213 / 0.211			
AIC	62096.928			

Appendix H



Appendix I

Fixed and Random Effects Summary of Linear Model			
	Job Satisfaction		
Predictors	*Estimates*	*CI*	*p*
(Intercept)	6.73	6.47 – 7.00	**<0.001**
Gender	0.09	0.03 – 0.14	**0.002**
Household Income	0.05	0.04 – 0.06	**<0.001**
Total Hours Worked Per Week	0.00	0.00 – 0.01	**0.001**
Can Decide Start and Finish Time	0.18	0.13 – 0.22	**<0.001**
Can Decide Place of Work	0.02	0.01 – 0.04	**0.010**
Too Tired After Work	-0.42	-0.45 – -0.39	**<0.001**
Manager Supports Balancing Work/Life	0.21	0.19 – 0.22	**<0.001**
Manager Supports in Work	-0.27	-0.31 – -0.23	**<0.001**
Random Effects			
σ^2	2.83		
$\tau_{00\ \mathrm{cntry}}$	0.04		
ICC	0.01		
N_{cntry}	22		
Observations	16010		
Marginal R^2 / Conditional R^2	0.196 / 0.207		