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Modelling Economic Policy Issues

Modeling the employment decisions of young men and women in nine European countries: An application of random utility theory and revealed preference

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ABSTRACT

In this paper we examine the decisions of over 15,000 young adults aged 18–35 from nine European countries to choose employment over unemployment or remaining in education. Instead of focusing only on who makes those decisions as is typically done, we attempt to answer the question of why a particular decision is made. Using data from the Cultural Pathways to Economic Self-sufficiency and Entrepreneurship (CUPESSE) project, we estimate a series of country and gender-specific conditional logit (CLGT) models adjusted for individual work values, soft skills, demographic characteristics and local labor markets. We find that young women in Czechia, Germany, Greece, Hungary and Italy and both men and women in Spain and the United Kingdom, respond to exogenous wage offers providing some evidence for job search theory and for the reservation wage hypothesis. Our uptake rate simulations show that a 10% increase in wages have the potential to increase employment by as little as 2 percentage points in the UK and by as much as 14 percentage points in Czechia and Spain. Further, if unemployment benefits are also simultaneously reduced by 10% employment increases in these latter countries by 20 and 17 percentage points. We demonstrate the ways that revealed preference (RP) analysis can aid policy makers through strength of preference, uptake rate and willingness-to-pay applications.

1. Introduction

The unemployment rates of young adults (ages 18–35) in Europe and America have been consistently higher than the overall unemployment rates for as long as these statistics have been collected. Such data also show that the unemployment rates for young adults, whether measured as youth-to-overall unemployment ratios or time-to-(re)employment period(s) are considerably more sensitive to economic calamity (International Labor Organization (ILO), 2017; OECD.STAT, 2022). The COVID-19 pandemic and the Great Recession of 2008 are prominent, recent examples of major labor force disruptions. Youth unemployment, moreover, appears to be not only detrimental to the economic health of a locality or nation, it is also bad for personal health as well. The emotional scarring and erosion of self-confidence that can result from futile job searches, short-term employment contracts and intermittent or extended layoffs have been well documented (Jagannathan and Camasso, 2021; Miroz and Savage, 2006; Pastore, 2018; Tanzi, 2022).

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There is a vast literature on youth unemployment and a great deal of it has focused on identifying which individuals are more prone to seek employment, postpone employment while pursuing additional education/training, or who eschew employment completely. In these studies, the focus has typically been placed on personal characteristics like gender, level of attained education, overeducation, family responsibilities, prior work history and a variety of human capital indicators (see, for example, (Caliendo and Schmidl, 2016; Carneiro and Heckman, 2003; Freeman and Wise, 1982; McGuinness et al., 2018; Mincer, 1974)). While providing a great deal of useful information on the youth unemployment problem, these studies do not answer the critical policy-relevant question of *why* individuals make the decisions they make; instead, they infer without empirical test, the decision criteria individuals actually use from personal characteristics. An alternative approach and the one we use in this paper, is to directly examine with revealed preference modeling the decision criteria used by young adults, i.e., wages and benefits, when choosing to seek employment (McFadden, 1986; Hoffman and Duncan, 1988; Train, 2009).

We examine the decisions of over 15,000 young adults from nine European countries (Austria, Czechia, Denmark, Germany, Greece, Hungary, Italy, Spain and the United Kingdom) to follow one of three pathways, viz, engage in paid employment, remain in school to pursue a degree or work credential, or live on income from sources other than paid work, e.g., unemployment benefits, redundancy pay, parental or spousal support, governmental or non-governmental social programs. We will call this last decision pathway the unemployment choice. Our statistical modeling specifies the choice among these three alternatives as a function of the exogenous wage and unemployment benefits of each alternative along with a set of personal-level characteristics that include age, gender, presence of a work history, education level attained, self-assessment of overeducation, and a set of soft skills and work values. These statistical models are estimated using the random utility approach developed by McFadden (1975; 1986) and applied to a wide range of consumption decisions (Camasso and Jagannathan, 2001; Jagannathan and Camasso, 2021; Phillips et al., 2002; Villas-Boas et al., 2020; World Health Organization (WHO), 2012). Unlike the more widely used multinomial logit (MNLGT) that models the “characteristics of the decision maker,” random utility models through the estimation of parameters with conditional logit statistical technique (CLGT) provide a more direct understanding of an individual’s behavior by modeling the “characteristics of the decision alternative” (McFadden, 1986; Hoffman and Duncan, 1988). This more direct understanding, in turn, offers more focused insights into how policies can be formulated to provide explicit incentives and disincentives in order to affect young people’s employment choices.

Our approach to extending the research on the labor force attachment decisions is distinctive in two ways. First, unlike the limited number of studies that use random utility models to examine employment decisions (Demel et al., 2019; Eriksson and Kristensen, 2014; Vooren et al., 2019; Wehner et al., 2020) we do not construct simulations in a stated preference (SP) experiment. Instead, we have opted for a revealed preference framework where our principal choice-specific attribute, expected income, is constructed as an exogenous variable retrieved from published, country-specific records of earnings detailing the amount of hourly income an individual can expect to receive from employment, while pursuing education, or from unemployment benefits. These published records allow us to further personalize expected income from working or pursuing education full-time by the individual’s level of educational achievement and by his/her work experience and age in the case of unemployment benefits. Second, our personalized income variable together with a series of country-specific and gender-specific (within country) analyses allow us to address sources of potential heterogeneity in individual preferences due to gender, experience, education and market/institutional differences across countries through research design rather than through a reliance on a series of mixed models that posit interactions between choice attributes and characteristics of the decision maker. Parameter estimates from decision models where conditionality is built into the choice design, ceteris paribus, provide clearer parameter interpretations and, potentially, policy interventions with fewer provisos.

2. Human capital, labor market demand and the employment decision

Following neoclassical economics theory, labor supply decisions like the choice to enter the labor market are the result of the prospective employee’s motivation to maximize his/her utility, i.e., acquire what he/she wants constrained by what she/he can get. This decision depends on preferences for the type and amount of consumer goods (C), hours of leisure time (L) and hours of work (H). From this perspective it is quite natural to view the decision to participate in paid work as a complement of the individual consumption decision (Borjas, 2008; Killingsworth, 1984; McFadden, 1986). The decision to supply labor while conditional on wages, prices and personal/family assets is also dependent on an individual’s preferences that arise out of the accumulation of human capital, e.g., a person’s knowledge, skills, health, cultural values, social skills (Becker, 1964; 1993; 1996).

A basic assumption of human capital theory (HCT) is that businesses and workers adjust their capital investments and requirements to complement changes in market supply and demand. For Becker (1964, 1993) it is clear that the onus is on the individual to acquire the education and experience that, in turn, will provide him/her with valued knowledge, skills and abilities (KSAs) leading to long-term utility maximization. A number of economists, however, have discussed the limits of HCT as a complete explanation for the decision to supply labor, pointing up a series of demand-side constraints that circumscribe “what she/he can get” at a given point in time (Blau and Kahn, 2003; Caliendo and Schmidl, 2016; Marques et al., 2022; Thurow, 1979).

Thurow’s (1979) Job Competition model, for example, asserts that economies with highly rigid labor markets stemming from slow growth and low levels of business re-design often result in a bidding down of wages. In these types of job markets, human capital endowment and individual choice are limited as job seekers are confronted with the probability of accepting a job below their education and experience levels. Hall (2018) notes that the mixed-market economies that are characteristic of many southern European countries, where the state is responsible for a great deal of public-private sector coordination, and where the production regime is focused on low technology goods and services, markets have been unable to respond to dramatic changes in education and training. Research by Marques et al. (2022) identify three demand drivers that result in the mismatch between a country’s production profile and the growth of a skilled labor force, viz., low levels of output in the high-tech services sector, low levels of output in high-tech manufacturing and slow growth in GDP levels.

Two supply-side theories of labor supply, however, tend to support HCT, i.e., the Career Mobility thesis and the Job Search model. The former offered by Sicherman and Galor (1990; 1991) maintains that workers look at both wages and the prospects for promotion when choosing employment over future schooling or unemployment. Noting that HCT is a life-cycle theory, Sicherman discusses evidence from the Panel Study of Income Dynamics (PSID) in the United States which shows that while younger workers report wage penalties of (on average) 5 % in earlier stages of their careers they also report increasingly positive returns to education and experience, on average about 5 % in subsequent years. A country with a flexible labor market coupled with strong economic growth presents an environment where upward job mobility can flourish (Caliendo and Schmidl, 2016; Pastore, 2018; Zimmermann et al., 2013).

In the Job Search model, individuals are also considered to be rational actors who deploy their human capital strategically; they only accept employment if the earnings are higher than their reservation wage – the minimal earnings they will request (and accept) to take up employment (Caroleo and Pastore, 2018; Nicaise, 2001; Hoffman and Duncan, 1988). The theory assumes a labor market of low unemployment where jobs are readily available but where individuals with high quality human capital choose unemployment (or additional education) over positions for which they deem themselves overqualified. The choice of unemployment, moreover, is reinforced by the existence of institutional and/or market factors (for example, family obligations and supports) that make unemployment, at least in the short run, both conceivable and practical.

Both Job Search and Job Competition models, by extending the discussion of labor supply to consideration of what "she/he can expect to get," have important implications for the decision to select employment over unemployment or remain in education. In a labor market that supports active job search (United States) it would be expected that individuals with the greatest earnings potentials would be more likely to be observed in the labor market while those with less opportunity due to lower levels of human capital would choose to remain out of the labor force or remain in education. In such markets, observed wages in OLS earnings regressions with truncation (due to non-participation or individuals who have selected unemployment and who do not earn wages) overestimate the wages offered by employers (Observed > Offered) (Baldwin and Johnson, 1992; Ermisch and Wright, 1994). This reservation wage hypothesis has been confirmed more often with young women than young men (Blau and Kahn, 2017; Hartog and Oosterbeek, 1988; Nicaise, 2001). Conversely, in slow growth economies (Spain, Greece), human capital factors that increase the probability of employment decrease the observed wages found in OLS earnings regressions. Here, below-average wage offers are accepted and become observed (Observed < Offered), leading to considerable job competition and a "crowding out" of individuals with higher levels of human capital. If these "crowded out" individuals were to select employment they could expect to receive higher wage penalties than average because below-average wage offers will be accepted and become observed (Caroleo and Pastore, 2018; López Fogués, 2017; Marques et al., 2022). The phenomenon has been observed among young men in a number of European countries (Caroleo and Pastore, 2018; Nicaise, 2001). It should be noted that the employment/unemployment choice and the observed-offered wage distinction provide conceptual underpinning for the employment selection approach to labor force attachment pioneered by Heckman (Ermisch and Wright, 1994; Heckman, 1979).

The acknowledgment that labor demand conditions vary by country and specific labor markets within country does not obviate the principal arguments of HCT; rather, it highlights the theory's conditionality on institutional and market factors and the importance of country-specific analyses. Hobson's choices, available in some country contexts, are still choices after all. One within-country factor of pivotal importance for understanding the decision for a young person to supply his/her labor as we have noted is the construction of markets and institutions (policies) in response to gender difference. Despite a narrowing over the past 50 years, the wage gap between men and women remains significant in European and American labor markets (Barroso and Brown, 2021; Borjas, 2008; European Commission, 2021; Goldin, 2014; Jagannathan et al., (n.d.)). Whether based on occupational segregation, presence/effectiveness of governmental interventions or sex discrimination, the choices faced by young adult women and men often necessitate different paths to utility maximization (Becker et al., 2010; Blau and Kahn, 2017; McGuinness et al., 2018).

3. The labor force attachment of young adults

The most widely used strategy for gaining insight into the labor force attachment of young adults has been to conduct macro level analyses with country or labor market level data or to combine these aggregated data with information on individual respondents from surveys like the Current Population Survey (CPS), the National Longitudinal Survey of Youth (NLSY) or the European Union Labor Force Survey (EU-LFS). Macro level predictors typically include measures of strength of economy (GDP, economic growth rate, consumer price index, labor productivity, etc.) and legislative/institutional factors (active labor market policies, unionization levels, minimum wage rates, etc.). Individual level characteristics measure human capital factors like attained educational degrees or certificates, training and work experience and a variety of demographic identifiers. One of the pioneering efforts using this type of data is the research of Freeman and Wise and their associates (1982). The consensus of this research collection was that economies with strong economic growth produce the lowest levels of youth unemployment while individual characteristics like academic performance and work experience while in high school, while significant predictors, are less important than macro factors. It is a pattern of results that has been replicated many times since (Bayrak and Tatlı, 2018; Caliendo and Schmidl, 2016; Pastore, 2018; Zimmermann et al., 2013; Marques et al., 2022; Rodríguez-Modroño, 2019). As Hoffman and Duncan (1988) point out these types of studies fail to answer that important question of "why" certain individual choices are made in dynamic or stagnant economies and often result in interpretations that make reference to characteristics of decision attributes which are not directly tested (p.418).

The choice theory approach to understanding youth employment is a less common approach. When choice level analyses have been undertaken they have typically assumed the form of stated preference (SP) experiments. Individuals are offered a series of hypothetical situations, for example, Job A, Job B or Job C, where each alternative has distinctive combinations of attributes (e.g., varying pay levels, benefit packages, work schedules, etc.). Demel et al. (2019) use SP in several European countries to inquire about the type(s) of company that is most appealing to business majors. They find that a hypothetical business that offers long-term career prospects is of utmost importance, holding more utility than even higher initial pay or fringe benefits. Using a Job A, Job B or Job C design, Doiron et al. (2014) find that new nursing school graduates value a job with supportive management and a reputation for high quality care more than nine other nonpecuniary job attributes. Eriksson and Kristensen (2014) examine the trade-off between wages and benefits in an SP experiment involving Danish employers. These researchers find the expected exchange between these two considerations and identify hypothetical combinations that employers use to sort out the type of employees they would like to hire. Other examples of SP experiments in the employment literature are Wehner et al. (2020), Vooren et al. (2019) and Gyarteng-Mensah et al. (2022).

The principal criticism of SP approaches is that the choices may not correspond closely to a person's real world options and that some of the choices offered may not have any significant probability of ever becoming extant (Wardman, 1988). Revealed preference applications, such as the one we propose in this paper, while quite common in transportation and marketing, are underrepresented in studies of labor force attachment. A criticism of revealed preference offered by Kroes and Sheldon (1988) is that the data collected often lacks sufficient variation on the decision variables of interest. This is not the case in our study where ample within-country variation in income across alternatives is readily observable.

4. Data and methods

4.1. Sample characteristics, study variables and data sources

The data used to examine the employment decision of young adults (aged 18–35 years) was generated from the Cultural Pathways to Economic Self-Sufficiency and Entrepreneurship (CUPESSE) survey research project (Table 1). Young men and women in 11 countries were queried in 2016–2018 on a broad range of economic and social issues including, labor force attachment, school-to-work transitions, perceptions of job skill levels and work values.[1] Each of the participating countries was required to conduct interviews with at least 1000 respondents that represented the (age-adjusted) employed, unemployed and in-school segments of their populations. Most of these interviews were conducted using CATI or CAPI technologies with Turkey the exception; here, survey administration relied on traditional paper and pencil methods. Resources for the CUPESSE surveys were provided by the European Commission from February 2014 through January 2018 (Tosun et al., 2019). Data cleaning, youth proofing (to insure relevance for the target population) and translation protocols can also be found in Tosun et al. (2019) and in the deliverables listed on the CUPESSE website.

In Table 2 we provide descriptive data for young men and women in the nine sample countries included in our analyses. These data include the proportions of young men and women who reported being employed, unemployed or in-school full time.

Table 2 also provides gender-specific information on the respondents' education, work experience and their perception that they are overeducated for their current job, if they had one or from previous jobs if they were currently unemployed. The sample profile in the Table includes data on a number of work values and work skills along with demographic details on age, religious affiliation and immigration status. Information on how each of these variables was measured and coded for analysis is given in Table 3.

The demographic measures, including gender, are taken directly from the CUPESSE questionnaire. Education on this survey instrument was coded by interviewers using the ES-ISCED coding schema. We converted these coded responses to years using the UNESCO Country-Specific Comparison Chart. This conversion is consistent with a measure used in standard, Mincerian returns-to-education modeling. Our work experience measure also follows a Mincerian definition. The measure of overeducation was gleaned from the question asking the respondent if he/she felt they were a good match for their current job or previous job(s) if unemployed. Our dummy coding of this variable follows that of Sicherman (1991).

We incorporate five measures of soft skills and work values into our regression models. These items appear in versions of the European Social Survey, the German Socio-Economic Panel (youth questionnaire) and/or the International Social Survey Programme (ISSP). Four measures, i.e., willingness to change, grit, intrinsic/extrinsic motivation and work centrality are multi-item scales, the fifth, risk aversion is a 10-point, one-item scale. Principal components analysis (PCA) was performed to determine if any of these multi-item scales were multi-dimensional based on the customary criterion of an eigenvalue exceeding 1. The willingness to change scale contained two dimensions – geographic mobility (a,b) and openness to retraining (c, d). PCA also indicated that the 9-item grit scale (Duckworth and Yeager, 2015) and 9-item intrinsic/extrinsic motivation scale (Carneiro and Heckman, 2003) also contained two dimensions. The former contained a perseverance component (b, d, f) along with a second indicating long-term goals (a, c, k); the latter contained intrinsic motives (c, d, e, f, g, h, i) and extrinsic incentives (a, b). PCA of work centrality revealed only one dimension.

When we repeated our regression analyses using the multiple dimensions for willingness to change, grit and intrinsic/extrinsic motivation we find no difference in either sign or significance from our original regression analyses. This is not surprising inasmuch as the second dimension in these analyses barely made the eigenvalue cutoff.[2] Cronbach alpha for single dimension scales ranged from 0.63 (willingness to change) to 0.78 (intrinsic/extrinsic motivation).

In Table 4 we show the country-specific "hourly compensation" levels available to respondents in their country when making the decision to pursue employment or the alternatives of unemployment or remaining in school. It is important to note that the attribute

[1] Switzerland and Turkey were excluded from our analyses, the former due to near 0 unemployment levels for both men and women and the latter due to the lack of within-group variance and resultant collinearity.

[2] The results from these additional regressions are available from the authors upon request.

Table 1
General description of the CUPESSE young adults database**.

Country	Number of obs.	Gender (%)		Mode			
		Male	Female	CAT1	CAP1	P&P	F2F
Austria	1684	44	56	*			
Czechia	1214	43	57	*			
Denmark	1142	56	44	*			
Germany	3279	49	51	*			
Greece	1538	40	60		*		
Hungary	1295	45	55	*			
Italy	1008	54	46	*			
Spain	1826	49	51	*			
UK	3004	49	51	*			
Total	**15,990**	**47**	**53**				

** Excludes Switzerland and Turkey.
* Mode indicates the following interviewing method used for the Country:
CAT1 - Computer-Assisted Telephone Interviewing, CAP1 - Computer Assisted Personal Interviewing,
P&P - Paper and Pencil, F2F - Face-to-Face.

levels associated with each alternative are not the actual hourly wages or other income received, but rather are the prevailing median wage or other alternative income that the respondent was faced with when he or she was in the process of making their decision in 2016–17. This relationship between the characteristics of exogenous potential income and a set of prices they imply, on the one hand, and a decision maker's preference for a specific alternative on the other, is perforce, the individual's utility function[3] (Becker, 1964; Killingsworth, 1984; McFadden, 1986, 1993).

When constructing the income attributes of the three alternatives we used this protocol:

1. First, we obtained the median hourly earnings in euros of employees classified by ES-ISCED category for the years 2017–18 as compiled by Eurostat (Eurostat, 2021). These data were available for firms that employed 10 or more individuals. As is evident from Table 4, Denmark exhibited the highest across-the-board earnings in our 9-country sample while Hungary was the lowest.
2. Using the OECD Tax Benefit Model (OECD, 2020) and applying it to 2017–18 earnings we computed the average country-specific, unemployment benefits (UI) defined as a percentage of after-tax income. In the case of Austria that was 55 % of the average reference earned income. For individuals who have exhausted UI or if the person was in need due to prolonged unemployment/no recent work history, the state provided unemployment assistance (UA) at a rate of 92 % of the basic UI benefit. As Table 4 shows, means-tested (UA) and non-means tested benefit levels vary widely from country to country. It should be noted that these wage fractions represent UI and UA only and are not adjusted to account for other benefits, i.e., housing assistance, family benefits, childcare subsidy, benefits that could augment or decrease the size of the reference benefit level. The compensation available to individuals does, however, reflect the country-specific adjustments for previous work history.
3. Lastly, the average compensation of a respondent who chose the education option was taken from the OECD (OECD, 2021) report of "Earnings of Students Relative to Non-students." The report provides age-adjusted estimates through 2018 for 6 of the 9 countries in our sample. We use the overall averages across all education levels for 18–24 year olds and 25–35 year olds. In Austria, for example, young students (18–24 years) are faced with the prospect of receiving on average 38 % of the income that they would receive from full time employment. This income could come in the form of grant in aid, part-time work or aid from family/friends. In Czechia, Greece and Hungary, where data was not reported to OECD, in 2017–18 we employed the weighted average for the reporting, European, OECD countries.

Data available from these reports allowed us to tailor the expected income receipt for each individual in our sample. For example, in Austria an individual with an ISCED I or II level education, aged 24 or younger, with a work history could expect an hourly income of 11.15 euro if he/she chose employment, 6.13 euro from unemployment and 4.24 euro if the education choice was made.

One controversial assumption that is inherent in the conditional logit (CLGT) models is the Independence of Irrelevant Alternatives (IIA) (Allison, 2012; Cheng and Long, 2007; Long and Freese, 2014). The general strategy requires that for each alternative, you delete individuals who choose that alternative and re-estimate the model for the remaining alternatives. The IIA assumption is violated if the estimates for the new and original models are significantly different. In our study we tested the IIA assumption using the Hausman-McFadden test where we compare results from our full model with all three choices (employed, unemployed and in school) to restricted models where one of the choices is omitted.[4] Of the total 54 tests, the IIA assumption was satisfied in half of them. Cheng and Long (2007) describe the problematic nature of the IIA tests this way:

[3] The use of actual wages earned or other remuneration would result in a model where (a) the unit of analysis becomes the individual and not his/her choices, (b) the wages are endogenous since they depend on a choice made, and (c) the decision-making process is obscured in a reduced-form, non-behavioral form of analysis (McFadden, 1968; Hoffman and Duncan, 1988).

[4] We performed tests for All vs. Unemployed omitted; All vs. Employed omitted and All vs. Education omitted for 9 countries, separately for young men and young women.

Table 2
Sample Characteristics for Males and Females on Nine Study Countries

Country	Austria		Czechia		Denmark		Germany		Greece	
Characteristics	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Number of Cases	745	939	521	693	636	506	1603	1676	612	926
Employment Status (Percent)										
Employed	57	46	70	48	54	42	76	61	60	46
Unemployed	17	21	7	33	17	19	9	18	23	37
In School	26	32	23	19	29	39	15	21	16	17
Education/Experience+										
Education in years	14.81	15.46	13.92	14.43	14.70	15.06	15.08	14.92	16.09	16.33
	(2.78)	(2.46)	(2.54)	(2.74)	(2.84)	(2.78)	(2.59)	(2.61)	(2.14)	(1.91)
Experience in years	5.94	5.15	8.09	8.07	7.81	7.37	7.38	6.79	7.65	6.93
	(5.09)	(4.90)	(4.65)	(4.63)	(4.25)	(4.26)	(5.00)	(5.16)	(4.71)	(4.60)
Overeducation (1 = Yes)	0.205	0.266	0.199	0.233	0.227	0.208	0.191	0.202	0.399	0.371
	(0.404)	(0.442)	(0.400)	(0.423)	(0.420)	(0.406)	(0.393)	(0.402)	(0.491)	(0.483)
Soft Skills/Work Values										
Motivation - Willingness to Change (WILLINGSUM)	9.55	9.38	9.36	8.95	9.61	9.45	9.31	9.26	9.94	9.86
	(1.73)	(1.72)	(0.459)	(1.54)	(1.64)	(1.52)	(1.83)	(1.78)	(1.65)	(1.64)
Work Centrality (WKVALUEMEAN)	2.74	2.72	3.10	2.72	2.77	2.71	2.86	2.87	2.75	2.65
	(0.589)	(0.593)	(0.423)	(0.514)	(0.589)	(0.539)	(0.602)	(0.551)	(0.555)	(0.505)
Grit (GRITMEAN)	2.93	2.94	2.84	2.87	2.86	2.94	2.86	2.89	2.95	3.01
	(0.420)	(0.401)	(0.391)	(0.368)	(0.353)	(0.340)	(0.395)	(0.396)	(0.404)	(0.391)
Risk-Taking	5.66	4.97	5.78	4.93	5.03	4.69	5.09	4.46	5.43	5.21
	(2.15)	(2.28)	(2.44)	(2.34)	(2.32)	(2.22)	(2.15)	(2.17)	(2.55)	(2.44)
Motivation - Intrinsic and Extrinsic (JOBIMPMEAN)	3.23	3.30	3.10	3.15	3.06	3.18	3.12	3.21	3.45	3.52
	(0.441)	(0.371)	(0.423)	(0.390)	(0.373)	(0.319)	(0.401)	(0.381)	(0.423)	(0.405)
Demographics										
Age (Years)	26.00	25.76	27.13	27.39	27.32	26.48	27.75	26.93	28.56	27.95
	(4.99)	(5.00)	(4.98)	(5.06)	(4.84)	(4.97)	(4.08)	(4.85)	(4.76)	(4.79)
Religious (1 = Yes)	0.417	0.455	0.176	0.147	0.275	0.400	0.375	0.403	0.554	0.587
	(0.493)	(0.498)	(0.381)	(0.354)	(0.447)	(0.490)	(0.484)	(0.491)	(0.498)	(2.440)
Immigrant (1 = Yes)	0.128	0.132	0.032	0.020	0.030	0.031	0.074	0.090	0.037	0.011
	(0.333)	(0.339)	(0.177)	(0.141)	(0.170)	(0.117)	(0.262)	(0.290)	(0.190)	(0.257)

Country	Hungary		Italy		Spain		United Kingdom	
Characteristics	Male	Female	Male	Female	Male	Female	Male	Female
Number of Cases	581	712	510	498	893	933	1,479	1,525
Employment Status (Percent)								
Employed	72	58	56	43	45	43	75	69
Unemployed	10	30	36	50	27	35	10	10
In School	16	13	8	8	28	22	15	17
Education/Experience+								
Education (Years)	12.93	13.12	15.46	15.74	14.62	15.06	14.66	14.42
	(3.16)	(3.07)	(2.27)	(2.15)	(3.75)	(3.65)	(2.85)	(2.81)
Experience (Years)	7.94 (6.11)	8.57 (5.92)	6.55 (4.28)	6.45 (4.14)	7.73 (5.78)	7.63 (5.57)	7.07 (5.62)	6.66 (5.69)
Overeducation (1 = Yes)	0.122	0.107	0.107	0.118	0.233	0.202	0.258	0.273
	(0.328)	(0.309)	(0.310)	(0.323)	(0.423)	(0.402)	(0.437)	(0.446)
Soft Skills/Work Values								
Motivation - Willingness to Change	9.36 (2.08)	8.98 (2.21)	10.09	9.91 (1.44)	10.27	10.06	9.47 (1.87)	9.33 (1.81)
			(1.43)		(1.61)	(1.70)		
Work Centrality	2.92	2.86	2.96	2.94	2.72	2.65	2.87	2.86
	(0.500)	(0.497)	(0.501)	(0.511)	(0.544)	(0.572)	(0.560)	(0.518)
Grit	2.96	2.92	2.79	2.84	2.92	3.03	2.82	2.83
	(0.425)	(0.435)	(0.386)	(0.409)	(0.436)	(0.425)	(0.385)	(0.376)
Risk-Taking	5.58 (2.46)	4.62 (2.60)	5.53 (2.44)	5.49 (2.60)	5.56 (2.44)	5.52 (2.57)	5.41 (2.18)	5.15 (2.15)
Motivation - Intrinsic and Extrinsic	3.39	3.41	3.20	3.31	3.27	3.39	3.19	3.22
	(0.455)	(0.430)	(0.453)	(0.443)	(0.429)	(0.397)	(0.428)	(0.424)
Demographics								
Age (Years)	26.51	27.11	27.36	27.33	27.39	27.70	27.01	26.37
	(5.17)	(5.00)	(4.54)	(4.40)	(4.97)	(5.04)	(5.17)	(4.98)
Religious (1 = Yes)	0.356	0.408	0.521	0.540	0.228	0.298	0.255	0.257
	(0.479)	(0.492)	(0.500)	(0.499)	(0.420)	(0.453)	(0.436)	(0.437)
Immigrant (1 = Yes)	0.015	0.022	0.036	0.022	0.057	0.071	0.091	0.026
	(0.123)	(0.148)	(0.186)	(0.147)	(0.231)	(0.258)	(0.289)	(0.331)

+Table entries indicate variable means and standard deviations *This includes the response: "On employment benefits", "Income from other social benefits programs", "Income from savings, inherited money, investments", "Support from parents/relatives", "Support from spouse/partner" and "Other non-social benefits". ( ) Variable names used in regression analyses.

Table 3
Description of the characteristics of the Decision-Maker used in the (Mixed) CLGT Regression.

Variable Description	Regression Model Label	Detailed Description
Demographics		
Respondent Age	AGE	CUPESSE question - How old are you? (Years)
Respondent Religiosity	RELIGIOUS	CUPESSE question - Do you consider yourself belonging to a particular religion? Coded 1 = Yes, 0 = No
Respondent Immigrant	IMMIGRANT	CUPESSE question - Do you belong to a minority ethnic group? Coded 1 = Yes, 0 = No
Education/Experience		
Formal Education	EDUCATION	CUPESSE survey coded highest level of education using ES-ISCED Categories I, II, III, IV,V Converted into years using UNESCO Country Specific Comparison Charts (2011).
Work Experience	EXPERIENCE	Measured as Potential Experience (age - years of schooling - 6) Mincer definitions. Also EXPERIENCE Squared, Mincer definition
Currently / Recently Overeducated	OVEREDUCATED	CUPESSE survey asked "Do you think your job is a good match with your overall qualifications": Yes - Good Match / No - I am overqualified / No - I am underqualified.
Soft Skills/Work Values		
Motivation - Willingness to change	WILLINGSUM	Willingness to change or new jobs: Sum over four questions - Coded 1 = No, 2 = Maybe, 3 = Yes **Cronbach's alpha = 0.63** (a) I would be willing to move within country. (b) I would be willing to move to a different country. (c) I would be willing to learn new skills such as a new language, computer programs. (d) I would be willing to learn completely new skills or retrain to get a job.
Value-Centrality of work on life	WKVALUEMEAN	Mean value calculated over five questions - Coded 1 = Strongly Disagree, 2 = Somewhat Disagree, 3 = Somewhat Agree, 4 = Strongly Agree **Cronbach's alpha = 0.67** (a) To fully develop your talents you need to have a job. (b) It's humiliating to receive money without having to work. (c) If welfare benefits are too high there is no incentive to work. (d) Work is a duty towards society. (e) Work should always come first even if it means less spare time.
Grit (Perseverance)	GRITMEAN	Mean value calculated over nine items - Coded 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree **Cronbach's alpha = 0.69** (a) I often set a goal but later choose to pursue a different one. (b) I have difficulty maintaining my focus on projects that take more than a few months to complete (c) New ideas and projects sometimes distract me from previous ones (d) I always finish whatever I begin (e) Setbacks discourage me (f) I am hard working (g) I am confident that I can deal efficiently with unexpected events (h) Usually I do more than I am asked to do (i) My life is determined by my own actions
Aversion to risk	RISK	Coded on a scale of 0 (I tend to avoid risks) to 10 (I am fully prepared to take risks)
Motivation - Importance of intrinsic and extrinsic	JOBIMPMEAN	Mean value calculated over nine items - Coded 1 = Very Unimportant, 2 = Rather Unimportant, 3 = Rather Important, 4 = Very Important **Cronbach's alpha = 0.78** (a) …a job that is secure (b) …a high income (c) …a job that allows me to help other people (d) …a job that allows me to work independently (e) …a job that allows me to learn new things (f) …a job that leaves me enough time for leisure activities (g) …a job that allows me to develop my creativity (h) …a job that allows me to meet and interact with people (i) …a job that gives me a feeling of self-worth

"In a variety of substantive applications, we have found that even with reasonable model specifications, these tests often reject IIA when the alternatives seem distinct and that they do not reject IIA when the alternatives can reasonably be viewed as close substitutes. Moreover, variations of IIA tests applied to the same data using the same model often provide inconsistent results regarding the violation of IIA in the full model." (p.586). Using a series of Monte Carlo simulations, these authors conclude that "… the tests are not useful for assessing IIA." (p.586)

Long and Freese (2014) include tests for IIA in their Stata software programs but DO NOT encourage their use. They note that these tests often provide conflicting results (e.g., some tests reject the null while others do not) and that various simulation studies have shown that these tests are not useful for assessing violations of the IIA assumption. They further argue that the models work best when the alternatives are dissimilar and not just substitutes for one another (e.g., if choices were take car to work, take a blue bus, or take a red bus, the two bus alternatives would be very similar and the IIA assumption would likely to be violated, whether the tests showed it

Table 4
The Potential Hourly Compensation Attribute Levels Used to Determine the Employment Decision for 2017 (Estimates in Euros).

Country	Employment*			Unemployment**		In Education[A]	
	ISCED I-II	ISCED III-IV	ISCED V or More	Work History	No Work History	18 - 24 Years	25 - 35 Years
Austria	11.15	14.40	19.36	Wage X 0.55	Wage X 0.55 X 0.92	Wage X 0.38	Wage X 0.61
Czechia	4.00	5.12	7.46	Wage X 0.65	Wage X 0.65 X 0.93	Wage X 0.51[B]	Wage X 0.51
Denmark	21.46	25.08	30.20	Age > 25 Wage X 0.90 Age <= 25 Wage X 0.55	Age > 25 Wage X 0.72 Age <= 25 Wage X 0.65	Wage X 0.40	Wage X 0.43
Germany	10.92	15.50	25.36	Wage X 0.64	Wage X 0.64 X 0.9	Wage X 0.70	Wage X 0.50
Greece	6.01	6.50	11.00	Wage X 0.55	Wage X 0.20	Wage X 0.51[B]	Wage X 0.51
Hungary	2.92	3.57	6.05	Wage X 0.60	Wage X 0.30	Wage X 0.51[B]	Wage X 0.51
Italy	10.63	12.40	18.41	Wage X 0.75	Wage $X < 0.10$	Wage X 0.30	Wage X 0.73
Spain	8.24	9.26	14.08	Wage X 0.70	Wage X 0.70 X 0.80	Wage X 0.60	Wage X 0.52
Switzerland	22.99	28.47	41.29	Wage X 0.70	Wage $X < 0.10$	Wage X 0.40	Wage X 0.33
Turkey	2.12	2.37	4.49	Wage X 0.40	Wage X 0.40 X 0.25	Wage X 0.80	Wage X 0.75
United Kingdom	11.96	12.61	19.63	Wage X 0.20	Wage $X < 0.10$	Wage X 0.59	Wage X 0.54

* Source: Eurostat Median Hourly Earnings by Educational Attainment [eam.SES.Pub2i] 25.01.2021.
** Source: OECD Tax Benefit Model (Version October 2020) www.oecd.org/els/benefitsandwages.html.
(A) OECD, STAT, Education and Earnings: Age Adjusted Earnings relative to non-students. Data extracted for 2017 on Feb 2021. 19:58 UTC (GMT).
(B) Relative Earnings of Students not reported for 2011–2018. The Weight used reflects an overall average for reporting OECD European Countries.

or not). Our experience would lead us to concur with the inconsistency of IIA tests when used to assess alternatives (employment, unemployment, education) that are conceptually quite distinctive. While we rely mainly on the results from CLGT,[5] as a sensitivity check, we also estimate random parameters logit (RPL) models[6] that do not require the IIA assumption inasmuch as they allow correlation of the error terms across alternatives (Cameron and Trivedi, 2005; McFadden and Train, 2000; Train, 2009; Revelt and Train, 1998; Brownstone and Train, 1997; Ben-Akiva and Bolduc, 1996; Bhat, 1998). In these models, the coefficient of Expected Income Rate (our only alternative-specific variable) is allowed to vary randomly, with the magnitude and statistical significance of the variance used as indicators of the amount of individual heterogeneity in preferences emanating from unobserved factors (Bhat, 2000). We note that in nearly all instances[7] the variance of the random coefficient was not statistically significant, indicating that heterogeneity across individual preferences is mostly determined by observed characteristics in the model.

4.2. Statistical modeling

We estimate a conditional logit (CLGT) model where the choice among three alternatives, viz., employment, unemployment or schooling/training is a function of the exogenous hourly wage or wage derivative associated with each alternative. This model has the form:

$$P_{ij} = \exp\left(Z_{ij}\alpha\right) \Bigg/ \sum_{k=1}^{J} \exp(Z_{ik}\alpha) \tag{1}$$

where Z_{ij} is the characteristics of the j^{th} alternative for individual i;

α is the regression parameter ;

J is the number of unordered alternatives (in our case $J = 3$) assumed constant for all individuals; and

P_{ij} is the probability that individual i chooses alternative j

Like the multinomial logit model, CLGT is based on the assumption that the error term follows an extreme value distribution. As we have noted, our tests of IIA the assumption were inconclusive, a condition that required us to continue to rely upon the conceptual premise that employment, unemployment, remaining in education are distinctive alternatives with pronounced income implications that are weighted independently by the decision maker.

We also estimate a CLGT adjusted for a set of decision maker characteristics, i.e., a mixed CLGT, which has this form:

$$P_{ij} = \sum_{k=1}^{J} \exp\left(X_i\beta_j\right) + \ Z_{ij}\beta \Bigg/ \exp(X_i\beta_k + Z_{ik}\alpha) \tag{2}$$

[5] We also continue to rely on the conceptual premise that our choice set contains distinctive choices that are weighted independently by the decision maker.

[6] The RPL has been variously referred to in the literature as random coefficient logit, random parameters logit, mixed multinomial logit, error components logit, or simply mixed logit.

[7] The exceptions are Germany and Italy, where the RPL models exhibit significant variability of the random coefficient for females. This is also verified by an approximate likelihood ratio test of the CLGT and the RPL that tests the null hypothesis that there is no preference heterogeneity due to unobserved individual characteristics.

where Z_{ij}, α, and P_{ij} are as in [1];

X_i represents characteristics of the individual; and

β_j is the regression parameter for each explanatory variable.

The Xs used in our mixed CLGT are displayed in Table 4.[8]

In order to estimate models [1] and [2] it was necessary to restructure the CUPESSE database from one that is based on the individual to one that is structured around $J = 3$ alternatives. An illustration of this transformation of $J = 3$ alternatives can be seen in this simple illustration of a CLGT mixed model with one Z and two X variables.[9]

Respondent	Alternative	Dependent Variable	Z	X_1	X_2
1	1	0	Z_{11}	24	1
	2	0	Z_{12}	24	1
	3	1	Z_{13}	24	1
2	1	0	Z_{21}	31	0
	2	1	Z_{22}	31	0
	3	0	Z_{23}	31	0
3	1	1	Z_{31}	19	1
	2	0	Z_{32}	19	1
	3	0	Z_{33}	19	1
4	1	0	Z_{41}	19	0
	2	1	Z_{42}	19	0
	3	0	Z_{43}	19	0

Here, Z_{11} is the value for respondent 1 for income associated with alternative 1, and Z_{12} and Z_{13} are his/her value associated with the distinctive income associated with alternatives 2 and 3. Individual 1 has selected alternative 3, remain in education, and country-specific, adjusted income expected from this choice (as shown in the third column). The X_1 and X_2 variables in the last two columns represent the introduction of a characteristic that is specific to the individual decision-maker and therefore is invariant across alternatives. X_1, in this example, references the continuous variable experience of the respondent and X_2 is a dummy variable indicating immigrant status with a 0 for non-immigrant and 1 for immigrant.

5. Results

The results from our country- and gender-specific CLGT statistical models are presented in Table 5 with 'remain in education' as the reference category. Each column in the Table provides the odds ratio ($\exp(\widehat{\beta})$) and its standard error. Significance of the odds ratio at the 0.05 level is noted by an asterisk. The first entry in a column is the effect that an increase of 1 euro in expected income will have on the odds of choosing an option. For example, in column 4 the significant odds ratio for Czechia women indicates that a one-euro increase in expected available income for each option would increase the odds of that option 3.33 times. Inasmuch as we are estimating a mixed version of CLGT we can also examine the effect of decision-maker characteristics, in addition to the choice-specific attribute on an individual's choice. Continuing with Czechia women, we see that the odds of choosing employment over continued education (the reference category) are 1.45 times higher for each year of education the woman possesses. Similarly, the odds of choosing employment relative to staying in school are 2.27 times higher as experience increases by a year. This woman's odds of choosing unemployment over education increases even more however with each year of education (1.85) or experience (2.55).

Note that although a respondent has the same odds ratio for the choice-specific variable, i.e., 3.335 for the exogenous income rate, this does not mean that the variable has no effect on her choice of alternatives. Since the regression coefficient (log) 3.335 or 1.204 is positive and significant, it (a) reflects a basic model assumption that a one-euro of income, no matter the source, is equally valuable in each alternative, and (b) that higher income increases the value of an alternative. As Equation [2] would indicate, a Czech woman's income rate affects her choice, conditional on how her income varies across alternatives. Continuing with our example, we see in Table 3 that a woman (or man for that matter) in Czechia with an ISCED III-IV level education can expect to earn a median income rate of around 5.12 euros from paid employment, expect 5.12 euro x 0.65×0.93 from unemployment if she does not have a work history and 5.12 euro x 0.51 if she selects education. For a one-euro increase, her utility would rise by 1.204×5.12 for employment, 1.204 x $(5.12 \times 0.65 \times 0.93)$ for unemployment and 1.204×0.51 for staying in school. In addition to the expected absolute increase in hourly income that an alternative offers, her utility for an alternative could be conditioned by the relative changes in income due to a one-euro increase, viz., a 19 % increase in employment income (5.1 to 6.1 euro/hour) and 38 % increase in education income (2.6 to 3.6 euro/hour).

For the nine country samples shown in Table 5, the pattern of coefficients (shown in $\exp(\widehat{\beta})$ form) reveal these overall results.

[8] We note that we did not detect any multicollinearity among our Xs as indicated by the Variance Inflation Factor (VIF) of less than 5 in the case of each country and gender.

[9] This simple tableau is adapted from (Hoffman and Duncan, 1988).

Table 5
Odds Ratios[+] and Standard Errors for Mixed CLGT Country- and Gender-Specific Models

Country	Austria		Czechia		Denmark		Germany		Greece	
Variable	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
Expected Income Rate (EIR)	1.157	1.001	1.216	3.3352*	0.7883*	1.088	0.923	1.1699*	1.190	1.2237*
	0.113	0.068	0.678	1.344	0.078	0.143	0.071	0.078	0.112	0.089
Employment Choice										
Education	1.146*	1.2509*	1.6212*	1.4532*	1.6956*	1.4665*	1.3911*	1.109	1.257	1.8251*
	0.067	0.066	0.296	0.227	0.131	0.148	0.127	0.094	0.204	0.283
Overeducated	0.3203*	0.5723*	1.399	0.2262*	0.1494*	0.3044*	0.3567*	0.3539*	1.426	0.439
	0.094	0.128	0.874	0.128	0.053	0.138	0.098	0.087	0.816	0.209
Experience	1.3603*	1.2584*	2.6456*	2.2762*	1.2688*	1.1894*	1.2407*	1.2499*	1.4516*	1.3519*
	0.073	0.046	0.443	0.361	0.051	0.053	0.033	0.032	0.093	0.081
Risk	0.875	1.031	0.985	1.138	1.099	1.065	0.931	1.002	1.065	0.891
	0.061	0.049	0.121	0.133	0.074	0.089	0.048	0.048	0.122	0.084
Willingsum	0.7623*	0.8288*	1.281	0.720	0.827	0.846	0.809*	0.936	0.993	0.909
	0.069	0.054	0.219	0.140	0.083	0.108	0.054	0.058	0.162	0.127
Jobimpmean	0.701	0.929	1.091	0.565	2.2645*	1.945	1.230	0.773	2.006	1.133
	0.232	0.264	0.683	0.401	0.946	1.164	0.357	0.220	1.183	0.614
Wkvaluemean	2.0201*	1.7955*	2.289	2.253	1.552	0.993	1.7153*	2.5011*	1.911	3.5235*
	0.510	0.315	1.284	1.241	0.406	0.337	0.317	0.458	0.815	1.527
Gritmean	0.979	1.470	0.704	1.588	1.749	0.761	0.762	0.791	1.245	2.348
	0.333	0.394	0.490	1.340	0.751	0.462	0.216	0.216	0.790	1.437
Immigrant	1.716	0.947	0.131	0.207	0.2098*	0.090	0.679	1.557	0.501	0.773
	0.780	0.298	0.166	0.271	0.152	0.060	0.252	0.595	0.350	0.557
Religious	0.797	0.858	0.291	2.234	2.103	1.456	1.253	0.4961*	1.759	1.550
	0.218	0.175	0.197	2.150	0.739	0.544	0.291	0.102	0.908	0.663
Intercept	0.112	0.003	0.000	0.000	0.000	0.003	0.044	0.026	0.000	0.000
	0.227	0.005	0.000	0.000	0.000	0.008	0.067	0.040	0.000	0.000
Unemployment Choice										
Education	1.123	1.060	1.318	1.8469*	1.4328*	1.5035*	1.066	1.066	1.302	1.712
	0.087	0.064	0.255	0.249	0.106	0.137	0.074	0.064	0.221	0.264
Overeducated	1.365	0.657	1.832	0.2759*	0.3707*	0.496	0.920	0.7298*	1.286	0.434
	0.527	0.188	1.521	0.164	0.152	0.237	0.333	0.199	0.790	0.214
Experience	1.3002*	1.3226*	2.6383*	2.549*	1.2478*	1.1504*	1.1639*	1.2711*	1.2869*	1.4305*
	0.076	0.053	0.471	0.410	0.060	0.059	0.042	0.037	0.088	0.089
Risk	0.8232*	1.050	1.049	1.113	1.136	1.053	0.964	0.936	1.043	0.872
	0.072	0.062	0.178	0.137	0.093	0.101	0.074	0.054	0.126	0.085
Willingsum	0.6845*	0.8025*	1.167	0.6216*	0.7788*	0.726*	0.7118*	0.928	1.162	0.913
	0.077	0.063	0.277	0.126	0.091	0.106	0.066	0.070	0.208	0.133
Jobimpmean	1.319*	0.682	0.863	0.428	1.125	1.718	1.693	0.574	1.886	1.619
	0.536	0.235	0.726	0.317	0.558	1.164	0.707	0.200	1.201	0.928
Wkvaluemean	1.205	1.144	0.916	1.886	0.918	0.693	0.790	1.8247*	1.425	3.250
	0.387	0.244	0.702	1.084	0.294	0.271	0.209	0.409	0.652	1.469
Gritmean	0.2591*	0.705	0.478	2.118	0.706	0.483	0.436	0.686	1.239	2.074
	0.122	0.232	0.482	1.868	0.366	0.331	0.185	0.229	0.850	1.331
Immigrant	3.2945*	1.485	0.000	0.145	0.324	0.221	0.753	1.320	1.174	1.454
	1.715	0.561	0.000	0.207	0.296	0.160	0.428	0.613	2.103	1.083
Religious	0.880	1.002	0.513	3.187	1.219	1.611	1.039	0.935	2.106	1.915
	0.321	0.255	0.464	3.148	0.527	0.685	0.376	0.235	1.169	0.859
Intercept	8.004	0.656	0.000	0.000	0.013	0.081	9.988	0.270	0.000	0.000
	19.580	1.177	0.000	0.000	0.031	0.244	20.651	0.483	0.000	0.000
Sample size	1653	2166	1176	1611	1446	960	4008	3852	1341	1890
Log Likelihood	-357.6	-611.9	-106.0	-351.6	-336.9	-257.8	-561.8	-814.4	-231.8	-433.7

Country	Hungary		Italy		Spain		United Kingdom	
Variable	Male	Female	Male	Female	Male	Female	Male	Female
Expected Income Rate (EIR)	1.832	2.1843*	1.055	1.0986*	1.5168*	1.783*	1.1689*	1.1035*
	0.958	0.622	0.039	0.039	0.232	0.288	0.064	0.050
Employment Choice								
Education	0.4732*	0.060	1.8245*	4.4059*	1.113	0.941	1.2063*	1.3269*
	0.141	0.270	0.276	2.457	0.096	0.091	0.086	0.107
Overeducated	0.813*	0.014	0.284	0.146	0.4222*	1.011	0.5729*	0.5461*
	0.042	0.073	0.282	0.224	0.165	0.449	0.151	0.139
Experience	1.585	1.264	1.043	1.222	1.255*	1.1795*	1.4439*	1.6475*
	0.255	0.713	0.098	0.193	0.054	0.056	0.060	0.077
Risk	0.674	1.264	1.018	0.336	0.957	1.136	0.950	1.015
	0.158	0.713	0.174	0.196	0.067	0.086	0.061	0.057
Willingsum	0.583	3.111	0.971	1.171	0.948	0.782	0.7612*	0.951
	0.200	2.861	0.242	0.694	0.104	0.103	0.064	0.065

(continued on next page)

Table 5 (*continued*)

Country	Hungary		Italy		Spain		United Kingdom	
Variable	Male	Female	Male	Female	Male	Female	Male	Female
Jobimpmean	0.142	0.000	4.938	3.868	1.356	2.434	1.306	0.524
	0.238	0.000	4.821	8.190	0.574	1.156	0.442	0.163
Wkvaluemean	2.975	0.276	0.880	0.251	2.098*	1.841	1.9826*	1.4649*
	2.700	1.128	0.815	0.489	0.674	0.587	0.479	0.341
Gritmean	1.138	2.517	3.399	2.987	0.959	0.680	1.570	0.780
	1.614	1.719	4.571	1.527	0.377	0.311	0.566	0.262
Immigrant	0.904	2.095	0.488	0.589	1.019	6.927	0.602	0.951
	0.907	1.900	0.618	0.629	0.893	7.605	0.274	0.375
Religious	1.165	4.011	1.108	3.251	0.770	1.143	0.750	1.105
	1.328	4.055	0.861	4.632	0.293	0.466	0.218	0.298
Intercept	4.308	4.147	0.000	0.000	0.001	0.005	0.003	0.005
	3.409	1.250	0.000	0.000	0.003	0.012	0.005	0.008
Unemployment Choice								
Education	0.4207*	0.066	1.5324*	3.8901*	1.063	0.920	1.118	1.2383*
	0.123	0.294	0.241	2.165	0.078	0.074	0.084	0.104
Overeducated	0.420	0.007	0.313	0.177	0.660	0.858	1.329	0.654
	0.985	0.035	0.327	0.274	0.272	0.400	0.458	0.209
Experience	1.624	0.667	0.957	1.204	1.2237*	1.2699*	1.4405*	1.7036*
	0.271	3.222	0.092	0.190	0.061	0.067	0.067	0.086
Risk	0.760	0.111	1.057	0.3157*	0.885	1.111	0.872	0.993
	0.190	0.450	0.188	0.184	0.068	0.090	0.071	0.069
Willingsum	0.744	0.168	0.912	1.277	0.975	0.7754*	0.7508*	0.9261*
	0.267	0.364	0.238	0.765	0.117	0.108	0.077	0.078
Jobimpmean	0.276	0.000	3.278	2.203	0.995	1.889	1.122	0.492
	0.482	0.000	3.350	4.674	0.468	0.970	0.484	0.184
Wkvaluemean	3.958	0.177	1.538	0.124	1.763	1.416	0.827	0.698
	3.935	0.725	1.492	0.242	0.626	0.484	0.254	0.201
Gritmean	0.187	1.617	2.062	0.191	0.878	1.006	0.975	1.008
	0.283	1.119	2.859	0.307	0.388	0.495	0.456	0.417
Immigrant	0.154	3.548	0.232	0.840	3.851	3.207	0.541	1.061
	2.855	4.700	0.364	0.280	3.326	3.714	0.340	0.517
Religious	0.855	0.002	1.649	3.402	0.649	0.852	0.695	1.538
	0.857	0.002	1.340	4.900	0.280	0.380	0.269	0.512
Intercept	1.008	8.347	0.000	0.000	0.056	0.013	0.494	0.036
	3.608	1.650	0.000	0.000	0.152	0.035	1.115	0.075
Sample size	1347	1524	900	714	1578	1704	3762	3888
Log Likelihood	-116.9	-253.6	157.5	-129.9	-377.8	-399.3	-498.7	-656.8

[+] All models are adjusted for NUTS regions.
[*] indicates statistical significance at 0.05 level.

5.1. Results summary

1. Women in seven of the nine countries analyzed (Czechia, Germany, Greece, Hungary, Italy, Spain and the United Kingdom) exhibited a positive, statistically significant effect on the alternative-specific variable, expected income rate. The odds of selecting an option ranged from 3.335 in Czechia to 1.098 in Italy.
2. For men, a significant effect of the alternative-specific variable was found in only three instances, Denmark, Spain and the United Kingdom. In Denmark, moreover, the effect was negative indicating that a one-euro increase in income reduced the utility of each alternative, a finding that is on its face quite illogical.
3. Two characteristics of the decision-maker – education level and previous years of work experience – were often statistically significant factors in the decision to choose employment over continued schooling. For both men and women in Austria, Czechia, Denmark, Italy and the United Kingdom, education level was a significant factor in choosing employment over continued education. It was also an important factor for men in Germany and Hungary and for women in Greece.
4. Work experience had a statistically significant impact on the selection of employment over schooling for both men and women in Austria, Czechia, Denmark, Germany, Greece, Spain and the United Kingdom.
5. Years of education and work experience played a less significant role in the choice of unemployment vs. staying in education. Among men and women in Austria, Czechia, Denmark, Spain and the United Kingdom, experience was a significant factor; this was also the case for women in Greece and men in Germany.
6. Among our work values/soft skills measures only work centrality demonstrates a consistent impact on the choice of employment over unemployment or staying in education.

As we noted earlier, it is also possible to fit a series of mixed CLGT models that incorporate interactions between the choice-specific, expected income variable and the 10 individual characteristics (Xs). The purpose of positing such models is to identify heterogeneity in individual preferences, e.g., how the employment decision varies across individuals with different observable characteristics and income potential. Our approach has been to build potential moderating effects into the research design by utilizing country-specific and gender-specific regression models that use a decision variable that is adjusted for attained education, experience and age. In this way we preclude the false positive problem associated with post-hoc, multiple interaction tests (Aguinis and Gottfredson, 2010; Andersson et al., 2014; Jaccard and Turrisi, 2003; Shieh, 2009; Toothaker, 1991).

5.2. Policy simulations and sensitivity analyses

Perhaps a more informative, policy-relevant way of presenting the results in Table 5 is to examine the predicted probabilities of a choice and the change in these probabilities when wages and/or monetary benefits are altered. Such changes can occur when labor supply/demand equilibria are reset or when government intervenes in the labor market. In Table 6a and b we show how the predicted probabilities generated by our CLGT change for (a) 10 % increase in wage income over the country median and (b) for a 10 % increase in wage income and a 10 % decrease in unemployment benefits effected simultaneously. In addition, we also show these marginal effects from the RPL estimates. Here we will focus only on statistically significant gender and country effects.

Recall that among men the alternative-specific variable, i.e., expected available income rate, was significant in Spain, the United Kingdom and in Denmark only, with Denmark manifesting a difficult to understand or interpret negative utility. In Spain and in the United Kingdom, the prediction of these changes in income and benefits demonstrate the expected positive increase in the probability of employment and the necessary decline in both the unemployment and remaining education choices. In Spain employment rises by 8.3 percentage points if wages increase by 10 % over the base in the country and by 11.4 percentage points (accompanied by a 9 percentage point decrease in unemployment) if wages increase by 10 % and unemployment benefits are reduced by 10 %. In the United Kingdom, the increases and much smaller, 2.3 and 2.5 percentage points, no doubt reflecting the higher wage base in the country. The RPL marginal effects, by way of comparison, are virtually the same for Spanish males while the employment effects are slightly larger (by 1 percentage point) in the case of UK.

On the other hand, we reported in Table 5 that among women the alternative-specific expected income rate was significant and positive in all countries excepting Austria and Denmark. In Czechia and Spain we can see from Table 6b that the 10 % increase in wage has a dramatic effect on employment, increasing it by 14 percentage points in the former country and by 12 percentage points in the latter. Reducing unemployment benefits further spurs the movement to employment to a 20 percentage point increase in Czechia and a 17 percentage point increase in Spain, with a concurrent reduction in unemployment by 18.6 and 14 percentage points, respectively. The RPL estimates again are nearly identical. The marginal changes in the predicted probabilities of employment from CLGT are not as large in Germany, Greece, Italy, Hungary or the United Kingdom; nonetheless, they are notable, ranging from 2 to almost 5 percentage points for a 10 % wage increase and from 2.2 to 7 percentage points when wages and unemployment benefits are altered

Table 6a
Predicted Probabilities of an Individual Choosing Employment, Unemployment or Education and the Expected Change in that Probability Under Conditions of a 10% Increase in Wages and a 10% Increase in Wages Coupled with a 10% Decrease in Unemployment Benefit (Males).

Country	Average Predicted Probability			Marginal Changes Under 10% Increase in Wages			Marginal Changes Under 10% Increase in Wages and 10% Decrease in Unemployment Income		
	Educ.	**Emp.**	**Unemp.**	**Educ.**	**Emp.**	**Unemp.**	**Educ.**	**Emp.**	**Unemp.**
Austria									
CLGT	0.171	0.707	0.122	−0.021	0.038	−0.017	−0.019	0.047	−0.027
RPL	0.171	0.708	0.122	−0.022	0.039	−0.017	−0.020	0.047	−0.027
Czechia									
CLGT	0.102	0.857	0.040	−0.005	0.008	−0.033	−0.004	0.009	−0.005
RPL	0.102	0.857	0.041	0.001	−0.002	0.001	0.001	−0.002	0.001
Denmark									
CLGT	0.180	0.666	0.153	0.032	−0.072	0.040	0.022	−0.100	0.078
RPL	0.180	0.666	0.153	0.032	−0.072	0.040	0.022	−0.100	0.078
Germany									
CLGT	0.084	0.859	0.056	0.011	−0.018	0.007	0.010	−0.023	0.013
RPL	0.085	0.859	0.056	0.010	−0.017	0.007	0.010	−0.022	0.012
Greece									
CLGT	0.053	0.803	0.143	−0.004	0.022	−0.017	−0.004	0.030	−0.026
RPL	0.053	0.802	0.145	−0.007	0.023	−0.016	−0.007	0.029	−0.022
Hungary									
CLGT	0.020	0.902	0.077	−0.004	0.016	−0.011	−0.004	0.021	−0.018
RPL	0.020	0.902	0.078	−0.004	0.016	−0.012	−0.004	0.022	−0.018
Italy									
CLGT	0.037	0.790	0.173	−0.001	0.011	−0.010	−0.001	0.017	−0.016
RPL	0.040	0.785	0.175	−0.002	0.012	−0.010	−0.001	0.018	−0.017
Spain									
CLGT	0.108	0.671	0.220	−0.027	0.083	−0.057	−0.023	0.114	0.091
RPL	0.108	0.671	0.221	−0.026	0.083	−0.057	−0.023	0.115	−0.091
UK									
CLGT	0.075	0.852	0.072	−0.011	0.023	−0.012	−0.010	0.025	−0.015
RPL	0.074	0.853	0.073	−0.019	0.033	−0.013	−0.019	0.032	−0.013

Table 6b
Predicted Probabilities of an Individual Choosing Employment, Unemployment or Education and the Expected Change in that Probability Under Conditions of a 10% Increase in Wages and a 10% Increase in Wages Coupled with a 10% Decrease in Unemployment Benefit (Females).

Country	Average Predicted Probability			Marginal Changes Under 10% Increase in Wages			Marginal Changes Under 10% Increase in Wages and 10% Decrease in Unemployment Income		
	Educ.	**Emp.**	**Unemp.**	**Educ.**	**Emp.**	**Unemp.**	**Educ.**	**Emp.**	**Unemp.**
Austria									
CLGT	0.252	0.557	0.191	−0.0002	0.000	0.000	−0.0001	0.0004	0.0003
RPL	0.251	0.558	0.191	−0.008	0.013	−0.005	−0.012	0.015	−0.003
Czechia									
CLGT	0.081	0.579	0.339	−0.017	0.141	−0.124	−0.017	0.203	−0.186
RPL	0.082	0.579	0.339	−0.018	0.142	−0.124	−0.017	0.203	−0.186
Denmark									
CLGT	0.174	0.609	0.216	−0.011	0.029	−0.018	−0.008	0.040	−0.032
RPL	0.175	0.609	0.217	−0.011	0.032	−0.022	−0.012	0.043	0.031
Germany									
CLGT	0.114	0.749	0.137	−0.020	0.047	−0.027	−0.019	0.062	−0.043
RPL	0.113	0.749	0.138	−0.019	0.071	−0.052	−0.01	0.087	−0.080
Greece									
CLGT	0.051	0.667	0.282	−0.004	0.040	−0.035	−0.004	0.057	−0.053
RPL	0.051	0.667	0.282	−0.007	0.040	−0.034	−0.007	0.054	−0.046
Hungary									
CLGT	0.006	0.759	0.234	−0.001	0.047	−0.045	−0.001	0.070	−0.069
RPL	0.006	0.759	0.235	−0.001	0.042	−0.041	−0.001	0.061	0.060
Italy									
CLGT	0.034	0.689	0.277	0.001	0.025	−0.024	−0.001	0.038	−0.037
RPL	0.041	0.689	0.269	−0.004	0.065	−0.061	−0.004	0.090	−0.086
Spain									
CLGT	0.080	0.627	0.292	−0.029	0.120	−0.090	−0.027	0.167	−0.140
RPL	0.081	0.627	0.292	−0.029	0.120	−0.091	−0.027	0.167	−0.140
UK									
CLGT	0.102	0.789	0.108	−0.008	0.020	−0.011	−0.008	0.022	−0.014
RPL	0.103	0.789	0.108	−0.019	0.030	−0.011	−0.019	0.032	−0.013

simultaneously. However, the marginal effects implied by the RPL are larger in the case of Germany and Italy by anywhere from 2.5 to 5 percentage points. We should note that such larger effects have also been found by others in the literature (e.g., Brownstone and Train, 1999; Bhat, 2000) in the presence of significant heterogeneity of preferences induced by unobserved factors.

6. Discussion and conclusions

Our research examines the decision of young adults (18–35 years) to seek employment, remain in school or live on unemployment and other unearned income benefits. Our approach has been to estimate a series of country- and gender-specific conditional logit models (CLGT) which focus on a set of exogenous income conditions that are specific to the choice of employment, unemployment or enrollment in education or training. These structural models, which provide us with some insight into why choices are made (McFadden, 1975; McFadden, 1986; Hoffman and Duncan, 1988) are augmented by a set of individual-specific covariates that provide us with some additional understanding around which individuals make such choices.

We find that the exogenous, choice-specific, income variable was more likely to influence the choices of women in Czechia, Germany, Greece, Hungary and Italy. Both men and women were influenced in Spain and the UK. This sensitivity to market wages is consistent with the Job Search model of labor force attachment (Blau and Kahn, 2017; Caroleo and Pastore, 2018; Caroleo and Pastore, 2016; Nicaise, 2001; Sicherman, 1991). According to this conceptual framework, workers deploy their human capital strategically, i.e., they only accept a job if the earnings are higher than their reservation wage. The choice of unemployment or education, moreover, is reinforced by the existence of institutional and market factors, for example, family obligations and supports which make these latter options both necessary and viable, at least in the short run. The reservation wage hypothesis would appear to hold in both low unemployment labor markets (i.e., United Kingdom, Germany) and high unemployment conditions (Greece, Italy, Spain).

Our findings are also consistent with studies of sample selection bias in employment earnings analyses (Heckman, 1979; Heckman et al., 2006). These analyses often suffer from the problem of sample truncation since wages are only observed for individuals in the sample who worked for wages. Here the observed wages are greater, on average, than the wages employers are willing to offer, and while these above-average wages are accepted the below-average wages are not (Observed > Offered). Women, more often than men, have been found in these analyses to be "positively selected," i.e., to choose unemployment or education, (Baldwin and Johnson, 1992; Dolton and Makepeace, 1986; Hartog and Oosterbeek, 1988; Nicaise, 2001; Borjas, 2006) suggesting high reservation wages and high opportunity costs when faced with lower than expected offer wages.

One factor that could account for both the strategic deployment of young women's human capital and their relative absence from earnings models is gender discrimination and the gender pay-gap it often portends (European Commission, 2021; Blau and Kahn, 2017; Borjas, 2008; Jagannathan et al., (n.d.)). Whether the origin is occupational segregation, institutional neglect or prejudice-based discrimination, women often earn less than men when measured as the gender pay ratio (women's average earnings / men's average earnings) or the pay-gap ((1-gender pay ratio)*100). Note that in Table 4, our exogenous income variable reflects the average compensation that both men and women can expect to receive by choosing employment, unemployment or education according to published, government sources. A gender pay-gap, whether real or imagined, would likely result in a woman's rejection of employment under conditions of a sub-average wage offer given (a) appropriate or superior education and experience credentials, and (b) reasonable levels of alternative income support.

As would be expected, the individual characteristics that influence our choice set are attained education and previous work experience: the more educated and experienced typically choose employment. Among our soft skills/work values measures, only the centrality of work affects the employment decision consistently, increasing the odds of employment significantly for both women and men in Austria, Germany, Greece, Spain and the United Kingdom.

A major advantage of CLGT modeling is that the analysis is well suited for situations where governmental economic policies can be used to prioritize intervention. In a report authored by the World Health Organization (World Health Organization (WHO), 2012) the authors lament the poor guidance that both qualitative studies (focus groups, key informants, etc.) and traditional quantitative studies (regression analysis, etc.) have provided to policy makers attempting to address the shortages of qualified workers. Traditional methods, they note, provide "laundry lists" of significant factors – salary, incentives, career opportunities – without a clear protocol to prioritize those factors. A solution to this quandary the authors maintain is to conduct discrete choice, stated preference (SP) experiments. We concur, but believe such experiments should be augmented with the reality checks offered by revealed preference (RP) analyses.

Both RP and SP provide policy makers with several useful tools for tailoring interventions. In addition to allowing the policy maker to assess the strength of a preference from the odds ratio (Table 5 regressions) it is possible to simulate a series of "uptake rates" and "willingness to pay" scenarios (Eriksson and Kristensen, 2014; Wardman, 1988). In Table 6a and b, for example, we examine the uptake rate changes in each country in our sample with both a 10 % increase in wages and a combination of a 10 % increase in wages and a 10 % decline in unemployment benefits. Uptake rates can be calculated under a variety of circumstances, providing policy makers with a menu of options that can be further studied in small demonstrations or exploratory projects with SP techniques before an intervention (e.g., changes to minimum wage or to unemployment benefit levels) is widely introduced. Where prices (wages) are included in workforce issues it is also possible to determine how much income a respondent would be willing to give up to receive improvements in other aspects of jobs. Such willingness to pay analyses can be used by policy makers following a revealed preference study that pinpoints existing baseline pay rates (see, for example, (Demel et al., 2019; Eriksson and Kristensen, 2014; Vooren et al., 2019; World Health Organization (WHO), 2012)).

The study is, of course, not without its limitations. We have constructed our decision variable (Table 3) using data sources believed to be most reliable that were available at the time of the CUPESSE survey. The goal here was to construct income measures that were realistic expectations for our three alternatives. Revealed preferences, however, may not reduce to income considerations alone; intrinsic aspects of a choice may also be at play including future career prospects (Carneiro and Heckman, 2003; Sicherman, 1991). While we have attempted to account for these motivational factors with individual-level covariates, their accommodation at the choice-set level was not possible due to data availability. For example, in the career mobility thesis offered by Sicherman and Galor (1990; 1991) it is maintained that workers look at wages and the prospects for advancement when choosing employment. It would have been informative to expand our choice set to distinguish employment as a job vis-à-vis employment as a career if such data were readily available in published sources such as OECD or the World Bank. Notwithstanding these limitations, we believe we have made a useful contribution to the labor economics literature by demonstrating how revealed preference can offer important insights into the *why* of labor force attachment decisions.

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