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Reichenberg, Olof

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In and Out of Control

How Class and Occupation Conditions the Relationship between Job Skills and Job Control (Task Discretion) in Four Western European Countries

Olof Reichenberg
Department of Social Studies, Linnaeus University, Växjö, Sweden
olof.reichenberg@lnu.se

Abstract

The present study aimed to predict job control (i.e., task discretion) based on class and occupation with skill use as a (hypothesized) mechanism in four Western European countries by using the OECD adult skill survey (PIAAC). The countries were Denmark, Belgium, Italy, and the United Kingdom (UK). The study used a Bayesian approach that included multilevel models combined with measurement models. The study uses the international standard classification of occupations with two digits (clustering variable) as well as the European socioeconomic classification (ESeC) measured with three social classes. The results indicate that greater worker technical skills (computer use) and social skills (e.g., negotiate and influence) predict higher levels of job control. Social classes interact with skills to predict job control (except Belgium). Occupational computer skills predict job control (in Belgium and Italy). In conclusion, the study supports predictions by neo-Durkheimians, neo-Weberians, New Structuralists, and relational approaches to inequality.

Keywords

job control – task discretion – job skills – occupations – social class – sociology of work

1 Introduction

Workers' control over their tasks at work constitutes an indicator of a good job (Kalleberg, 2011; Gallie, 2012). Job control (i.e., task discretion) correlates with high job and life satisfaction (Lopes et al., 2014; Drobnič et al., 2010).

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Consequently, greater job control reduces workers' psychological demands and stress. Workers who exercise greater job control turn chores into meaningful accomplishments. In contrast, reduced job control turns good jobs into bad jobs (Gallie, 2012) because the decreases in job control decrease workers' health and job satisfaction.

From a policy perspective the issue of job control shifts attention from employment to job quality (i.e., good jobs). In contrast to earnings, job control centers on the conditions of workers' behavior at work (e.g., control over what, how, and when to do work tasks). Improving the workplace increases workers' control and thus improves job satisfaction (Lopes et al., 2014; Drobnič et al., 2010). Although the determinants and consequences of job control have been studied, researchers still do not understand its mechanisms (processes). In the current study I propose the following theoretical contribution.

I argue for the importance of skill use to predict job control, conditional upon class and occupation. In agreement with New Structuralism (Kalleberg, 1988, 2011), I consider both social class and occupation as important (Kalleberg, 2011, 1988). Inspired by New Structuralism (Kalleberg, 2011; Kristal, 2020), I consider skill use as the workers' labor power. Elaborating on new structuralism, I emphasize that skill use involves a process at the workplace that emerges out of the relations between workers and managers (Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019).[1]

Following Liu and Grusky (2013), I distinguish between technical (e.g., computer) and social (e.g., negotiate and influence) skills. Control over technical and social skills captures workers' bargaining power (Kristal, 2020; Tomaskovic-Devey and Avent-Holt, 2019). Bargaining power improves job quality, such as job control (Breen, 2005). Therefore, I argue that computer and social skills predict job control conditional upon social class, whereas occupational computer skills predict job control. Thus, my argument agrees with the effort to elaborate on New Structuralism toward relational approaches to the mechanisms of workplaces inspired by Tilly (1998) and Tomaskovic-Devey and Avent-Holt (2019).

I elaborate on the argument and justify the predictions in the framework section. Next, I discuss the purpose, research questions, and disposition.

1 The workers-managers relation include professionals. Depending on the context professionals have bargaining power vis-a-vis managers or other workers such as the relation between (a) "non-professional workers" – "professionals" and (b) "professionals-mangers". (Tomaskovic-Devey and Avent-Holt, 2019).

1.1 *Purpose and Research Question*

In the present study I *aim to predict* job control (i.e., task discretion) based on class and occupation with skill use as a (hypothesized) mechanism in four Western European countries. For this purpose, I used the OECD adult skill survey (PIAAC) and selected the following labor markets: Belgium (coordinated), Denmark (Nordic), Italy (Mediterranean), and the United Kingdom ([UK], liberal). The study asks the following research questions:

Q1 How does social class and occupation differ descriptively in job control?
Q2 How does social class and occupation predict differences in job control, on average, after adjustments?
Q3 How does worker skill use predict differences in job control conditional on social class, on average, after adjustments?

To explain differences in job control, I address the (hypothetical) determinants and mechanisms (Tilly, 1998; Gross, 2009) proposed by New Structuralists (Kalleberg, 2011) and elaborations based on relations and interactions (Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019).

The organization of the paper follows. First, I discuss the concept of job control and its measurement, along with the study's framework. Second, I discuss the country selection, data, variables, and strategies. Third, I report the study's results. Fourth, I discuss the study's conclusions, implications, and limitations.

2 Previous Research on Job Quality and Job Control

I begin by conceptualizing job control and its measurement. Next, I outline neo-Weberian and neo-Durkheimian arguments about class and occupation. I synthesize the arguments based on New Structuralism (Kalleberg, 2011). Finally, I elaborate on job skills as a mechanism of job control, drawing on arguments that elaborate on New Structuralism with relational approaches to workplace mechanisms (Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019).

2.1 *Concept and Measurement of Job Control*

Job control constitutes one indicator of job quality; other indicators include security, working conditions, satisfaction, and earnings (Kalleberg, 2011). Workers' job control levels indicate the quality of their work behavior. Thus, job quality extends beyond employment and earnings (Kalleberg, 2011).

Job control correlates with stress, life satisfaction, and job satisfaction (Lopes et al., 2014; Drobnič et al., 2010; Kalleberg et al., 2009). Greater control reduces the psychological demands at work (Green, 2006), whereas reductions in job control deteriorate workers' job satisfaction. Less control means that the work shifts to a menial chore (Kalleberg, 2011; Gallie, 2012).

Previous studies (e.g., Pullman and Jongbloed (2019); Aspøy (2020)) overlooked issues of job control as a latent variable. Instead, I suggest that workers' capacity for job control is not directly observable (i.e., a latent variable of behavioral structures). Accordingly, researchers can infer job control from behaviors, such as control over hours, order or sequence of tasks, and how or when to perform tasks. Greater control should vary in contribution. Consequently, I model job control using a measurement model (see the method section).

Researchers have also neglected to test whether job control has the same meaning across countries (Davidov et al., 2018). Different meanings bias the validity, scope, and measurement. Thus, I tested if the measurement had the same meaning across countries.

Theoretically, researchers overlook how to model occupations and social classes jointly and their mechanisms. In contrast, I model both inspired by New Structuralism (Kalleberg, 1988; Weeden et al., 2007). Next, I go beyond class and occupation to include job skill use as a mechanism.

3 Framework: Class, Occupation, and Skill Use as Mechanisms of Job Control

In this section, I address the determinants of job control. I organize this section by suggesting class and occupation as determinants and skills mechanisms.

Next, I focus on job skills use (hereafter: skills) as mechanisms (hypothetical process). I refer to skills as workers' (relational) capacity to perform job tasks required by the workplace, such as writing, programming, scheduling, negotiating, and advising (Handel, 2003; Green, 2013). Skills represent a worker or collective labor power (Kalleberg, 2011). Thus, skills capture the workers and occupations' power to bargain with employers (Kalleberg, 2011; Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019). Social classes or occupations with greater control over skills have greater bargaining power and thus dominate others in terms of job control.

3.1 *Class and Occupational Determinants of Job Control*

Below, I contend that social classes or occupations with greater control over skills have greater bargaining power and thus dominate others in terms of job control (Kalleberg, 2011; Tomaskovic-Devey and Avent-Holt, 2019). I start with social class and continue with occupations.

Neo-Weberian social class theory suggests that *social class* determines workers' attitudes and behaviors. According to this theory, social class captures the shared labor market (skill requirements) and employment (contract) position (Breen, 2005). Workers' market positions depend on skill requirements. Professionals require the highest skill levels.

Social classes share skills as labor power (Breen, 2005; Kalleberg et al., 1987). Possessing greater skill means having greater bargaining power with the employer (Tomaskovic-Devey and Avent-Holt, 2019). In addition, greater skill makes workers (e.g., professionals) difficult to monitor (McGovern et al., 2007; Breen, 2005). Difficulty in monitoring increases skilled workers' bargaining power (Tomaskovic-Devey and Avent-Holt, 2019). Thus, those with higher social class (professionals and managers) have greater control of their skills.

The empirical measure of social class assumes a skill component without measuring it. Attempts to validate the skill component have been successful (i.e., predictor validity (Breen, 2005)). Consequently, social class helps researchers to understand differences in job control (Edlund and Grönlund, 2010; McGovern et al., 2007; Williams, 2017).

Individuals occupying higher social class (e.g., professionals and managers) dominate those occupying a lower social class (McGovern et al., 2007; Breen, 2005). Consequently, individuals with higher social class exercise a greater power compared to those with lower social class (Tomaskovic-Devey and Avent-Holt, 2019).

> **Hypothesis 1 (H1)**: *Higher social class predicts a greater level of job control, compared to lower social class.*

Previous studies overlooked skill use as a mechanism of job control. However, explanations of the regularities of job control require a model. A predictive model puts this mechanism to the test.

Neo-Durkheimian theories propose replacing social class with occupations (Grusky and Galescu, 2005). *Occupation* refers to clusters of jobs (i.e., people with similar tasks). Tasks indicate the division of labor based on technical skills (Grusky and Galescu, 2005). Whereas social class represents shared positions in the labor market, occupations represent shared technical tasks (Grusky and Galescu, 2005). The differences between social class and occupation need to be tested (Kalleberg et al., 1987; Weeden et al., 2007).

In agreement with a relational approaches to inequality (Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019), I focus on social class; however, I include occupation as a complement. Social classes (managers and professionals or "salariat") control technical and social skills, whereas occupations control technical skills due to the division of labor.

3.2 *Skill Use as Mechanisms of Job Control*

Here, I address the hypothetical question of why skills matter. I focus on two types of skill use: (a) technical skills, such as computer use, and (b) social skills (e.g., negotiate and persuade). In agreement with New Structuralist theories (Tomaskovic-Devey and Avent-Holt, 2019; Tilly, 1998), I suggest that skill use (labor power) allows workers to bargain (i.e., negotiate and routine claims-making) for greater job control. In turn, skill use depends upon class and occupation (Tomaskovic-Devey and Avent-Holt, 2019; Tilly, 1998).

In addition, skill use realizes workers' capacities to adapt to problems and solve them based on social experience (Gross, 2009; Dewey, 2002). Thus, a skilled worker can become indispensable to employers and respected by coworkers' due to the relational value of their work (Tilly, 1998; Tomaskovic-Devey, 2014) e.g., artistic nail salon workers, handy janitor, or innovative barrister, or savvy barber.

I suggest that skill use to be considered as bargaining power (New Structuralist) and capacities that privileged workers (i.e., professionals and middle managers) have monopolized (i.e., neo-Weberian and neo-Durkheimian). Thus, I agree with elaborations of New Structuralism and underscore that workplace relations determine skill use (Tomaskovic-Devey and Avent-Holt, 2019).

Use of skills have gained importance due changes in to demand and supply restrictions in the labor market. The labor market's demand for education, knowledge, and skills has increased, changing the division of labor (Castells, 2002; Autor and Handel, 2013; Goldin and Katz, 2009). In addition, the need for services has increased, e.g., professionals can work as software developers or analysts, whereas working class individuals find jobs as food delivery persons. Demand for workers with technical skills and social skills has increased, making technical and social skills valuable to employers (McGovern et al., 2007; Tomaskovic-Devey and Avent-Holt, 2019).

Whereas economists attribute these changes to technological change (Autor and Handel, 2013; Goldin and Katz, 2009), sociologists stress the importance of: institutions, supply restriction, and relations at the workplace (Tilly, 1998; Kalleberg, 2012; McGovern et al., 2007; Tomaskovic-Devey and Avent-Holt, 2019). First, skilled workers restrict access to higher education, cutting off the supply of skills (e.g., professional and business education). Second, skilled workers restrict access to job-specific skills, cutting off the job-specific skill supply (Tomaskovic-Devey and Avent-Holt, 2019). In other words, economists stress demand, whereas sociologists stress supply. Workers with more skills exercise greater bargaining power in exchanges with employers (McGovern et al., 2007; Tomaskovic-Devey and Avent-Holt, 2019; Kalleberg, 2011).

Regarding to technical skills, workers with lower social class face greater risks (Tomaskovic-Devey and Avent-Holt, 2019). Lower social class varies not only with lower skill levels, but also with routine tasks (e.g., assembly workers), which might be replaced by automation (e.g., artificial intelligence and robotics). Beyond automation, routine workers risk offshoring (e.g., relocating the production to low-wage countries) or outsourcing (e.g., hiring workers from low wage countries, such as in construction businesses). These risks undermine workers' bargaining power in routine jobs (Tomaskovic-Devey and Avent-Holt, 2019; Kalleberg, 2011).

Institutions moderate the importance of technology. A labor market with high union density and strong left-wing party representation in the cabinet may protect workers. Unions may contribute to norms of fairness or threats of strikes, and left-wing parties promote social protections and workers' rights (Tomaskovic-Devey and Avent-Holt, 2019; Kristal, 2020).

Although institutions moderate the importance of technology, technical skills vary with differences in job control at the workplace. Economists often stress technological changes such as those related to computers. However, economists neglect the fact that computer skills offer social classes and occupations bargaining power exchange with employers (Grusky and Galescu, 2005; Kristal, 2020). Bargaining power originates in restricted supply and the difficulty of monitoring technically skilled workers (Tomaskovic-Devey and Avent-Holt, 2019; Kristal, 2020). Higher social classes exercise greater control over skills and have jobs with the highest monitoring difficulties (i.e., professionals and managers). Consequently, technical skills predict inequality at work.

> **Hypothesis 2 (H2)**: *Greater computer skill use varies with greater job control, conditional upon social class*.

Beyond technical skills, social skills have increased in importance and correlate with the need for middle managers, supervisors, and team leaders to monitor workers (Liu and Grusky, 2013; Weeden and Grusky, 2014; McGovern et al., 2007). Social skills means managing relations at work (Tomaskovic-Devey and Avent-Holt, 2019; Hallett and Hawbaker, 2021).

Managers use social skills to bargain with workers, for example, for individual benefits (e.g., annual reviews), job interviews, negotiate coalitions, struggles over influence, during supervision, or staff meetings. The use of social skills has likely increased with digital technology (e.g., emails, online meetings, and reporting) as it simplifies monitoring (McGovern et al., 2007). Social skills contribute to introducing managerial practices (McGovern et al., 2007), new technologies, "business strategies", or "fads" (Hallett and Hawbaker, 2021). Beyond monitoring and supervision, managers use social skills to bargaining with workers in supervision, e.g., persuade and negotiate with workers.

Thus, managers have increased their bargaining power relative to workers due to e.g., increased job insecurity, rise of temporary employment, decreases in employment duration (Kalleberg, 2011), threats of layoffs if firms move oversees, and declining union size (Tomaskovic-Devey and Avent-Holt, 2019). Indeed, managers gain the advantage relative to workers with their authority due to threats of sanctions (e.g., promotions, hiring/firing, fringes, etc). Finally, managers use social skills for advising and influencing workers. Similar to professionals, managers increased their standing and thus job control, by offering workers expert advice and opinions (e.g.; coaching employees) (Bandelj, 2012; Hallett and Hawbaker, 2021). As workers become dependent on managers, managers increase in bargaining power relative to workers and thus job control.

Professionals (e.g., doctors, lawyers, engineers) use social skills such as advising, influencing, organizing, and negotiating with clients (e.g., treatment, therapy, or counseling). Clients depend on professionals' expert advice and opinions due to the authority in their professions (Hallett and Hawbaker, 2021). The dependency relation places professionals at a greater bargaining advantage.

Thus, professionals with greater social skills gain control because other workers depend on them for advice and guidance, resulting in more negotiations and influence (Tomaskovic-Devey and Avent-Holt, 2019; Hallett and Hawbaker, 2021). Examples include the capacity to coordinate, influence, plan for others, set agendas, define the situation and so forth. Consequently, professionals use social skills to gain control in various contexts, such as client, team, and staff meetings, as well as annual reviews (Fligstein and McAdam, 2012; Tomaskovic-Devey and Avent-Holt, 2019). Thus, professionals with social skills have greater bargaining power in the workplace and can negotiate and influence others to gain control, that is, exercise authority (Tomaskovic-Devey and Avent-Holt, 2019; Fligstein and McAdam, 2012; Hallett and Hawbaker, 2021).

Consequently, social class exerts unequal control over skills. Higher social classes exercise greater control than do lower social classes. Thus, members of higher social classes exercise greater bargaining power (Tomaskovic-Devey and Avent-Holt, 2019).

> **Hypothesis 3 (H3)**: *Greater use of social skills varies with greater job control, which is conditional upon social class.*

However, social class and occupation may behave differently (Kalleberg, 1988; Tomaskovic-Devey and Avent-Holt, 2019). Aggregation of technical skills may be determined by occupations, as proposed by the neo-Durkheimians (Grusky and Galescu, 2005). Previous research has indicated that class biased technological change may be perpetuated by occupations (Kristal, 2020). Occupational skills emerge from the technical division of labor (Grusky and Galescu, 2005; Kristal, 2020). The aggregation of technical skills by occupation leads to restriction of skill use. Thus, technically skilled occupations exert greater bargaining power at the expense of others (Tomaskovic-Devey and Avent-Holt, 2019; Kristal, 2020).

> **Hypothesis 4 (H4)**: *Greater occupational computer use varies with greater job control.*

3.3 *Country Selection*

For the study, I selected the following labor market (i.e., "employment regimes"): Belgium (coordinated), Denmark (Nordic), Italy (Mediterranean), and the United Kingdom (liberal). I choose these countries based on theoretical differences, availability of variables, and metric similarities (Kalleberg, 2018; Gallie, 2009). To measure job control in different countries, one must ensure that job control has the same meaning in those countries.

Western European nations share a history, which I suspect increases the shared meaning of job control. Although meaning differences exist, their magnitude seems small at best, based on differential item function tests (see Method section). Thus, the measurement bias between countries was minimal. However, institutional differences remains.

Belgium represents the coordinated labor market (Bismarckian) with a high degree of coordination between vocational education and firms (e.g., apprenticeship). The labor market favors permanent employees in terms of firm-based training, careers, and promotions. Italy represents the Mediterranean labor market which resembles the coordinated labor market (e.g., Belgium). However, the Mediterranean labor market have a lower earnings inequality but higher job insecurity than coordinated labor markets (Kalleberg, 2018).

The United Kingdom represents the liberal labor market with a lower degree of labor regulation with individualized risks (Kalleberg, 2018). Liberal labor markets depend on competition with limited protection for workers with high importance given to education. Denmark represents the Nordic labor market. The Nordic countries have strong unions, high degrees of regulation, and inclusive labor market polices. Due to strong unions relative to management, regulations protect workers and enhance working conditions. Workers gain greater job control in exchange for work cooperation and loyalty (Kalleberg, 2018).

4 Method

I begin by describing the data, including sampling and justification. Thereafter, I describe the study's variables and measures. Finally, I elaborate on the strategies for data analysis (i.e., Bayesian multilevel and measurement models).

4.1 *Data*

The PIAAC uses a complex random sample. During 2012 and 2014, the OCED collected data on several member countries. The implementation of the sample design varies by country. However, all countries were sampled in steps (i.e., using stratified cluster sampling). The stratifying unit varied, as did the clusters.

The PIAAC includes variables related to skills used at work and at leisure, individual characteristics (e.g., education, sex, age, and immigration status), workplace characteristics (e.g., size), and work behaviors and attitudes. Here, I disregard variables related to leisure, as those exceed the study's scope. Finally, the PIAAC includes a test of reading, numeric, and problem-solving abilities. However, I am concerned with work behaviors, not test variables. Here, I lean on research by sociologists.

I selected the PIAAC for its measure of skills and comparative designs. Compared to PIAAC, the European Labor Force Study (LFS) and the International Social Survey (ISSP) offer rather few measures of skill use and control. The only comparable study seems to be the European Working Conditions Survey (EWCS), which would have been a viable alternative to PIAAC. I return to this issue in the limitations section.

4.2 *Variables and Measurement*

4.2.1 Outcome

I scaled four variables as outcomes. The variables measured how often workers have flexibility regarding: (Q1) the sequence of tasks, (Q2) how to do tasks, (Q3) the speed to do tasks, and (Q4) hours worked. Each question had the following response options: "*not at all*" (= 1), "*very little*" (= 2), "*to some extent*" (= 3), "*to a high extent*" (= 4), and "*to a very high extent*" (= 5). The flexibility measure has almost the same coverage as that reported in the EWCS.

Table 1 shows the median for variables by country. I used the median simply because the variables are ordinal.

To scale the variables, I estimated a Bayesian item response theory (IRT) model (or latent trait) based on the code in Congdon (2019). IRT might be a more appropriate alternative to principal component or factor analysis with ordinal variables (see Table 2).

TABLE 1 Median values for ordinal variables used for Graded Response Model

	Bel	Dnk	Ita	UK
hours	3.00	3.00	2.00	3.00
how to do tasks	4.00	4.00	3.00	3.00
speed	4.00	4.00	3.00	3.00
sequence	4.00	4.00	3.00	3.00
spreadsheets	4.00	2.00	4.00	4.00
Word	4.00	4.00	5.00	5.00
discussion	1.00	1.00	1.00	1.00
info	4.00	4.00	5.00	4.00
influence	3.00	4.00	2.00	4.00
negotiate	3.00	2.00	1.00	4.00
advice	4.00	4.00	4.00	5.00
plan others	1.00	2.00	1.00	3.00

SOURCE: PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. COUNTRIES: DENMARK, BELGIUM, ITALY, AND UNITED KINGDOM

Prior to fitting the Bayesian model, I conducted a classical analysis of the graded response model (GRM) and the generalized partial credit model (GPCM). Although not directly comparable, the GRM seemed to contain more information relative to the GPCM. I also found that the unrestricted GRM had the best fit. For a single dimension, the GRM matches the results of categorical confirmatory factor analysis. Nevertheless, the interpretation differs.

In essence, one estimates a capacity parameter for each worker (analogous to a factor score). Next one estimates k–1 cut-points/thresholds for each survey question with k responses (i.e., k = 5). Finally one estimates discrimination parameters for j questions (i.e., j = 4). The discrimination parameter has a similar interpretation to factor loading coefficients; higher values indicate a sharper distinction between high and low capacities for job control. Thus, higher discrimination indicates something analogous to higher reliability. One discrimination parameter was fixed to 1 for model identification (instead of e.g., a lognormal prior) (Congdon, 2019).

To ensure comparability, I tested whether the measurement had the same meaning across countries, i.e., "differential item testing" (Davidov et al., 2018). Researchers want to ensure the same meaning of measurement among countries to avoid bias. According to an ordinal test, the countries differed significantly. However, the magnitude of the difference seemed negligible as indicated by the change in pseudo r-square (≤ 0.02). Therefore suspect I that sample size might bias the test.

After fitting the model I checked several diagnostics such as: Rhat below 1.1, negligible autocorrelation, density plots (no multimodality), and mixing of chains. To reduce autocorrelation I used a lengthy burn-in period and multivariate priors. To save computer memory I had to used a slight thinning of 10. Thereafter, I use the median of the estimated posterior distribution.

4.2.2 Focal Predictors (Level 1)

I measured *computer use* with four variables. Use of computers for: (a) work related information, (b) spreadsheets, (c) Microsoft Word (or equivalent text

TABLE 2 Grade response model for job control by country

Estimated parameter	Bel	Ita	Dnk	UK
Discrimination Q1	1.00	1.00	1.00	1.00
Discrimination Q2	3.53	3.59	2.31	3.91
Discrimination Q3	2.22	2.53	2.19	1.93
Discrimination Q4	1.17	1.49	1.29	1.03
Cutpoint Q1	−2.55	−1.32	−3.62	−2.34
Cutpoint Q1	−1.74	−0.54	−2.50	−1.32
Cutpoint Q1	−0.54	0.54	−0.78	0.33
Cutpoint Q1	1.23	2.25	0.74	1.59
Cutpoint Q2	−6.28	−3.68	−5.28	−5.38
Cutpoint Q2	−4.58	−2.01	−3.53	−2.85
Cutpoint Q2	−1.84	0.23	−1.15	0.93
Cutpoint Q2	2.43	4.31	1.22	3.90
Cutpoint Q3	−4.64	−3.35	−5.20	−3.47
Cutpoint Q3	−2.91	−1.82	−3.02	−1.64
Cutpoint Q3	−0.56	0.12	−0.43	0.71
Cutpoint Q3	2.13	3.27	1.55	2.47
Cutpoint Q4	−1.06	−0.54	−2.02	−1.13
Cutpoint Q4	−0.30	0.20	−0.97	−0.22
Cutpoint Q4	0.89	1.45	0.53	1.34
Cutpoint Q4	2.26	3.06	1.75	2.36

SOURCE: PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. COUNTRIES: DENMARK, BELGIUM, ITALY, AND UNITED KINGDOM. SOFTWARE: ESTIMATED WITH JAGS editor), and (d) real-time discussions. The response options were: “Never” = 1, “Less than once a month” = 2, “Less than once a week but at least once a month” = 3, “At least once a week but not every day” = 4, and “Every day” = 5.

The other variables measured rather typical work activities that any worker could engage in for any task. Unsurprisingly, programming requires a different form of computer skill that few possess. Similar to job control, I estimated a GRM model for computer use. I followed the same procedure as described above, which yielded the same result.

In addition I included *social skills* inspired by Tomaskovic-Devey and Avent-Holt (2019); Fligstein and McAdam (2012); Hallett and Hawbaker (2021); Bandelj (2012). I measured skills by how often workers: (a) negotiated with people, (b) advised people, (c) planned others’ activities, and (d) influenced people. Once again, responses were on (“never” = 1) to (“every day” = 5) scale. See Table 1.

Theoretically, computer use indicates the technical dimension of job requirements in the division of labor (Liu and Grusky, 2013). Some jobs requires greater technical skills, stressing a worker’s technical expertise. By contrast, other jobs stress social skills that involve working with people (e.g., coworkers, customers, and patients). Combined technical and social skills comprise a worker’s bargaining power.

I used the European socioeconomic classification (*ESeC*) to measure social class. ESeC expands on the Goldthorpe class schema a (Rose and Harrison, 2007). The schema differentiates classifiction based on one’s labor contract, skill requirements, career prospects, and difficulty of monitoring/autonomy (Breen, 2005). I used a scale of four social classes excluding unemployment: working class, intermediate class, petite bourgeoisie, and upper class (the salariat e.g., professionals, mangers, etc.). I used the highest position, professionals (i.e., the salariat), as a reference. The measurement and concept of ESeC is qualitatively distinct from the alternatives, such as the International Socioeconomic Index (ISEI). ISEI captures occupational status by adjusted income and education rather than the shared employment market situations of workers (Christoph et al., 2020). As a quantitative measure, ISEI offers statistical advantages (Christoph et al., 2020), whereas ESeC offers conceptual advantages (Rose and Harrison, 2007).

4.2.3 Focal Occupational Predictors (Level 2)

To capture the importance of occupational level predictors, I used the International Standard Classification of Occupations (ISCO) as a clustering variable. Specifically, I used a two-digit level of detail. Two digit granularity offers greater detail than one digit. However, three digits would make the occupational cells rather sparse, which could compromise the computational stability.

For computer use I computed the occupational averages for mean estimates. Computer use measures occupations' technical skills and thus bargaining power (Kristal, 2020; Grusky and Galescu, 2005).

4.2.4 Adjusting Predictors (Level 1)

I included variables to adjust for spurious associations and to improve prediction.

I measured the level of *education*. PIAAC includes measures of the International Standard Classification of Education (ISCED). Here, I included binary dummy variables (1 = yes) for education levels: low education (lower secondary or less), intermediate education (upper secondary or post-secondary), and higher education (tertiary education or above). I also experimented with including years of education, as some authors suggest this captures different sources of variation. However, as one might expect, including the years of education contributed to correlated predictors, which made some standard errors unreasonable.

Three additional binary variables adjust for worker attributes. First, part-time work may be central to predicting job control. *Part-time* work reflects the labor contract and hence the institutional norms of work. To measure part-time work, I used the official International Labor Organization definition of fewer than 35 hours a week (reference: full-time). I also tried using fewer than 30 hours, which did not make much of a difference. Second, *job training* as self-reported job training. Workers may simply have greater control because of so called "job ladders." Third, *need training* was the self-reported need for training to do one's job (yes = 1; no = 0).

Two variables account for workplace characteristics – *size of workplace* and *workplace employment changes*. A greater share of jobs increases the chance of matching workers with good jobs instead of bad jobs. Next, increasing the share of workers or simply keeping a large workforce suggests that a firm negates threats of offshoring services and production to low-wage countries. Consequently, I dummy-coded (1 = yes; 0 = no) workplace employment using increase (reference), about the same, or decrease. Size was coded using binary categories of 1 to 10 people (reference), 11 to 50 people, 51 to 250 people, 251 to 1000 people, or more than 1000 people.

Dummies for *first-* or *second-generation immigrant status* were used, with native status as reference. First-generation immigrants tend to work in bad jobs (i.e., low control), for at least their first jobs. However, a disagreement exists if second-generation immigrants suffer the same disadvantage.

Age adjusts for differences across life phases. *Females* gender (= 1; males = 0) adjusts for a gendered division of labor. Initially, I also included a binary dummy variable for the presence of children to adjust for family responsibilities that may collide with work responsibilities and careers. However, this predictor only deteriorated the fit, so I removed it.

I standardized years of age by subtracting the mean and dividing by the standard deviation. However, for age, I first computed the log to increase the weight of small increments and to account for nonlinearity. A squared term seemed theoretically implausible.

Figure 1 reports descriptive statistics by country with bar charts for pooled proportions.

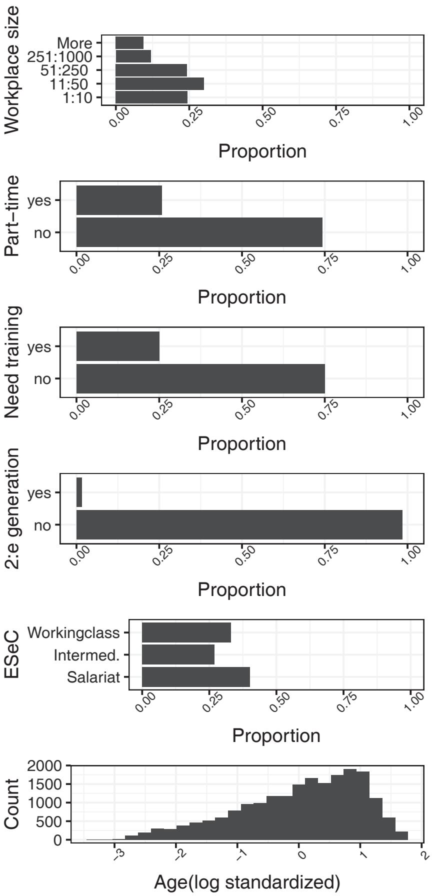

FIGURE 1 Plots of descriptive statistics for all four countries (pooled)
PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. POOLED COUNTRIES: DENMARK, BELGIUM, ITALY, UNITED KINGDOM

4.2.5 Adjusting Occupational Predictors (Level 2)

For adjusting variables, I employed a slightly different approach. First, I computed proportions of *females* and *first-generation immigrants* in each occupation. Next, I multiplied these proportions by 100.

Finally, I standardized the variables by subtracting the means and dividing by the standard deviations. Standardizing simplifies the interpretations and improves the computation (Gelman and Hill, 2006). One interprets standardized variables as standard deviations from the means.

4.3 *Strategies of Data Analysis*

I used a Bayesian approach for data analysis. Essentially, a Bayesian approach permits treating of data as fixed and of parameters as random variables (Gelman and Hill, 2006). One adds additional information to the estimated model parameters in terms of a prior probability density distribution. By combining the prior distribution with a likelihood function (the model), one estimates a posterior distribution (Congdon, 2019).

With large samples, the importance of prior data diminishes and the model approximates the maximum-likelihood counterpart. However, Bayesian models can be used to fit models that would not be possible in the classical sense. Interpretation also becomes simpler. Thus, the main advantages come down to interpretation and computation (Congdon, 2019).

I conducted Bayesian multilevel analysis (i.e., hierarchical model or mixed models). The analysis captures H2 and H3. Multilevel analysis allows one to model the worker (*L*1) and occupational level (*L*2), whereas occupational dummy variables in a regression would simply not model the occupational variation (Gelman and Hill, 2006).

I used priors with weak information. For coefficients, I used normal priors with a mean of zero and substantive standard deviation. A large standard deviation reflects greater uncertainty, which is common in social sciences.

I used R (Team, 2013) together with JAGS for measurement models (Plummer, 2003). Here I used R2Jags. For the multilevel models, I used the brms-package which supports Stan as a "wrapper" (Bürkner, 2017; Carpenter et al., 2017). For plots I used ggplot2 (Wickham, 2016).

To assess the relative importance, I standardized the two skills variables from a logit into z-scores (subtracted the mean and divided by the standard deviation). In the result section, I used "SD" for standard deviations.

4.3.1 Missing Data

I used Bayesian imputation for missing data for the scores in the GRM models (Congdon, 2019). In other cases, I merely deleted the rows for the missing data.

5 Results

First, I begin with a descriptive analysis based on means comparisons. Second, I report the predictive analysis with a multilevel model without interactions. Third, I continue with the predictive analysis with a multilevel model with interactions.

5.1 *Descriptive Analysis of Job Control by Country*

I begin by graphing the scores predicted by the measurement models. Note that the outcome variable have been re-scaled into standard deviations. Figure 2 shows occupational average job control (y axis). The x axis includes the occupations. Each country has its own panel. A reference line has been placed at the mean (i.e., zero).

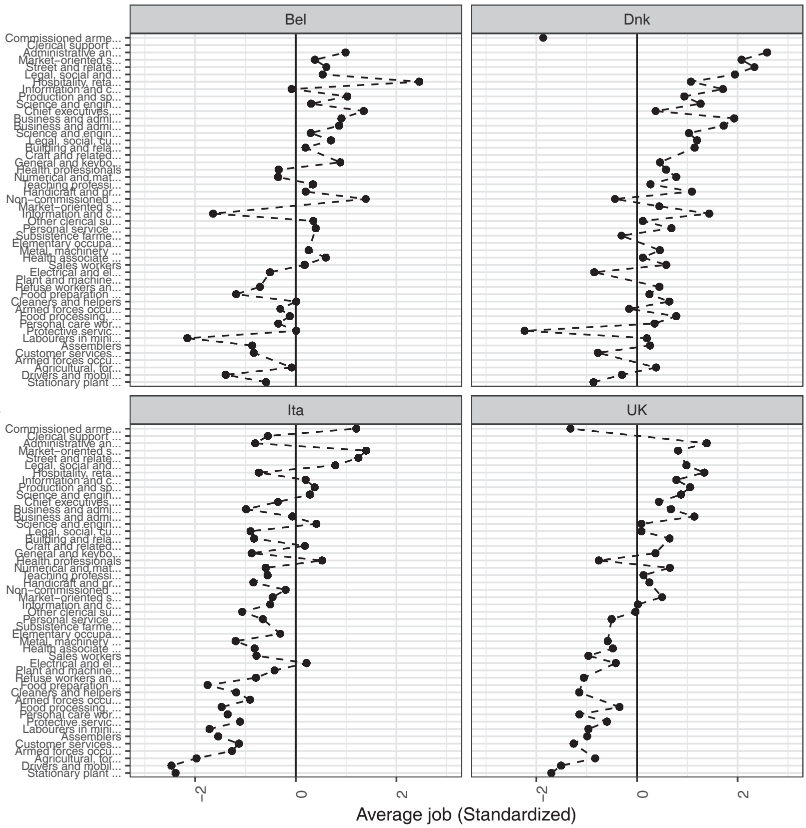

FIGURE 2 Plots of estimated job control (y-axis) by occupation (x-axis)
PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. COUNTRIES: DENMARK, BELGIUM, ITALY, UNITED KINGDOM. SOFTWARE: ESTIMATED WITH JAGS

All countries share a divide between occupations with low to high levels of job control. The score for job control ranges between −3 and 3 on a standardized scale. Looking closer, one finds nuances in the differences. Denmark displays the highest and the lowest scores. Overall, The UK has the lowest spread in the job control score. Italy has rather low scores. Nevertheless, the patterns seem rather rough and one should be careful not to over-interpret the data (e.g., due to data sparseness).

Stationary plant and machine operators score lowest in the UK (second lowest in Italy). Drivers and mobile plant operators have the lowest score in Italy. Laborers in mining, construction, manufacturing, and transport score lowest in Belgium.

At the top we find managerial and professional occupations with a few exceptions. Administrative and commercial managers score highest in the UK and Denmark. Hospitality, retail and other service managers score highest in Belgium.[2]

TABLE 3 Averaged job control (standardized) by country and ESeC

Country	ESeC	Score
Bel	Salariat	0.28
Bel	Intermediate employee/small employers	0.18
Bel	Working class	−0.49
Dnk	Salariat	0.19
Dnk	Intermediate employee/small employers	0.27
Dnk	Working class	−0.38
Ita	Salariat	0.35
Ita	Intermediate employee/small employers	0.22
Ita	Working class	−0.51
UK	Salariat	0.38
UK	Intermediate employee/small employers	0.25
UK	Working class	−0.55

SOURCE: PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. COUNTRIES: DENMARK, BELGIUM, ITALY, AND UNITED KINGDOM. SOFTWARE: ESTIMATED WITH JAGS

2 Surprisingly, market-oriented skilled agricultural and fishery workers score highest in Italy. Although, the occupation can entail managerial duties, I suspect that the Italian results indicate sparseness of the data. Supposedly, sparseness may contribute to that protective services workers score the lowest in Denmark.

Turning to Table 3, we see the differences between social classes (ESeC). The overall pattern indicates that the salariat has the highest job control score (roughly 0.19 to 0.35 SD above the mean), whereas the working class has the lowest score (roughly 0.38 to 0.55 SD below the mean). However, Denmark diverges from the pattern. In Denmark, the intermediate class has slightly higher average job control scores than the salariat has. Accordingly, the institutional differences seem rather obvious if we look at social class rather than occupation.

5.2 *Predictive Analysis of Social Class, Occupation, and Skill Mechanism of Job Control by Country*

We begin with the baseline model that included no interaction and continue with a model with interactions between class, computer skill and social skill use. Table 4 shows the (averaged) coefficients of the multilevel model with credibility intervals (CI). The credibility intervals captures 95% of the estimated (posterior) distribution. Coefficients have been rounded to two digits.

5.2.1 Social Class (ESeC) (**H1**)

The model suggests that the main difference in job control lies between the salariat and the lower working class (skilled vs. semi-and non-skilled workers). Unsurprisingly, the salariat has higher predicted levels of job control compared to the working class, on average, after adjustments. However, the social class differences seem to be greater in the UK. The working class has a lower job control score compared to the salariat (≈ −0.42, *CI*[−0.55 : −0.30]), on average, after adjustments. In Belgium the expected difference seem to be the lowest between the saliarate and the working class (≈ −0.23, *CI*[−0.39 : −0.08]).

Consequently, class differences exist in all four countries favoring **H1**. The first prediction favors the neo-Weberian argument, New Structuralist and the relational approach to inequality. However, the difference between the salariat and intermediate class tends to be unreliable. In most countries, no reliable difference exists.

5.2.2 Use of Computer and Social Skill (**H2**, **H3**)

Computer use is positively associated with job control. In the UK, workers with one SD greater computer use score 0.14 (*CI*[0.10 : 0.17]) SD higher on job control, on average, after adjustments. Other countries have slightly lower magnitudes. However, the association remains small, as one-for-one SD association mimics a correlation (on a ± 1 scale). A two-for-one SD association approximates a binary predictor (0.14 * 2 = 0.28) (Gelman and Hill, 2006). Recall that computer use does not refer to high-level skills such as programming. Rather, the measure captures proficiency at everyday computer tasks. Thus, the association may be interpreted as the bargaining power of computer skills, resulting in greater capacity for job control (**H2**).

Social skills vary positively with job control, suggesting that workers with greater management skills have greater job control. The association extends to all countries. In Italy, we observe the strongest association (≈ 0.21, *CI*[0.18 : 0.24]). The other countries score slightly lower at roughly similar magnitudes. Thus, we should interpret the differences as differences in labor markets. Surprisingly, social skills seem to have greater importance than computer skills.

Workers' skills predict their job control, and social class predicts skills. However, the differences tend to be more reliable regarding the difference between the salariat and the lower class. The strongest difference in skills seems to be related to social skills, as expected (**H3**). Social skills reflect leadership; thus, authority at work explains such differences because ESeC based social class measures depend on authority.

5.2.3 Occupational Skill Use (**H4**)

The positive difference in occupational averages due to occupational computer use holds in all four countries except Denmark (**H4**), suggesting that technical skills vary with occupation. Consequently, the neo-Durkheimian argument holds, meaning that occupations relate to job control via the technical division of labor.

Although the association does hold after conditioning on class, it seems rather meager. In the UK, occupations with one SD greater use of computer has 0.08*CI*[0.01 : 0.15] SD higher predicted job control, on average, after adjustments for other predictors in the model. Italian occupations score roughly the same. We can compare the magnitude of occupational skill use to class and thus, the former has lower predicted importance in the UK. However, the predictive importance seems similar in Belgium (≈ 0.13, *CI*[0.04 : 0.21]). If we multiply by 2 (Gelman et al., 2020) to get something like a dummy variable (0.13 * 2 = 0.26) the magnitude seems comparable to that of class for computer skills.

Workers with job training have greater job control compared to workers without job training. People in part-time work have a slight disadvantage in job control compared to those in full-time work on average. Larger workplaces offer greater job control to workers compared to small ones. On average, females have lower job control compared to men after adjustments. First-generation immigrants suffer a disadvantage in job control compared to natives.

TABLE 4 All predictors for Italy and UK (rounded); outcome: job control

	BEL		
	Estimate	l–95% CI	u-95% CI
Intercept	0.07	−0.11	0.25
first generation (ref: native)	−0.21	−0.34	−0.07
second generation (ref: native)	0.13	−0.12	0.39
z.age	0.07	0.04	0.11
female (ref: male)	−0.04	−0.12	0.04
workp.size 11 to 50 people (ref: 10 or lower)	−0.17	−0.27	−0.07
workp.size 51 to 250 people (ref: 10 or lower)	−0.17	−0.26	−0.07
workp.size 251 to 1000 people (ref: 10 or lower)	−0.28	−0.40	−0.16
workp.size More than 1000 people (ref: 10 or lower)	−0.16	−0.30	−0.02
emp.increased Decreased (ref: increased)	−0.12	−0.23	−0.02
emp.increased Stayed more or less the same (ref: increased)	−0.08	−0.16	−0.00
parttime (ref: fulltime)	−0.03	−0.11	0.06
need training (ref: no)	0.04	−0.04	0.12
job training (ref: no)	−0.03	−0.10	0.04
intermediate education (ref: loweducation)	0.19	0.07	0.31
high education (ref: low education)	0.25	0.11	0.38
z.computer skill use	0.11	0.07	0.15
social skill use	0.19	0.15	0.23
ESeC Intermediate employee small employers	−0.04	−0.16	0.09
ESeC Working class	−0.23	−0.39	−0.08
z.m.occupational computer skill use	0.13	0.04	0.21
z.m.occupational immigrant origin	0.00	−0.06	0.07
z.m.occupational females	−0.01	−0.08	0.07
sd (Intercept)	0.17	0.11	0.24
sd (Residual)	0.84	0.82	0.86
R2	0.23	0.21	0.26

Note: ref = reference category; “z” = z-score (standardized); “m” = occupational mean
SOURCE: PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS.

DNK			ITA			UK		
Estimate	l–95% CI	u-95% CI	Estimate	l–95% CI	u-95% CI	Estimate	l–95% CI	u-95% CI
0.35	0.20	0.50	0.17	0.03	0.30	0.29	0.13	0.44
−0.16	−0.23	−0.09	0.04	−0.06	0.14	−0.07	−0.17	0.03
0.15	−0.19	0.48	−0.17	−0.67	0.35	−0.07	−0.22	0.08
0.13	0.10	0.16	0.06	0.03	0.09	0.05	0.02	0.09
−0.07	−0.14	−0.01	0.02	−0.04	0.08	−0.12	−0.19	−0.05
−0.19	−0.27	−0.11	−0.16	−0.22	−0.09	−0.12	−0.20	−0.04
−0.20	−0.29	−0.12	−0.17	−0.25	−0.10	−0.16	−0.25	−0.07
−0.16	−0.27	−0.06	−0.17	−0.28	−0.08	−0.21	−0.31	−0.12
−0.17	−0.29	−0.06	−0.15	−0.26	−0.05	−0.10	−0.20	0.01
−0.08	−0.16	−0.01	−0.22	−0.31	−0.13	−0.12	−0.20	−0.05
−0.01	−0.08	0.07	−0.18	−0.27	−0.10	−0.07	−0.14	0.01
−0.06	−0.14	0.01	0.05	−0.02	0.11	−0.02	−0.10	0.05
−0.10	−0.16	−0.03	0.03	−0.03	0.09	−0.05	−0.12	0.02
−0.09	−0.15	−0.03	−0.09	−0.15	−0.03	−0.07	−0.13	−0.01
0.08	−0.00	0.17	0.13	0.06	0.20	0.16	0.08	0.25
0.01	−0.09	0.11	0.19	0.09	0.29	0.19	0.10	0.29
0.10	0.07	0.13	0.06	0.04	0.09	0.14	0.10	0.17
0.17	0.14	0.21	0.21	0.18	0.24	0.16	0.13	0.20
−0.03	−0.14	0.08	−0.09	−0.18	−0.00	−0.12	−0.22	−0.02
−0.31	−0.45	−0.18	−0.32	−0.44	−0.21	−0.42	−0.55	−0.30
0.07	−0.02	0.16	0.09	0.03	0.14	0.08	0.01	0.15
0.04	−0.04	0.12	0.04	−0.02	0.10	−0.02	−0.07	0.02
−0.05	−0.12	0.03	−0.03	−0.09	0.02	−0.02	−0.08	0.04
0.19	0.14	0.26	0.11	0.07	0.17	0.13	0.08	0.19
0.88	0.86	0.90	0.82	0.80	0.84	0.84	0.82	0.86
0.19	0.17	0.21	0.20	0.18	0.22	0.25	0.23	0.27

5.2.4 Interactions: Skill and Class

In Table 5, I report the statistical interactions that predict job control. For Belgium and Italy, the model estimates how (1) class interacts with social skills; (2) class interacts with computer skills; (3) computer skills interact with social skills; and (4) the interaction between class, social skills, and computer skills. For UK and Denmark the model estimates how: (1) class interacts with social skills, (2) class interact with computer skills. Thus, I omit the dependency between skills in UK and Denmark.[3]

Interpreting statistical interactions requires care because the coefficients depend upon one another. Because the skill predictors have been centered at their means (zero) simplifies the interpretation somewhat. As statistical interactions can be interpreted hierarchically, I focus on the higher order term as discussed by Fox and Weisberg (2018).

When fitting the statistical interaction model a reliable relation between occupational computer skills and job control remain only in Belgium and Italy (**H4**) in Table 5. Overall, the Bayesian $R2$ indicates that the proportion of variance explained appears greater in Belgium and the UK than it does in Denmark and Italy.[4]

In Denmark and the UK, interactions exists between social class and social skill respectively social class and computer skills, supporting **H2** and **H3**. Unlike in Belgium and Italy, no interaction exists between social skills and computer skills. Based on Table 5, I interpret the statistical interactions taking the partial derivative (a.k.a. "marginals"). In the UK, one additional SD in computer skill use corresponds to, on average, a predicted difference in job control of −0.03 SD for the working class adjusting for other predictors. The partial derivative for the salariat is considerable higher at 0.20. In Denmark, one additional SD in the use of computer skill corresponds to a predicted difference of −0.034 SD, on average, after adjustment. Quite low compared to the salariat (0.20). In the UK and Denmark, the working class suffers a disadvantage due to the lower use of computer skills.

Considering social skill use in Denmark. One additional SD in the use of social skills corresponds to a difference of 0.012 SD in job control for the working class, on average, after adjustments, meanwhile, the working class uses

3 To establish interactions I first fitted a maximum likelihood model (with lme4-package) and compared the Akaike Information Criterion (AIC) (Fox, 2015). The AIC indicated complex pattern had the highest predictive power. Thereafter, I fitted the models using Bayesian estimation.

4 However, unlike the classical $R2$ the the Bayesian $R2$ cannot be used to compare the fit of different models for the same data.

social skills less at work compared to the salariat (0.13), social skills seem (hypothetically) to help the working class more compared to computer skills (depending on the level of computer skills). In the UK, one SD additional in use of social skills corresponds to 0.011 SD job control for the working class respectively 0.10 SD for the salariate.

In Belgium and Italy, an interaction on job control exists between social skill use, computer skill use and social class. Thus, how job control varies with skills depends on social class. In addition, computer skills and social skills depend upon one another (i.e., a three-way interaction). Three-way interaction can easily be misinterpreted (Fox and Weisberg, 2018). Consequently, I plotted the statistical interactions in Figure 3 and 4.

In Figure 3 and 4 I fitted the models statistical interactions between computer skill use, social skill use and social class.[5] In Italy and Belgium, the salariat can benefit greatly from social skills even at low levels computer skills. But the working class faces a disadvantage due to computer skills.

In summary, a modified version of **H2** and **H3** holds in Denmark, Italy, and the UK for the working class, but not clearly for the in Belgium (C.I. almost at zero for the working class). Whereas, **H4** holds in Belgium and Italy.

6 Discussion

Job control indicates the quality of a job (Kalleberg, 2011). Workers with higher job control have lower stress, greater satisfaction, and self-rated health.

In the study, I predicted job control (i.e., task discretion) based on class and occupation with skill use as a (hypothesized) mechanism in four Western European countries using the OECD adult skill survey (PIAAC). The study applied a Bayesian measurement and multilevel framework to the OECD adult survey. Therefore, I made the following conclusions.

C1 Descriptively, all countries show a roughly similar pattern to occupational variation in job control. However, a sharp difference in job control exists between the salariat and the working class (with exceptions in Denmark).

C2 Predictive differences in job control by social class exist, supporting the neo-Weberian class model (Breen, 2005). The result also holds for

5 However, I urge caution as the result might be a statistical artifact.

TABLE 5 Predictors for multilevel model (rounded); outcome: job control (standardized)

	BEL		
	Estimate	l–95% CI	u-95% CI
Intercept	0.13	−0.06	0.31
first generation (ref: native)	−0.19	−0.32	−0.06
second generation (ref: native)	0.12	−0.13	0.38
z.age	0.08	0.04	0.11
female (ref: male)	−0.03	−0.12	0.05
workp.size 11 to 50 people (ref: 10 or lower)	−0.17	−0.27	−0.07
workp.size 51 to 250 people (ref: 10 or lower)	−0.16	−0.26	−0.06
workp.size 251 to 1000 people (ref: 10 or lower)	−0.28	−0.39	−0.16
workp.size More than 1000 people (ref: 10 or lower)	−0.15	−0.29	−0.02
emp. increased Decreased (ref: increased)	−0.12	−0.23	−0.02
emp. increased Stayed more or less the same (ref: increased)	−0.08	−0.16	−0.00
parttime (ref: fulltime)	−0.03	−0.11	0.05
need training (ref: no)	0.03	−0.04	0.11
job training (ref: no)	−0.04	−0.11	0.04
intermediate education (ref: low education)	0.18	0.06	0.29
high education (ref: low education)	0.21	0.08	0.35
z.computer skill use	0.12	0.06	0.18
social skill use	0.14	0.08	0.20
ESeC Intermediate employee small employers	−0.07	−0.19	0.06
ESeC Working class	−0.29	−0.44	−0.13
z.m.occupational computer skill use	0.11	0.02	0.20
z.m.occupational immigrant origin	0.02	−0.05	0.08
z.m.occupational females	−0.01	−0.09	0.07
z.social skills use: ESeC Intermediate employee small employers	0.05	−0.06	0.15
z.social skills use: ESeC Working class	0.13	0.04	0.23
z.computer skill use: ESeC Intermediate employee small employers	0.01	−0.05	0.07
z.computer skill use: ESeC Working class	0.09	−0.00	0.19
z.computer skill use: z.social skills use	−0.03	−0.12	0.06
z.computer skill use: z.social skills use: ESeC Intermediate employee small employers	−0.12	−0.22	−0.02
z.computer skill use: z.social skills use: ESeC Working class	0.08	−0.00	0.17
sd (Intercept)	0.18	0.12	0.26
sd (Residual)	0.84	0.81	0.86
R2	0.24	0.22	0.27

Note: ref = reference category; “z” = z-score (standardized); “m” = occupational mean

SOURCE: PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS.

DNK			ITA			UK		
Estimate	**l–95% CI**	**u-95% CI**	**Estimate**	**l–95% CI**	**u-95% CI**	**Estimate**	**l–95% CI**	**u-95% CI**
0.32	0.17	0.47	0.22	0.08	0.36	0.32	0.17	0.47
−0.16	−0.23	−0.09	0.05	−0.05	0.15	−0.07	−0.16	0.03
0.15	−0.17	0.49	−0.15	−0.65	0.35	−0.09	−0.23	0.07
0.13	0.10	0.16	0.06	0.03	0.08	0.06	0.02	0.09
−0.06	−0.13	−0.00	0.02	−0.04	0.08	−0.11	−0.18	−0.05
−0.19	−0.27	−0.12	−0.16	−0.23	−0.09	−0.13	−0.21	−0.05
−0.21	−0.30	−0.13	−0.18	−0.26	−0.10	−0.16	−0.25	−0.07
−0.18	−0.29	−0.08	−0.19	−0.29	−0.09	−0.23	−0.32	−0.13
−0.19	−0.31	−0.08	−0.16	−0.26	−0.05	−0.11	−0.22	−0.01
−0.07	−0.15	0.00	−0.22	−0.31	−0.13	−0.12	−0.20	−0.04
0.00	−0.07	0.07	−0.18	−0.27	−0.10	−0.06	−0.14	0.01
−0.06	−0.13	0.01	0.05	−0.02	0.11	−0.03	−0.10	0.04
−0.09	−0.16	−0.03	0.03	−0.03	0.08	−0.05	−0.12	0.02
−0.09	−0.15	−0.03	−0.09	−0.16	−0.03	−0.07	−0.13	−0.01
0.08	−0.01	0.16	0.12	0.05	0.19	0.15	0.07	0.24
−0.00	−0.10	0.09	0.17	0.08	0.27	0.18	0.08	0.27
0.20	0.15	0.25	0.09	0.04	0.13	0.20	0.14	0.26
0.13	0.08	0.18	0.20	0.15	0.26	0.10	0.04	0.17
0.03	−0.08	0.14	−0.12	−0.22	−0.03	−0.13	−0.24	−0.02
−0.27	−0.41	−0.13	−0.36	−0.48	−0.25	−0.47	−0.61	−0.34
0.07	−0.01	0.16	0.08	0.03	0.14	0.06	−0.01	0.12
0.04	−0.03	0.12	0.05	−0.01	0.11	−0.02	−0.07	0.03
−0.04	−0.11	0.03	−0.04	−0.09	0.02	−0.02	−0.08	0.03
−0.00	−0.09	0.08	−0.01	−0.09	0.07	0.04	−0.05	0.13
0.09	0.02	0.16	0.04	−0.03	0.11	0.11	0.03	0.19
−0.15	−0.23	−0.07	0.02	−0.05	0.09	−0.03	−0.10	0.05
−0.17	−0.24	−0.10	−0.04	−0.11	0.03	−0.15	−0.22	−0.07
			−0.06	−0.10	−0.01			
			0.04	−0.03	0.11			
			0.11	0.05	0.18			
0.18	0.13	0.25	0.12	0.07	0.17	0.13	0.07	0.19
0.88	0.86	0.90	0.82	0.80	0.83	0.84	0.82	0.86
0.19	0.17	0.21	0.21	0.19	0.23	0.25	0.23	0.28

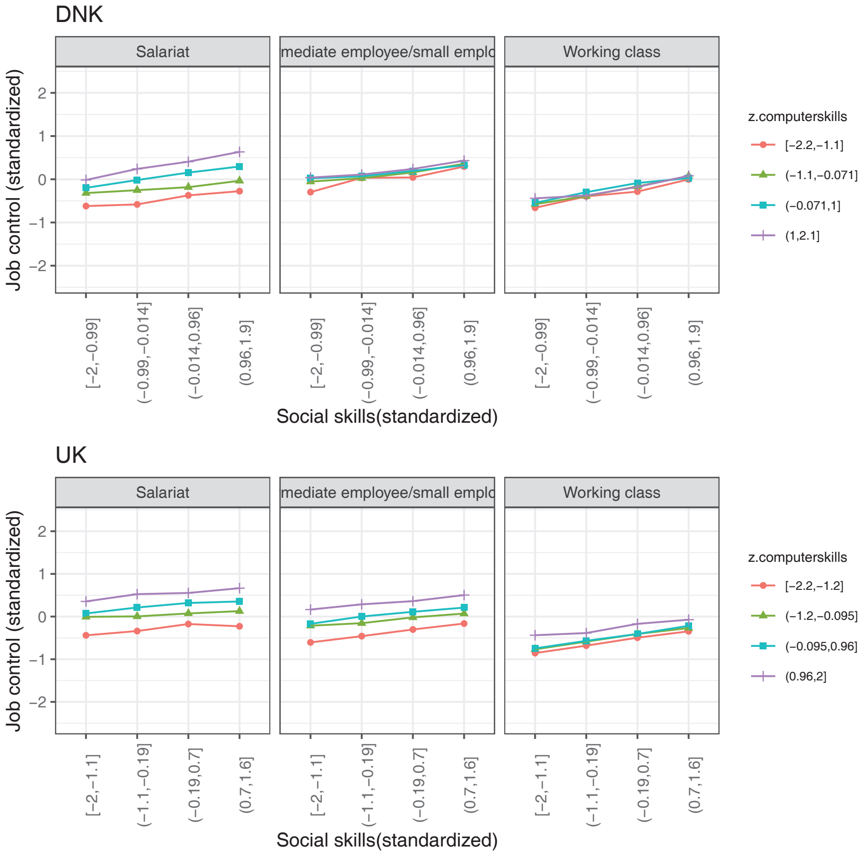

FIGURE 3 Plots of interactions with job control score as outcome with 95% CI of focal predictors
PIAAC OECD DATA. SEE TEXT AND TABLE 5 FOR MODEL SPECIFICATION. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. COUNTRIES: DENMARK, UNITED KINGDOM. SOFTWARE: ESTIMATED WITH BRMS USING STAN

occupational computer use in Italy and Belgium, a result that partly favors the predictions made by neo-Durkheimians (Grusky and Galescu, 2005) and New structuralists (Kristal, 2020). My result favors the idea that occupational and social class (ESeC) dependens on labor market institutions (Kalleberg, 1988; Tomaskovic-Devey and Avent-Holt, 2019).

C3 Computer and social skills interact with social class in predicting job control. The result strongly favors neo-Weberian class theory (Breen, 2005), but not full in Belgium. The results suggest that occupation and social class matter. Here, the results agree with New Structuralists (Kalleberg, 1988), and are due to relational mechanisms at the workplace (Tomaskovic-Devey and Avent-Holt, 2019).

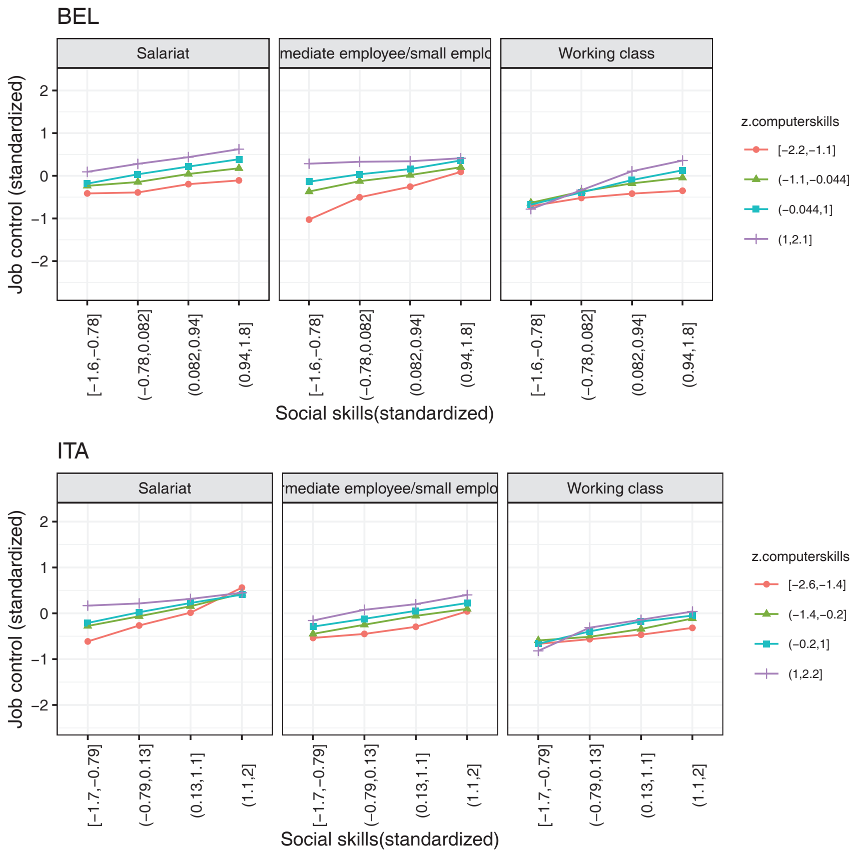

FIGURE 4 Plots of interactions with job control score as outcome with 95% CI of focal predictors
PIAAC OECD DATA. AUTHOR RESPONSIBLE FOR COMPUTATION AND ERRORS. SEE TEXT AND TABLE 5 FOR MODEL SPECIFICATION. COUNTRIES: BELGIUM, ITALY. SOFTWARE: ESTIMATED WITH BRMS USING STAN

Social class and occupation seem important (Kalleberg, 1988; Tomaskovic-Devey and Avent-Holt, 2019; Weeden et al., 2007). Thus, the result favors neo-Weberian class theory (Breen, 2005; Williams, 2017; McGovern et al., 2007) and neo-Durkheimian class theory. In agreement with New Structuralist (Kalleberg, 2011) and relational approaches to inequality (Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019), I suggest that occupation and social class should be considered as complementary determinants representing different mechanisms. Social classes (i.e., professionals and, managers) control for social and technical skills, whereas occupations center on technical skills.

The present study contributes to the debate on the hypothetical mechanisms of class and occupation on the labor market regarding several theories.

The novelty of the study concerns the distinct contributions of occupations and class as suggested by Kalleberg (1988) and hinted at by neo-Durkheimians (Weeden et al., 2007). Several studies analyze class and occupations separately, but few consider joint contribution as in the present study (Kalleberg and Berg, 1988). Therefore, I suggest that we should consider them in the context of the outcome (Kalleberg, 1988). By including both class and occupation, analysts improve their understanding of the mechanisms at work. Mechanisms operate within a context. Thus, one should expect occupation and class to vary in importance in producing the outcomes given of a context (Kalleberg, 1988). The novelty of emphasized skill use turns the emphasis toward relational processes at the workplace between management and workers. Workers' skill use allow them to bargain for greater job control depending on occupation and class (Tilly, 1998; Tomaskovic-Devey and Avent-Holt, 2019).

Specifically, the association between occupational computer use and job control indicates how technical skills matter to the division of labor (Grusky and Galescu, 2005; Kristal, 2020). Thus, computer skills contribute to workers collectives as bargain power (Kristal, 2020). The results partly favor the neo-Durkheimian argument (Grusky and Galescu, 2005) of the New Structuralists (Kristal, 2020). However, in the context of job control, social class seems to trump occupation in relative importance in the UK and Denmark – thus highlighting the importance of authority and difficulty of monitoring in workplace behaviors to gain control over one's work, a result that places professionals and managers at an advantage over the working class. The everyday use at work of computers as opposed to, for example, programming skills has favored the salariat in terms of job control.

The first theoretical implications center on how class and occupation generate workers' behaviors beyond economic rewards. The study suggests a substantive relationship between social skills and social class at work. Thus, the study extends recent theorizing that places social skills (e.g., negotiations and influence) as a mechanisms of inequality at work (Tomaskovic-Devey and Avent-Holt, 2019; Tilly, 1998). Primarily, I may suspect that the rise of professionals has contributed to differences in job control and hypothetically other dimensions of job quality. Thus, professionals and managers use social skills and computer skills to bargain for an advantage relative to other workers. Thus, my argument and results relate to worker-management relations and interactions as a basis for inequality in the workplace (Tomaskovic-Devey and Avent-Holt, 2019; Tilly, 1998; McGovern et al., 2007).

6.1 *Limitations*

All studies have problems. To improve understanding of the scope of the conclusions, I highlight the study's limitations. First, any conclusions beyond the countries studied remain difficult at best. Rather, the study serves to highlight a pattern in support of the different theories. Second, PIAAC samples households and not employees. Filtering workers raises concerns about selection bias and my study does not offer a good solution to this problem.

Third, all correlation studies can suffer from problems of omitted variables causing biases. Omitted variable bias raises concerns in predictive studies regarding magnitude. However, the bias must be rather strong to cause sign errors (Clarke, 2009). Consequently, this study hopefully recovers from these patterns, but one never knows the data-generating processes in social research. The nature of the data-generating processes echoes the importance of predictive (correlational) rather than causal claims (Gelman et al., 2020).

Fourth, all cross-sectional studies suffer from the major assumption of a single measurement occasion (Gelman et al., 2020). Although social research teaches that patterns tend to be consistent, things may change. Panel data on job control remains scarce, as well.

Finally, with regards to measurement, ESeC may also be sensitive to measurement errors (e.g., mis-classifications of occupations).

6.2 *Policy*

Despite limitations, I pose policy implications based on the results. The Nordic labor market provides a successful example (Kalleberg, 2011). Active labor market politics center on lifelong learning. Lifelong learning polices may mitigate occupational and class disadvantages in job control.The result in Denmark might reflect how the Nordic labor market has reduced class differences (Kalleberg, 2011). Consequently, policy needs to promote job skills to improve bargaining power of the least powerful (Tomaskovic-Devey and Avent-Holt, 2019). Examples include lifelong learning programs such as adult education, workplace training, and union courses. Employers need to take responsibility with the help of human resource management.

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