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Original Article

Welfare state policy and educational inequality: a cross-national multicohort study

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Proponents of welfare policy have argued that publicly funded early childhood education and care (ECEC), paid parental leave, and family benefits spending can weaken the influence of social background on educational outcomes by providing a supplementary source of early investment that particularly benefits disadvantaged families. We analyze whether the welfare state context in which children spend their early childhood (ages 0–5) moderates the association between parental educational attainment and the child's educational achievement at age 10. We combine data from two large-scale international student assessments with data about welfare state policies. Results from multilevel models show that countries with higher public ECEC spending and higher family benefits spending exhibited a weaker association between parental education and student math achievement. Countries with longer parental leave exhibited a stronger association between parental education and student math, science, and reading achievement. Findings provide evidence of the mixed role of welfare state policies for social inequality in student achievement.

Introduction

Research consistently finds children's educational outcomes to be strongly linked to their social background (Breen and Goldthorpe, 1997; Van de Werfhorst and Mijs, 2010). In fact, social inequality in cognitive achievement manifests even before children enter mandatory schooling, indicating that non-school factors play a critical role in shaping children's achievement (Nobel et al., 2015; Hippel et al., 2018; Skopek and Passaretta, 2020). Lack of investment in a child's early education has lifelong impacts on academic and social outcomes (Esping-Andersen, 2008; Chetty et al., 2011; Reardon, 2011; Heckman, 2017). Against this background, researchers argue that welfare state policies, such as publicly funded early childhood education and care (ECEC), parental leave and family spending, can weaken the influence of social background on educational outcomes by providing a supplementary source of investment and support to families that lack financial resources (Nolan et al., 2010; Bonoli, 2011; Busemeyer and Trampusch, 2011; Esping-Andersen, 2015).

Societies vary widely in how public services and goods are provided to citizens, resulting in different social investment patterns across countries and over time (Esping-Andersen, 2000; Bukodi et al., 2018). Ideally, welfare state policies disproportionately benefit the most vulnerable in society, supplementing their resources and reducing disadvantage (Nolan et al., 2010). For example, Esping-Andersen argues that welfare regimes reduce educational inequality (i.e., the effect of social background on educational outcomes) via two mechanisms: (i) by establishing high-quality, well-funded universal childcare institutions and (ii) by targeting families with specific social investment policies, such as generous parental leave and family benefits spending (Esping-Andersen, 2015). These welfare policies are promoted as effective means to enable parents to invest in their children's education by helping them retain income, thereby increasing the educational opportunities available to the most disadvantaged children. Whether such welfare policies effectively reduce social inequality in educational achievement, however, remains unclear. The answers provided by

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cross-national and cohort research to date have been limited. In this article, we analyze whether the welfare state context for children aged 0–5 moderates the effect of social background (measured here in terms of parental educational attainment) on children's educational achievement at age 10 (the fourth year of schooling).

Parental educational attainment—a key component of social background—has been found to be strongly predictive of children's educational achievement (Bukodi et al., 2018). This is in part due to the fact that better-educated parents are more likely to have greater knowledge of the education system and thus are able to monitor their child's educational progression, influence teachers, and mobilise resources to ensure better educational outcomes than less well-educated parents (Breen and Goldthorpe, 1997). Highly educated parents are also better equipped to assist their children with school-related tasks and tend to be more involved in their children's school life than their less-educated counterparts (Domina, 2005). Additionally, parental educational expectations and attitudes towards their child's education are correlated with their own educational experiences (Lee and Bowen, 2006). Better-educated parents are more inclined to push their children to the next educational attainment level compared to less-educated parents (Bernardi and Cebolla-Boado, 2014). Related studies have demonstrated that welfare states like Denmark exhibit higher intergenerational educational mobility than countries with a less developed welfare system such as the United States (Andrade and Thomsen, 2018). This international perspective on social background and educational outcomes highlights the importance of policy interventions in addressing achievement gaps related to parental education.

Early skill formation and educational achievement in countries with different welfare policies

From a life course perspective, early learning and skill formation have a lifelong impact on an individual's educational achievement. Research into children's early math skills has found a strong correlation with later mathematical and reading skills (Watts et al., 2014). This pattern also extends to non-academic skills such as emotional competence and self-regulation (Heckman, 2017). Children deprived of adequate early investment, however, are likely to fall behind and never catch up (Heckman, 2006; Esping-Andersen, 2015). Investment in a strong learning foundation during early childhood is therefore essential, producing effects that persist throughout the entire life course (Heckman, 2006). In countries with little public investment, children growing up in disadvantaged families are left exposed to early adversity and home environments that are not conducive to learning. Welfare state policies might provide an equalizing effect by supplementing resources available to the most disadvantaged children throughout the crucial early formative years. Although cross-country differences in welfare state policies are well documented, the extent to which they influence social achievement gaps is much less explored (Nolan et al., 2010).

Public early childhood education and care (ECEC) spending and educational achievement

Public ECEC has the potential to provide a beneficial learning environment for children who lack such an environment in their own homes. ECEC has also been shown to mitigate the negative effects of unfavourable home learning environments, especially for children from disadvantaged social backgrounds (Heckman, 2006; Burger, 2010; Barnett, 2011; Jensen, 2011; Sylva, 2014). Hence, ECEC typically improves the educational opportunities for children from disadvantaged family backgrounds (Esping-Andersen, 2008; Schütz et al., 2008). By providing enriching early experiences to disadvantaged children, ECEC may act as a surrogate for insufficient learning resources at home and thus increase the school readiness of children from disadvantaged social classes (Magnuson et al., 2004; Esping-Andersen, 2008; Schlicht et al., 2010). A study by Cebolla-Boado et al. (2017) found that socioeconomic background strongly influenced reading competence in most countries, with children from privileged backgrounds performing better. However, the availability of preschool education reduced this gap between advantaged and disadvantaged children (Cebolla-Boado et al., 2017). Heckman and Masterov (2007) posited that early childhood development investment is a cost-effective strategy for attenuating inequality through enhancing skills and long-term productivity, especially among disadvantaged children at risk of lagging behind their peers (Heckman and Landersø 2022). Additionally, several well-known ECEC programmes in the United States have demonstrated positive effects of early education on various outcomes. The Perry Preschool Project (Barnett et al., 2005) and the Abecedarian Project (Campbell et al., 2014) were two such programmes; both show long-lasting positive effects on a range of outcomes. The Carolina Abecedarian Project and the Carolina Approach to Responsive Education (Ramey and Ramey, 1998) were two closely related programmes that demonstrated positive effects on cognitive development, academic achievement, and social-emotional development. On the other hand, the Head Start Impact Study (Puma et al., 2010) found that, while Head Start had positive effects in the short term, these effects tended to fade over time. More recently, Durkin and colleagues (2022) argued that certain state-wide programmes in the United States might actually have had counterproductive impacts, reporting lower achievement for participants in the long term. Therefore, any equalizing effect of early education could occur only if the facilities had been provided on a broad and comprehensive basis, as limited availability or costs of high-quality institutions might have resulted in the exclusion of the most disadvantaged children (Schütz et al., 2008). In fact, previous research indicated a strong association between levels of public ECEC spending and ECEC attendance and quality levels (Jensen, 2011).

Family benefits spending and educational achievement

Research has indicated that government spending that targets families with young children directly can help mitigate the worst educational outcomes (Esping-Andersen, 2015). Family benefits spending policies generally have encompassed child-related cash transfers, income support payments for parental leave and sole parent families, public spending on services for families, as well as financial support through the tax system, including tax exemptions, child tax allowances, and child tax credits (OECD 2021a). Comparing different countries, Merry et al. (2020) found that government family spending was associated positively with educational achievement at age 15. Moreover, comparing 20 OECD countries, Engster and Stensöta (2011) found a significant positive correlation between family benefits spending and average educational attainment. Research also highlighted the potential of family benefits spending to curb multiple forms of inequality. For instance, Crettaz and Jacot (2014), analyzing 11 European countries, found that family-oriented public spending has had an inverse relationship to overall income inequality. Similarly, Mayer and Lopoo’s (2008) study revealed a trend of heightened income mobility in US states with extensive family spending. They attributed this to the strategic enhancement of resources for the most socioeconomically disadvantaged citizens. Such policy approaches might thus foster better educational outcomes overall, considering the robust association between family socioeconomic status and educational achievement. It is important to note that while the studies mentioned thus far have highlighted a potential reduction of educational inequality through family benefits policies, other studies emphasized possible downstream consequences of such policies, such as a reduction in female labour market participation. For instance, Stadelmann-Steffen (2011) demonstrated that the provision of cash benefits to families can decrease employment among women with lower to medium levels of education. These women may be more likely to stay at home, taking care of their children and fostering skills which will benefit educational achievement. Taken together, the majority of studies have indicated that family benefits spending could attenuate the relationship between parental education and children’s educational achievement, primarily through enhancing the achievement of children from disadvantaged families; hence, we anticipate similar results in our study.

Paid parental leave and educational achievement

Across economically developed nations, parental leave has been one of the main welfare policy instruments aimed at helping new parents balance work and family. This topic has gained particular prominence with the steady increase of female participation in the labour force over the past few decades (Danzer and Lavy, 2018). Parental leave has been lauded as allowing families with newborn children to invest time and care without having to suffer financially (Esping-Andersen, 2015). Pöyliö and Kallio (2017) found longer parental leave to significantly decrease intergenerational transmission of socioeconomic status, noting a ‘bottom-up effect’ for the lower end of the income distribution in Finland. Generous parental leave has been shown to allow parents to spend more time interacting and bonding with their children, which potentially has a positive effect on their cognitive development (Tanaka, 2005). Reducing this crucial bonding time, on the other hand, has been shown to have harmful effects on children’s health and cognitive development (Ruhm, 2004). Most recently, Ginja et al. (2020) found that children whose mothers had access to longer parental leave benefits also had better long-term life-course outcomes, including higher educational attainment and earnings. However, other authors have cast doubt on the assumed benefit of longer parental leave. Specifically, children in home environments that are not conducive to learning would accordingly be unlikely to benefit from spending more time in such an environment. In these cases, daycare may be more beneficial to children than the care provided at home (Liu and Skans, 2010). Similarly, Dustmann and Schönberg (2012) analyzed parental leave reforms in Germany and found no evidence supporting the hypothesis that the expansions in leave coverage improved children’s outcomes. Hence, the overall impact of parental leave on the relationship between parental educational attainment and children’s educational outcomes remains contested.

The present study

It is unclear whether welfare state policies moderate the effect of social background on a child’s educational achievement because relatively few studies exist in this field. Proponents of welfare expansion argue that additional investment into family-centred policies is likely to disproportionately benefit disadvantaged families, thus reducing social inequality in educational outcomes (Schlicht et al., 2010; Esping-Andersen, 2015). We thus put forward the following three hypotheses:

H1: Public ECEC spending moderates the association between parental educational attainment and student achievement.

H2: Family benefits spending moderates the association between parental educational attainment and student achievement.

H3: Paid parental leave moderates the association between parental educational attainment and student achievement.

To test these hypotheses, this study uses achievement data from two large-scale student assessment programmes. The study covers three waves per assessment programme and combines them with country-level government expenditure and welfare policy data from up to 30 countries. While not all countries participated in each wave, our sample does cover more than half a million students. On a country level, our analysis is longitudinal, following a country cohort over time. Figure 1 depicts the hypothesized causal model, showing how country-level welfare state policies offered during early childhood are assumed to moderate the association between parental education and a student's achievement (math, science, and reading) in primary school, when controlling for both country-level and individual-level covariates.

Methodology

We used the Trends in International Mathematics and Science Study (TIMSS) and the Progress in International Reading Literacy Study (PIRLS) large-scale student assessment datasets. TIMSS tests students' math and science achievement, while PIRLS tests students' reading achievement. Both tests were taken in year four of primary school, when the sampled students were in primary school and at an average age of 10. This measurement point was advantageous for our analysis as students had not yet been tracked or streamed into different classes according to ability or aptitude, allowing us to avoid this well-documented confounding effect

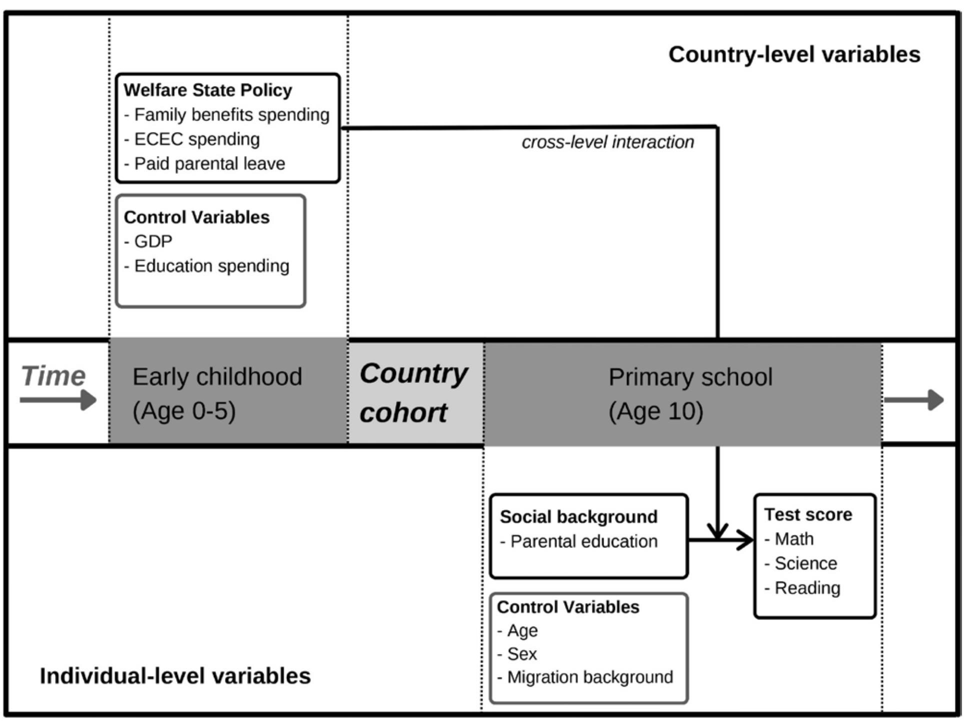

Figure 1 Hypothesized causal model. *Note:* Boxes outlined in black indicate variables of interest, and boxes below indicate control variables, defined in detail below. Solid black arrows denote causal pathways. The upper area represents the country level, while the lower area represents the individual level. The shaded areas in the centre represent the time periods at which measurements were collected for a respective country cohort, denoted within the dotted lines.Image of hypothesized causal model, showing how welfare state policy in early childhood moderates the association between social background and test scores during primary school at age 10.

(Roezer and van de Werfhorst, 2019). For a variety of reasons, countries did not participate continuously and fully in all waves of the assessment, meaning that some country data were missing in the statistical analysis. The TIMSS analytic subset did contain the three latest assessment waves from 2011, 2015, and 2019. This subset included data from thirty countries and 444,173 students, forming a total of 71 country cohorts. The PIRLS analytic subset, for the sake of comparison with TIMSS, contained the two latest waves from 2011 and 2016. It included data from 24 countries and 249,400 students, resulting in 44 country cohorts. The TIMSS sample contained six additional countries not contained in PIRLS, and the remaining countries were identical across both datasets (see online Supplementary Section A for details). Both datasets contained countries that did not fully participate in the assessment in certain waves and were thus not included. All data were publicly available and de-identified. All research procedures involving human participants conformed to the ethical standards as well as the applicable laws and guidelines of the institutions involved in the data collection. For the current secondary analysis, an examination by the Institutional Review Board of the [blinded] was therefore not required. Materials and codes are available from the corresponding author upon request.

Measures

The outcome, student achievement, was captured using five math and science plausible values (PVs) in TIMSS and five reading PVs in PIRLS. PVs are a representation of the range of abilities that a student might reasonably have. PVs take into account uncertainty associated with the fact that students in both assessments did not respond to all items and represent random draws from an estimated distribution for an individual student's achievement scores. In our ordinary least squares (OLS) regressions, we utilized weights assigned to student responses that were determined as the inverse of the probability of the student's selection in the sample, making the coefficients more generalizable to the entire population.

The main predictor, parental education, was measured by taking either of the parents' or legal guardians' highest level of education (university, post-secondary, upper secondary, lower secondary, some primary or little to no primary schooling) and converting it into a continuous measure of years of education for interpretability (following Burger, 2016). Family benefits spending was measured as any government spending that is exclusively targeted at families with children, as a percentage of gross domestic product (GDP). This includes an array of related policies such as: child-related cash transfers, income support payments for parental leave, and public spending on services for families. It also includes financial support provided through the tax system, such as tax exemptions, child tax allowances, and child tax credits (OECD, 2021a). Public spending on ECEC was measured as the percentage of GDP spent on pre-primary education (ISCED 0) (OECD, 2021b). Paid parental leave was measured as the total amount of legally protected weeks of paid maternity, paternity, and home care payments available to new parents (OECD, 2021c). For the welfare state policy variables, 5-year averages were used corresponding to when the respective cohort was 0–5 years old. Figure 2 visually presents the descriptive statistics of the three main welfare state policy variables.

Individual-level controls for age, gender, and migration background were included. Migration background was measured using a dichotomous variable assessing if either of the child's parents was born abroad or, if this information was unavailable, if the language spoken at home is different than the test language. We considered potential confounding factors by controlling for public education spending as a percentage of GDP and GDP per capita, adjusted for inflation. Additionally, in some robustness tests, we incorporated control variables for child poverty and income inequality, measured through the Gini coefficient. For most countries in the sample, the contextual data were sourced from the OECD Social Expenditure (SOCX) and World Bank government statistics databases. For the remaining countries, especially non-OECD members, a variety of sources were used, such as academic publications and government agency reports (see online Supplementary Section A for details on sample countries and data sources).

Missing data

Missing data represent a challenge in most cross-national comparative research. On a country level, we used 5-year averages, with an average of four values per country cohort (see online Supplementary Section A). On the individual level, the percentage of missing data ranged from 4 per cent to 15 per cent across items and waves (item non-response) and was about 5 per cent on average. Multiple imputation was used to adjust the estimation of model parameters to the presence of missing values, allowing for more accurate estimation (Zhang, 2016). This method avoided dropping observations that contain missing data in our analysis. We ran 50 multivariate imputations through chained equations using predictive mean matching for the individual-level variables only, using R and the 'mice' package, version 3.13.0 (Van Buuren and Groothuis-Oudshoorn, 2011). Table 1 shows the summary pooled statistics of the final datasets, post-imputation, for both TIMSS and PIRLS.

Analytic strategy

We matched cross-sectional student data with country-level data, thus forming multiple country cohorts

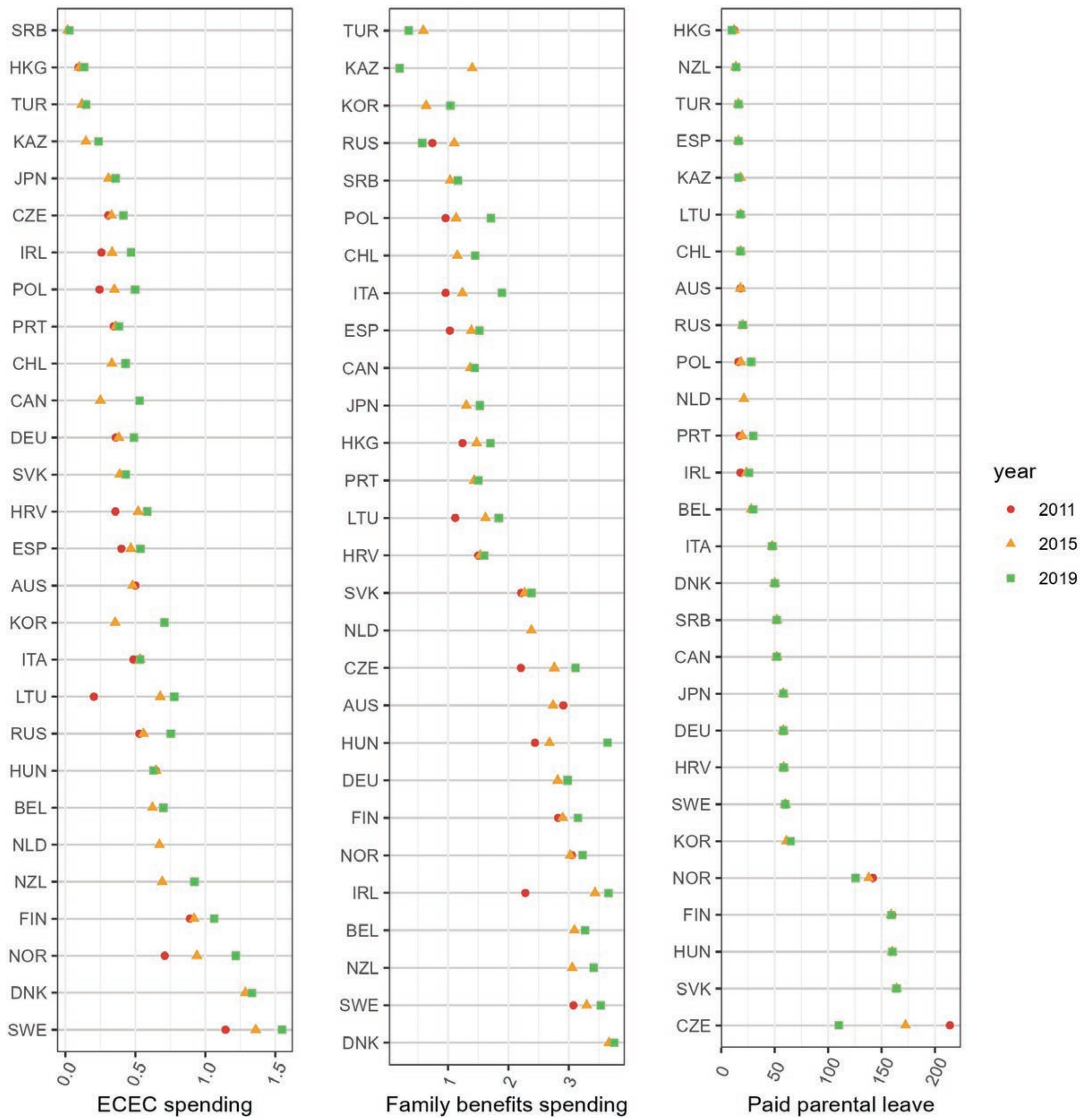

Figure 2 Welfare policy variables descriptive. *Note*: Paid parental leave is displayed in weeks, family benefits spending and ECEC spending both as % of GDP. Full data table in online Supplementary Section A.Image of distribution of three welfare polices across countries in sample.

(Hanushek and Woessmann, 2005; Roezer and Van de Werfhorst, 2019) to analyze whether three welfare state policies present during a child's crucial early development years (ages 0–5) moderate the degree to which parents' educational attainment was linked with their children's educational achievement in primary school (fourth year, age 10). We proceeded in three analytic steps. First, we determined the extent to which parental educational attainment was related to student achievement across our country cohorts (i.e., our measure of educational inequality). We achieved this by fitting OLS regressions estimating student performance as a function of parental educational attainment across each country cohort separately. Our OLS analysis utilized all five PVs, including student replicate weights, as recommended in the related literature (Caro and Biecek, 2017). This accounted for the complex sampling and test designs used in the student assessments, yielding more accurate coefficient estimates and standard errors (Caro and Biecek, 2017).

Table 1 Summary statistics of all TIMSS (left side) and PIRLS (right side) variables, post-imputation, pooled across all countries and waves

TIMSS statistic	*N*	Mean	SD	Min	Max	PIRLS statistic	*N*	Mean	SD	Min	Max
Math PV1	444,173	525.95	80.46	114.44	851.95	Reading PV1	249,400	543.68	71.41	139.31	829.34
Math PV2	444,173	526.08	80.86	80.88	885.26	Reading PV2	249,400	543.30	72.04	158.42	836.16
Math PV3	444,173	526.23	79.98	72.05	856.05	Reading PV3	249,400	542.87	71.94	119.79	859.87
Math PV4	444,173	525.81	80.55	84.48	868.08	Reading PV4	249,400	542.99	72.11	154.27	859.64
Math PV5	444,173	525.51	80.62	84.73	867.61	Reading PV5	249,400	543.04	71.83	140.91	835.04
Sci PV1	444,173	529.14	75.31	107.82	869.41						
Sci PV2	444,173	527.63	75.86	110.21	859.88						
Sci PV3	444,173	528.05	76.01	95.52	837.66						
Sci PV4	444,173	527.24	76.16	69.90	868.14						
Sci PV5	444,173	529.03	75.56	103.62	867.01						
Age	444,173	10.31	0.54	6.33	14.92	Age	249,400	10.23	0.55	6.17	14.92
Female	444,173	0.49	0.5	0	1	Female	249,400	0.49	0.5	0	1
Parents' education (years)	444,173	13.24	2.97	6	16	Parents' education (years)	249,400	13.32	2.91	6	16
Migration background	444,173	0.05	0.21	0	1	Migration background	249,400	0.13	0.34	0	1
ECEC spending (% of GDP)	30	0.52	0.30	0.02	1.55	ECEC spending (% of GDP)	24	0.48	0.29	0.09	1.36
Family benefits spending (% of GDP)	30	2.00	0.94	0.20	3.75	Family benefits spending (% of GDP)	24	1.98	0.84	0.74	3.67
Paid parental leave (weeks)	30	58.55	53.92	10	214	Paid parental leave (weeks)	24	57.02	55.34	7	214
GDP/10'000	30	29,132.86	18,665.03	3,375.77	98,182.99	GDP/10,000	24	28,652.92	15,989.64	3,375.77	84,052.52
Education spending (public)	30	4.95	1.04	2.67	8.17	Education spending (public)	24	5.02	1.00	2.71	8.21

Note: GDP was divided by 10,000 for ease of comparison. PV = plausible value. Country-level variables report *N* of countries.

Before selecting variables, bivariate correlations were assessed to avoid any problematic multicollinearity between variables (see online Supplementary Section B). Second, we determined the proportion of variance in our main outcome variable and in the moderators located across and between countries. For our main outcomes, namely student achievement scores, most of the variance was located within countries, as the between-country variance was relatively low (between-country variance of 5 per cent in reading, 16 per cent in math, and 8 per cent in science). Most of the variance in our welfare policy moderators occurred between countries (between-country variance of 93 per cent in family benefits spending, 97 per cent in paid parental leave, and 91 per cent in ECEC spending) (see online Supplementary Section C). Third, given the substantial cross-country variation in educational inequality and welfare policies, we used multilevel models to investigate whether variation in welfare policies explains cross-country differences in educational inequality. Multilevel models allowed us to differentiate between the extent to which educational achievement is predicted by context-specific features and individual-level characteristics (Raudenbush and Bryk, 2002). Using only OLS regression estimates would have violated the assumption of independent and identically distributed data (given that the data were nested in countries and cohorts). Multilevel models allowed us to jointly analyze data from multiple assessment waves, taking full advantage of the available data, and reducing the confounding influence of time-invariant (unmeasured) factors (Schmidt-Catran and Fairbrother, 2016). Our final models are represented as:

Table 2 Multilevel models 1–3 predicting student scores

Predictors	Model 1 (Reading) Estimate	SE	Model 2 (Math) Estimate	SE	Model 3 (Science) Estimate	SE
Intercept	500.77 ***	8.93	545.64 ***	6.45	543.70 ***	5.02
Parents' education (years)	6.72 ***	0.05	5.51 ***	0.09	4.86 ***	0.08
Female	13.29 ***	0.27	−6.99 ***	0.22	−2.75 ***	0.21
Age	−0.34	0.32	−2.54 ***	0.26	−1.33 ***	0.25
Migration background	−22.89 ***	0.41	−13.89 ***	0.54	−27.78 ***	0.52
ECEC spending (% GDP)	46.53 ***	2.89	8.66 ***	1.38	18.78 ***	1.33
Family spending (% GDP)	−9.66 ***	1.38	0.54	0.50	−2.75 ***	0.48
Paid parental leave (years)	1.87	1.58	−4.59 ***	0.71	1.71 *	0.69
Education spending (% GDP)	8.82 ***	1.22	−4.18 ***	0.42	−4.65 ***	0.40
GDP per capita	3.68 ***	0.50	2.33 ***	0.38	1.46 ***	0.37
Parents' education* ECEC spending	0.03	0.23	−0.73 ***	0.19	−0.55 **	0.18
Parents' education* Family spending	−0.20 *	0.08	−0.26 ***	0.06	−0.11	0.06
Parents' education* Paid parental leave	1.11 ***	0.05	1.83 ***	0.04	1.75 ***	0.04
Random effects						
σ^2	4,445.25		5,438.85		5,112.01	
τ_{00}	706.57 country		956.13 country		403.41 country	
	6.69 year		11.53 year		19.14 year	
N	24 country		30 country		30 country	
	2 year		3 year		3 year	
Observations	249,400		444,173		444,173	
AIC	2,802,821.456		5,081,256.314		5,053,707.986	
log-Likelihood	−1,401,394.728		−2,540,612.157		−2,526,837.993	

Note: To maintain comparability of results and to avoid methods artefact, we applied the same model specification across PIRLS and TIMSS. Mean random effect variance (σ^2), between-group variance at each level (year and country) (τ_{00}), N = number of cases, * $P < 0.05$ ** $P < 0.01$ *** $P < 0.001$.

$$y_{ijk} = \beta_{000} + \sum_{l=1}^{l} \beta l\, x^{l}{}_{ijk} + \sum_{m=1}^{m} \delta\, m\, C_{mjk} + \sum_{n=1}^{n} \gamma_n \left(x^{1}{}_{ijk} \cdot C_{njk}\right) + \nu\, j + x^{1}{}_{ijk} + \eta\, k + x^{1}{}_{ijk} + \varepsilon_{ijk}$$

The educational achievement Y of a student i in year j in country k was estimated as a function of the overall mean achievement across countries (β_{000}), a vector of individual-level variables ($x^1{}_{ijk}$ to x_{lijk}) with their coefficients (β_1 to β_l) and a vector of country-level variables (C_{1jk} to C_{mjk}) with their coefficients (δ_1 to δ_m). The model also included a vector of cross-level interactions between the individual-level variable 'parental education' and country-level variables ($x^1{}_{ijk} \cdot C_{njk}$), with the respective coefficients (γ_1 to γ_n). Three random terms were associated with the intercept and fixed effects, representing the residual variance ν j for the year, η k for the country (both estimates denoted as τ_{00}), and ε_{ijk} for the individual level, with σ^2 representing the mean random effect variance (see Table 2). Due to technical limitations regarding programming, multilevel models were limited to one PV at a time for the outcome variable. Our results did not change based on the selected PV. However, our estimates of the standard errors tended to be liberal because we limited the analyses to one PV. To adjust for these liberal standard errors, we utilized a bootstrap to resample the data with respect to the country clusters (see online Supplementary Section G for details). Individual-level predictors were centred at the country level. This is especially helpful with models such as ours which contain an interaction term with a continuous variable. The parental education variable was centred within each country in order to take into account country-specific distributions of educational attainment. Interpreting the regression coefficients was thus simplified by essentially referring to the country mean as a reference point (Bauer and Curran, 2005; Enders and Tofighi, 2007). As a supplementary analysis, we have estimated the models with a standardized parental education variable, which allows for interpreting the results as a change in the outcome that is related to a one standard-deviation unit change in parental education (see the online Supplementary Section F). All computations were done in *R*, version 4.0.2 (R Core Team, 2020). Data processing and visualizations were completed with the *tidyverse* packages (Wickham et al., 2019). OLS regressions were estimated using the *intsvy* package (Caro and Biecek, 2017). Multilevel models were estimated using the *lme4* package (Bates et al., 2015).

Results

First, we report the results from the OLS regressions that estimate the association between parental education and student achievement in each country. Figure 3 visualizes the unstandardized coefficients from OLS regressions predicting student math, science, and reading scores from parental education across each country and year (see online Supplementary Section D for details). The range of associations between parental education and student math scores extended from the highest coefficient of 14.95 to as low as 2.52, with the total sample average coefficient across all countries being 9.10, corresponding to a 0.09 standard deviation (SD). The association between parental education and student science scores ranged from the highest coefficient 13.85 to as low as 2.41, with the total sample average coefficient across all countries being 9.24, corresponding to a 0.09 SD. The range of associations between parental education and student reading scores extended from the highest coefficient 11.33 to as low as 2.44, with the total sample average coefficient across all countries being 7.9, which corresponds to a 0.08 SD. What became clear across all countries was that higher parental education was associated with higher scores in reading, math and science for children in year four. However, there was considerable variation across countries in the association between parental education and these scores.

In what follows, we present the results of the multilevel models investigating the extent to which cross-country variation in the links between parental education and children's achievement was moderated by country-specific welfare policies. Table 2 shows the results of these models. We estimated three main models, each including individual- and country-level control variables as well as the three cross-level interactions between parental educational attainment and given welfare policy (models 1–3).

The cross-level interactions allowed us to address our hypotheses, which we illustrate in Figure 4, showing the marginal effect of parental education on children's reading, math, and science scores across the range of possible values of the welfare policies variables.

Hypothesis 1 postulated that public ECEC spending moderates the association between parental education and student achievement. Models 2 and 3 predicted math and science scores, finding a significant negative interaction term ($P < 0.001$) for both. This means that countries with higher ECEC spending showed a weaker association between parental education and child achievement. Model 1 predicted reading scores and found a non-significant interaction term. However, this interaction term became significant and negative across different country samples and seemed to be sensitive to certain influential countries included in the main sample (see Section 3.1). Considering this, our results supported *hypothesis 1* for both math and science scores, but only partially for reading scores.

Hypothesis 2 conjectured that family benefits spending during early childhood moderates the association between parental education and student achievement. Both models 1 and 2 found a statistically significant negative interaction between family benefits spending and parental education ($P < 0.05$ and $P < 0.001$). Yet model 3, which predicted science scores, showed a non-significant interaction term. All in all, the findings across all three domains were not robust, changing direction and depending on the model specification or sample composition (see Section 3.1). This did not lend support for *hypothesis* 2.

Hypothesis 3 posited that paid parental leave during early childhood likewise moderates the association between parental education and student achievement. Models 1–3 tested this, finding a significant and positive interaction term for reading, math, and science scores ($P < 0.001$). Figure 3 illustrates these findings, showing that in countries with longer parental leave, the marginal effect of parental education on student math and science scores was indeed stronger. Overall, our results showed support for *hypothesis 3* consistently, across all three domains.

In what follows, we briefly discuss the main effects of the individual- and country-level variables from Table 2. Age had a significant and negative association with both math and science scores, as the poorest performing students were likely to be repeating the year. Additionally, children with a migration background had significantly lower reading, math, and science scores. Turning to the country-level controls, we found a significant positive effect of GDP per capita across all models on reading, math and science scores. Education spending had a positive association with reading scores, but a negative association with math and science scores.

Robustness tests

We performed several robustness tests focused on two aspects: sample selection and model specifications. We began by testing if sample selection and the inclusion of certain countries had any disproportionate leverage on our main results. First, we equalized the country samples between TIMSS and PIRLS in order to test whether our results were sensitive to the inclusion of different sets of countries in the sample. Specifically, we removed the six countries that were contained only

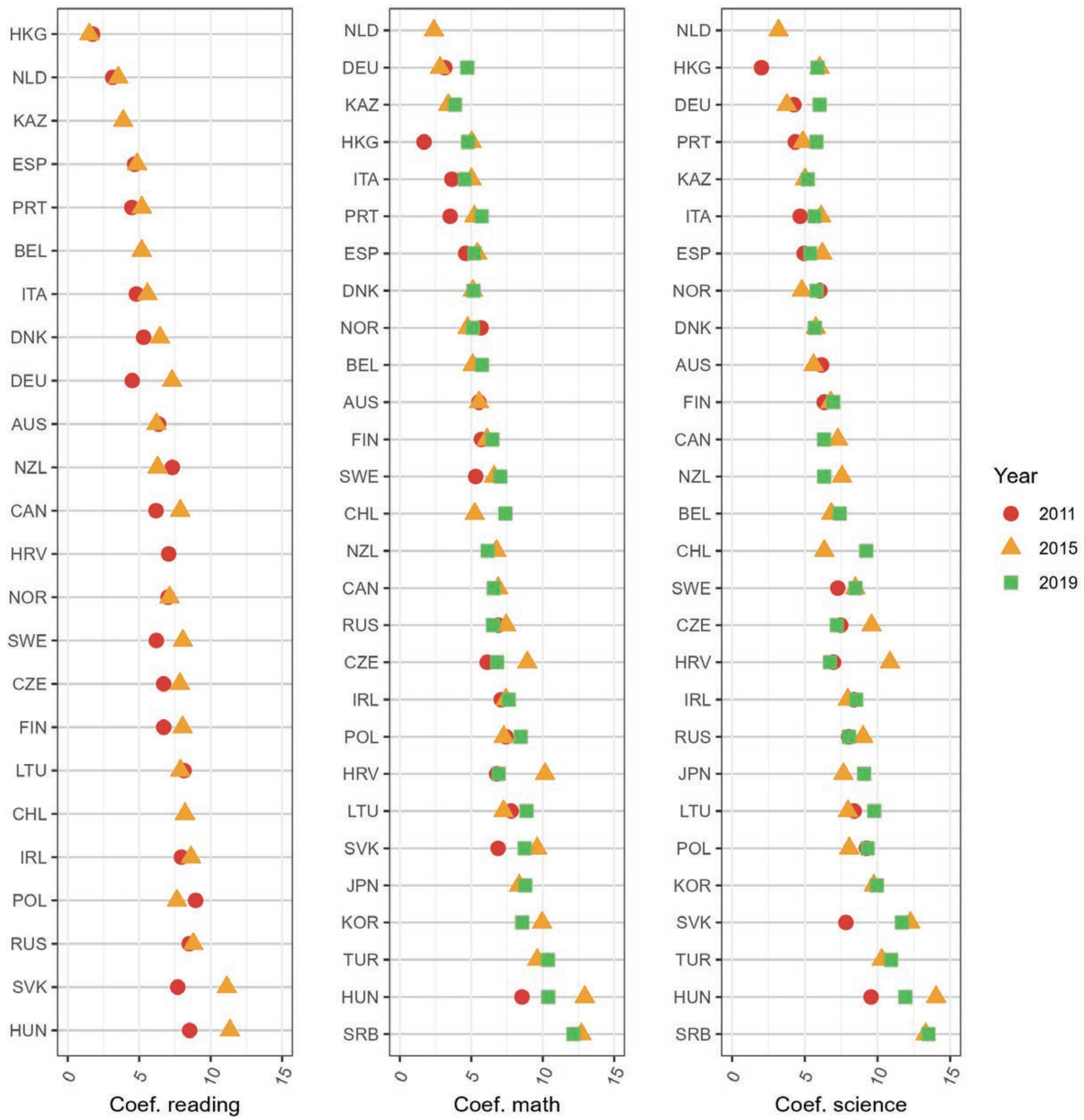

Figure 3 Unstandardized coefficients from OLS regressions predicting student reading, math, and science scores from parental education across each country and year. *Note:* OLS regression includes controls for sex, migration, age, GDP per capita, and public education spending. See full data table in online Supplementary Section D.Image of unstandardized coefficients from OLS regressions predicting student reading, math and science scores from parental education across each country and year including controls.

within the TIMSS sample to match those in the PIRLS country sample. Removing these additional countries from the TIMSS sample did not significantly change our main findings. Second, in order to ensure that our findings remained stable when focusing specifically on states that were democratic and more established welfare states, we restricted our analysis to a subset of well-established democratic welfare states. The main difference observed across this subsample was a change in the interaction between family benefits spending and parental education, with the coefficient across all three domains becoming positive and significant. When including only well-established democratic welfare states, countries with higher family benefits spending seemed to show significantly stronger impacts of parental education on student outcomes in math, science, and reading. Third, we then excluded countries randomly (2–5 at a time) from our analysis

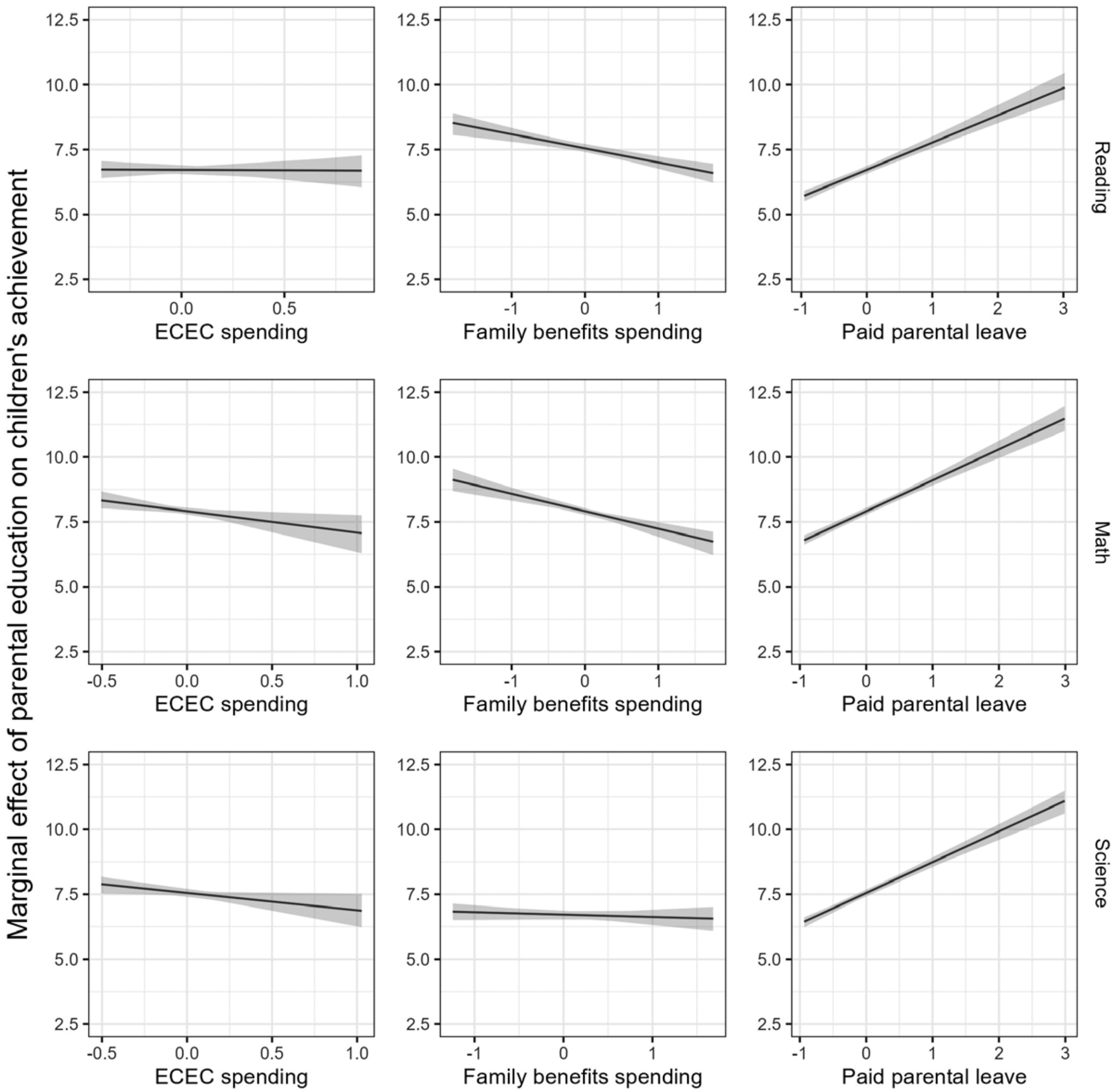

Figure 4 Marginal effect of parental education on student achievement, across the values of the welfare policy predictors. *Note:* Unstandardized coefficients, calculated via estimates from models 1–3, respectively, with welfare policy predictors centred.Image of marginal effect of parental education on student achievement, across the values of the welfare policy predictors.

to see which countries most affected our findings. In addition, we calculated Cook's distance measures to identify influential data points in our main models, which helped us to determine the impact of each group of observations (i.e., the countries) on the estimated coefficients and predicted values of the model, specifically the interaction terms (Gelman and Hill, 2006). We applied various cut-off points (distance > 5/10/20), each time dropping the most influential countries in our analysis. Notably, Norway, Turkey, and the USA were identified as the most influential countries in the TIMSS sample, while Norway and the Czech Republic were identified as the most influential in the PIRLS sample. Both approaches yielded similar results and highlighted that the inclusion of influential countries mainly only impacted the interaction between parental education and family benefits spending. Apart from this difference, changing the countries included in the sample did not significantly impact our main findings (see online Supplementary Section E for details).

Next, we proceeded to test various model specifications. First, to broaden our indicator of social background, we included an often-utilized self-reported measure of the number of books available within a child's home, thus replacing the parental education variable. Related literature using similar large-scale assessment data has often used the number of books in a home as an alternate proxy for a child's social background (Roezer and van de Werfhorst, 2019). Second, we enhanced the specificity of our main models by incorporating contextual control variables for income inequality and child poverty, which may explain a portion of the notable differences observed across our country sample. Third, we specified a model that categorized parental education as a binary variable (1 = post-secondary and higher, 0 = below post-secondary). Fourth, an ongoing discourse in the field posits that random slope terms ought to be included when modelling a cross-level interaction in multilevel models, resulting in potentially less biased estimates (Heisig and Schaeffer, 2019). However, other authors have cautioned that such an approach could yield standard errors that are excessively conservative, especially when the explained variance of the random slope term is near zero (Raudenbush and Bryk, 2002; Bell et al. 2019). We thus estimated fixed-effects models without random slopes and also estimated a model that included a random slope term as a robustness test (see online Supplementary Section F). Lastly, researchers have often cautioned that assumptions of mixed effects models may be violated to such a degree that biased estimators and incorrect standard errors result. A multilevel resampling method, such as a bootstrap, is often recommended in order to obtain consistent estimators and standard errors for inference (Leeden et al., 2008). We utilized the cases bootstrap, a fully nonparametric bootstrap that resamples the data with respect to the clusters in order to generate bootstrap samples (see online Supplementary Section G for details). Despite the various model specifications used, our two main results—the interactions involving ECEC and parental leave—maintained their significance and direction consistently across all three student achievement domains. However, the interaction term between parental education and family benefits spending demonstrated a change in both significance and direction across different model specifications (see online Supplementary Section F). Although we were unable to exclude spurious relationships between welfare policies and educational achievement, our main results in combination with the robustness tests provided initial evidence to support hypothesis 1 (ECEC) and hypothesis 3 (parental leave). However, hypothesis 2 (family benefits spending) was not supported, as the results proved sensitive to the inclusion or exclusion of countries in the sample.

Discussion

This study seeks to determine whether welfare state policies moderate the relationship between parental education and student achievement—that is, educational inequality—in primary school. Our results indicated that countries with higher public ECEC spending showed a weaker association between parental education and math and science achievement at age 10. Public spending on ECEC might thus reduce social inequality in math and science scores at the end of primary school. However, this moderating effect was not found for reading scores. Interestingly, when we limited the countries in our sample to more developed welfare states or removed particularly influential countries, we found a moderating effect of public spending on ECEC on educational inequality also when using reading scores as the outcome. We thus believe that the countries included in the sample are mainly responsible for the differences in our main results across domains. Previous studies have shown that well-funded public ECEC programmes have beneficial effects on student achievement throughout the course of education (Sylva, 2014; Cebolla-Boado et al., 2017; Kulic et al., 2019). Although public ECEC spending should benefit the most vulnerable (i.e., those who have the most to gain), it has been shown across some countries that middle-class families actually end up benefitting the most (Merry et al., 2020). While the most disadvantaged students might benefit disproportionately, they are nevertheless much less likely to attend preschool in the first place, and for much shorter periods of time (Burger, 2016; Heckman, 2017). Our study is unique, however, as it shows the moderating impact of public ECEC spending across three large-scale assessment domains and three different cohorts.

Our results indicate that higher family benefits spending is significantly associated with lower levels of educational inequality for both reading and math achievement, but not for science achievement. However, across our robustness tests, findings related to family benefits spending showed a strong sensitivity to both model specifications and countries included in the analysis (see Section 3.1). Previous studies, such as those by Crettaz and Jacot (2014) and Mayer and Lopoo (2008), have suggested that welfare spending can reduce income inequality and lessen educational disparities influenced by social background. However, our findings are more mixed. Depending on which countries are included in the sample, family benefits spending appears to either mitigate, have no significant association with, or even exacerbate educational disparities. Although the exact mechanism cannot be determined empirically in this study, we theorise that family benefits spending is likely the most complex and broad measure of the three welfare state policies analyzed. It covers a multitude of different cash and non-cash transfers, which are likely subject to varied implementations and generosity depending on the country included. We suspect that the large variation across our findings might include patchworks of family benefits spending which are well developed and targeted more exclusively at disadvantaged families, but also contain less developed and generous policies targeted more broadly at lower-middle-class families. Indeed, in our sample, we note a relationship between family benefits spending and both GDP per capita and public education spending. As such, in countries with less developed welfare systems, policies like family benefits spending may have a stronger equalizing effect, given the presumably higher levels of family poverty. The historical development and generosity of a country's welfare system are likely significant factors in determining the effectiveness of such policies.

Furthermore, countries with longer paid parental leave showed a significantly stronger association between parental education and students' achievement across all three domains at age 10 than countries with shorter paid parental leave. These findings remained robust across a range of model specifications and country sample robustness tests. This might be explained by the fact that the benefits related to paid parental leave are often tied to employment sector and type, which is strongly associated with parental education (Esping-Andersen, 2015). Moreover, Han and colleagues (2009) showed that better-educated women tend to take longer periods of family leave than their less-educated counterparts. Additionally, highly educated parents tend to spend more time interacting and playing with their children than less-educated parents (Guryan et al., 2008). It is thus possible that well-educated parents are better able to take advantage of their parental leave times, spending more time interacting with their children and fostering learning than less-educated parents do. Our findings are thus in line with recent studies evaluating the impact of parental leave durations on student outcomes, which found limited impacts of extended leave duration for children from more disadvantaged households (Liu and Skans, 2010; Dustmann and Schönberg, 2012).

Overall, our findings suggest that the level of educational inequality is sensitive to a country's public ECEC spending and the length of parental leave. Increased public ECEC expenditure when a child is in an early stage of development can equate to a weaker association between parental education and student achievement in primary school. Importantly, the small moderating effects do not imply that these welfare policies have no other beneficial effects, especially in the long run. It might well be that the chosen measurement points at age 10 are too early to accurately assess long-term consequences of these macro welfare policies. Other studies have confirmed so-called 'sleeper effects' where the actual impact of welfare policies, such as public ECEC spending, crystallized much later in life, with better income and employment outcomes (van Huizen and Plantenga, 2018). The countries exerting the greatest influence on our results were identified using Cook's distance, a method to calculate the impact of individual countries on the outcomes compared to that of other countries in the sample. The countries identified as most influential in our analyses exhibited the highest (Norway) and lowest (Turkey) levels of welfare state investment, respectively, across the three policies that we assessed. Our study also highlights that the association between welfare state generosity and inequality shifts when focusing on certain contexts such as developed welfare states, as with family benefits spending. It is important to note that while some policies such as public ECEC expenditure can reduce educational inequality, others such as parental leave might exacerbate educational inequality. More generally, whether welfare state policies amplify or mitigate educational inequality depends on the policy in question as well as on the country's context. These findings call for a more tailored approach in welfare policy research, which should recognize that a given policy may have varying impacts in different countries.

Note that our study has several limitations. Although we assessed educational outcomes in terms of reading, mathematics, and science scores, we did not assess other important domains such as non-cognitive or behavioural outcomes, which are also known to contribute significantly to educational success. Also, while welfare policy spending arguably measures the quality of welfare policy to some extent, it does so in limited respect, as it does not account for other quality dimensions (e.g., experience and qualifications of ECEC staff, ability to return to a job after leave or benefit transfer frequency) that might make a policy much more effective, as well as not assessing the effectiveness of the spending (Taguma et al., 2012; van Huizen and Plantenga, 2018). For example, broad political support and universal access for each child have been shown to be related to the quality and effectiveness of ECEC policies (Kulic et al., 2019). Additionally, this study is limited to analyzing a relatively heterogeneous sample of $N = 30$ countries. While most of our sample consists of OECD nations, the degree of their welfare state generosity, development, and history differs substantially, limiting the generalizability of our results (Nolan et al., 2010). This might also explain the modest effect sizes found. We acknowledge the limitation that certain countries included in our analysis may lack typical characteristics associated with 'welfare states'. However, we have conducted additional analyses in Section 3.1, wherein we excluded countries that do not conform to the stricter criteria of welfare states and nevertheless found confirmation for our results. Lastly, a common limitation often mentioned in the cross-country literature is the small country samples reported. It is likely that the debate regarding specific cross-country patterns is fuelled by different country samples, data and methodological approaches. However, it is also noteworthy that recent methodological research into cross-country comparison shows that, if the number of countries compared is greater than 25, linear models with fixed-effect coefficients and standard errors appear to be estimated accurately (Bryan and Jenkins, 2016). Given that omitted variable bias cannot be ruled out, causal inference cannot be established and thus the results remain associational. However, we did test the hypotheses on three different cohorts and thereby minimized the effect of confounding by time-invariant (unmeasured) country factors. This represents a strength of this study: by utilizing up to three waves per country and combining two large-scale student assessments, the total number of country cohorts in our analysis is 131 (87 TIMSS, 44 PIRLS). Regardless, there is a need for caution when interpreting the presented results.

Conclusion

Welfare state research has lacked empirical enquiry into the influence of social spending on educational inequality. Using data from two large-scale student assessment programmes and multiple cohorts, this study provides evidence that welfare state policies can reduce achievement gaps related to social background; however, they can also exacerbate such achievement gaps, depending on the policy. The welfare state literature often debates whether welfare state expansion in and of itself matters with regard to questions of social inequality. Our study contributes to this debate, suggesting that distinct welfare policies might not have a consistent impact on educational inequality. Especially cross-national studies should carefully consider how different policy implementation, generosity, and development can influence aggregate findings. Depending on the policy in question, these policies can either amplify or mitigate educational inequalities. In other words, welfare policies targeted at families with children may have intended and unintended impacts on educational inequality. However, our study also yielded consistent evidence supporting prior research which suggests that children from better-educated families are more likely to benefit in terms of their educational achievement from parental leave policies (greater spending on parental leave seems to be associated with greater educational inequality). We argue that the focus should thus be on making specific welfare policies particularly effective for less advantaged families. This would ensure that disadvantaged children benefit the most from these programmes and thereby enable a bottom-up equalization of achievement gaps related to social background.

Supplementary Data

Supplementary data are available at *ESR* online.

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Author contributions

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