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Abstract

We apply meta-regression analysis to assess the effect of the minimum wage on two types of human capital: 460 estimates of formal education enrolment and 428 estimates of on-the-job training. Raising the minimum wage reduces enrolment in all countries assessed. The minimum wage has a somewhat moderate positive effect on training in the US and a small positive training effect elsewhere. There is no publication bias in the formal education and modest bias in training literatures. Heterogeneity among reported estimates is primarily driven by alternative specifications and measures of the relevant variables and data differences.

JEL-Codes: J08, J24, J51, M53

Keywords: minimum wages, on-the-job training, education enrolment, meta-regression analysis

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1 INTRODUCTION

The effects of labour market regulations on human capital have been of active research interest at least since the influential contributions by Schultz (1961) and Becker (1962). This broad literature assesses the effects of labour unions, collective agreements, and rules and regulations in general. An important strand within this literature is the effects of minimum wage legislation. While minimum wages are praised by many as a means to reduce wage inequality (e.g. Krueger, 2015), they may have adverse unintended consequences for low skilled and low wage workers (e.g. Neumark and Wascher, 2008). Empirical research on minimum wages has probed multiple outcomes, principally employment, productivity, profits and prices (e.g., Addison *et al*, 2009; McLaughlin, 2009; Draca *et al.*, 2011; Harasztosi and Lindner, 2019), and also outcomes such as workers' satisfaction and physical capital investment (Bossler and Broszeit; 2017; Gustafson and Kotter, 2023).

In this article we assess the effects of minimum wages on human capital investment through a *quantitative* survey of the 1980-2023 empirical research. We perform a meta-regression analysis (MRA) of the effects of minimum wages on *formal* investment, using all comparable reported effects on high school and college enrolment, and *non-formal* investment, using all comparable reported effects on on-the-job training. We assess the effects of minimum wage legislation on individual decisions to continue formal education and training on one side, and on the provision of on-the-job training by firms on the other.

Our article contributes to quantitative research summaries of labour economics research in general, and wage policies in particular. An early example of this line of research is Card and Krueger's (1995) meta-analysis of 15 empirical minimum wage studies, finding negligible negative effects on US employment. This was later corroborated by a MRA of 64 US-minimum wage studies by Doucouliagos and Stanley (2009). Meta-analysis is an effective way of summarizing the findings of diverse and often conflicting empirical findings. Other examples include Haelermans and Borghans (2012) meta-analysis of the effects of on-the-job training on earnings of trainees and the Havranek *et al.* (2018) study on the effect of tuition fees on college enrolment.

Our study significantly extends the last overview of the minimum wage literature on human capital investment in Belman and Wolfson's (2014) book, *What Does the Minimum Wage Do?*. These authors compare the findings of the minimum wage literature over the period 1980-2010 regarding multiple outcomes: enrolment, employer-supplied training, and employer-provided benefits. They survey 14 enrolment and 6 training studies. Their summary is extensive, reviews numerous details on econometric methods, data, and highlights problems pervasive in the literature such as measurement issues of training and minimum wage variables. However, Belman and Wolfson (2014) do not offer a quantitative analysis of the overall effect of the minimum wage on enrolment and training. Our MRA extends Belman and Wolfson (2014) with a quantitative analysis of all reported estimates, including studies reported in more recent decades (2010-2023).

We identify 888 estimates from 38 empirical studies: 25 papers that report 460 effects on high school or college enrolment and 13 studies that report 428 effects of on-the-job training. There is substantial heterogeneity in these reported effects which we explain by differences in the datasets, and study characteristics like country, year, level of analysis, and how the variables of interest, minimum wages and enrolment/training, were operationalized across studies. We also model and control for publication selection bias.

Ignoring bias and heterogeneity, we find that the overall average effect is negative and statistically significant in both cases, but very small; in correlation terms the effect is only about -0.01. We detect no publication bias in the enrolment literature and modest bias in the training literatures. Taking publication bias and heterogeneity into account, we find that minimum wages reduce enrolment, but the magnitude varies from low to somewhat moderate. In developing countries, the correlation is between -0.05 to -0.12, depending on the level of data aggregation and individual income background. The adverse effect is larger in developed countries (correlation between -0.1 and -0.17). Minimum wages have a somewhat moderately positive effect on training in the USA (correlation between 0.08 and 0.14) and largely no effect in other countries (correlation between -0.01 and +0.04), depending on the data level and workers' age.

The following section provides an overview of theoretical models. In Section 3 we narratively summarize all studies included in the meta-analysis. The meta-data are discussed in Section 4 and the MRA methodology in Section 5. The MRA results are presented and discussed in Section 6. The last section concludes.

2 THEORETICAL CONSIDERATIONS

We commence with an overview of the key theoretical considerations. This helps us to make informed choices of potentially relevant moderator variables to include in the analysis of heterogeneity in our MRA.

2.1 Investment in education

From Becker (1962) it follows that due to the long length of the period of returns to education, an earlier investment in education is more efficient than later in life. Since the early empirical contributions in this literature, researchers considered investment in education collaterally with employment decisions, in the presence of an increase in minimum wages. Ehrenberg and Marcus (1980) predict that due to earning constraints, poorer youth will tend to prefer to switch away from schooling towards full-time employment. Mattila and Orazem (1986) hypothesize that the lost opportunities in firm-financed training arising from higher minimum wages may induce low skilled workers to seek formal training through vocational schools or colleges.

Agell and Lommerud (1997) assume the existence of primary and secondary labour markets. Increased minimum wage in the primary labour market motivates workers of intermediate ability to attain sufficient education to pass the hurdle to enter this labour market. These workers would, without minimum wages, remain in the secondary labour market. Ravn and Sørensen (1999) model a minimum wages contribution to long-run economic growth, showing it decreases training, but increases enrolment, as workers try to attain the necessary education level requisite for the new minimum wage. The net effect for the economy depends on whether the decrease in training or increase in enrolment prevails for labour productivity. Bárány (2016) shows that a decrease in minimum wages widens the gap between low skilled and high skilled workers. Due to the smaller minimum wage, more low skilled workers enter the labour market, decreasing the average skill quality among them. At the same time at higher skill levels, the skill premium increases and such workers are incentivized to attain more education, diverging further from the low-skilled. Thus, from Bárány's model it follows that a reduction in minimum wages leads to more education inequality. A similar standpoint, shared by many empirical researchers, is that higher minimum wages keep young workers in school to be better qualified for the higher wage jobs and equally, the prospect of a higher wage job after longer period of schooling reduces the opportunity costs of schooling (e.g., Neumark and Wascher, 2008). On the other hand, higher minimum wages will, very likely affect exactly the wages of youth and thus, conditional that such an employment can be found, make additional years of schooling less attractive.

These theoretical predictions identify several distinctive categories of individuals who might be more or less likely to invest in their education if minimum wages increase. Becker's perspective points to age as a factor in this education investment decision. In our analysis, we include sample mean age and distinguish by type of education, i.e., secondary vs. postsecondary, as moderators of the minimum wage effect on enrolment. Ehrenberg and

Marcus (1980) discuss the issue of earnings constrains as a hurdle to further education investment; thus we include an indicator of low-wage family background. Ehrenberg and Marcus (1980), Agell and Lommerud (1997), among others, model education decisions jointly with employment decisions. In our meta-analysis we use moderators that distinguish if the dependent variable combines school enrolment with employment in the empirical analysis.

2.2 Investment in training

The first theories on firms' training decisions originate in Becker (1962) who shows that training is provided only if the investing firm gains from the productivity increases due to the training. Two main consequences are derived from this model: firms will only invest in specific training and the investment costs will be compensated by lower wages. Wessels (1980) expands the standard labour demand and supply model to include changes in fringe benefits offered to workers, in addition to an increase in wages due to new minimum wages. This enhanced model predicts a reduction in the employment of low-wage workers and that remaining workers covered by minimum wage will be worse off, due to reduction in training and other working conditions. In Hashimoto's (1982) model of competitive labour markets, the introduction of a minimum wage increases training costs per worker and changes the slopes of the labour demand curves. This might lead to either a decrease or an increase in employment, but workers who remain employed experience a reduction in training.

Since the 1990s, models became less pessimistic in predicting training provision. Stevens (1994) proposes a model that allows for imperfect labour market competition in which training of transferable skills may still pay off for firms. Acemoglu and Pischke (1999a; 1999b) focus on labour market imperfections, and predict an increase in training even in the presence of a minimum wage. In the least favourable of the model variants, Acemoglu and Pischke (1999b) show that minimum wages increase training only for credit constrained workers, while they decrease training for workers taking wage cuts to finance their own training. Finally, Lechthaler and Snower (2008) present a hybrid finding in that an increase in minimum wages leads to a training increase for high skilled workers and a decrease for low skilled ones, further contributing to a skill gap between the two types of workers.

These theoretical perspectives assist with the choice of the relevant moderators in the meta-analysis. In the absence of labour market frictions, firms invest only in firm-specific training (Becker, 1962), but it remains unclear how firm-specific training changes when minimum wages increase, and it seems plausible that the *type* of training matters. We include a dummy variable for formal or specific training. From Acemoglu and Pischke (1999a) and Stevens (1994) it follows that labour market frictions can reverse the negative sign of the training investment, thus we use country dummies, helping to grasp the regional differences in the magnitude of labour market regulation. Lastly, the model of Lechthaler and Snower (2008) predicts differential training investments based on the skill levels of the workers. From this follows that age, gender, education, and skills background of individuals may play a role in training decisions.

3 OVERVIEW OF THE EMPIRICAL LITERATURE

In this section we present a chronological overview of studies covered by our MRA, from the earliest empirical studies published in the 1980s until 2023.[1]

3.1 Minimum wages and school enrolment

[1] Of the 38 studies, only Baker (2005) reports effects on both enrolment and on-the-job training, within a single paper. However Neumark and Wascher contribute notably to both topics with several studies (1995a; 1996; 2001, 2003).

Two broad econometric approaches are applied in the literature on minimum wages and school enrolment. The first strand in this literature uses a conditional logit model of discrete choices between four mutually exclusive states (McFadden; 1973) for aggregated state-year data or a multinomial logit model (e.g. Theil; 1969) for individual-year data. The employment-enrolment decisions fall into one of four categories: SNE: in **s**chool and **n**ot **e**mployed, SE: in **s**chool and **e**mployed, NSE: not in **s**chool and **e**mployed, and $NSNE$: **n**ot in **s**chool and **n**ot **e**mployed (e.g. Neumark and Wascher; 1995 and eight other studies use this approach). This system can be generally specified as:

$$\log\frac{SNE_{it}}{NSNE_{it}} = \alpha_{11}MW_{it} + X_{it}\beta_1 + \varepsilon_{1it}$$

$$(1) \qquad \log\frac{SE_{it}}{NSNE_{it}} = \alpha_{21}MW_{it} + X_{it}\beta_2 + \varepsilon_{2it}$$

$$\log\frac{ENS_{it}}{NSNE_{it}} = \alpha_{31}MW_{it} + X_{it}\beta_3 + \varepsilon_{3it},$$

where the main variable of interest, the minimum wage, MW_{it}, is either a dichotomous indicator, or more frequently a so-called minimum wage bite, defined e.g. as the minimum wage divided by the average wage in a region i, or workers' category i. In our data collection, we assemble estimates of α_{11}, α_{21}, i.e. the implied partial derivatives of minimum wages on the outcomes linked to schooling, SNE and SE, combined with or without employment. Estimation of the multinomial logit model is via generalized least square, seemingly unrelated regression, or maximum likelihood estimation techniques. The largest portion of studies, however, focus their attention solely on enrolment, ignoring the further employment breakdown. For example, Landon (1997) estimates for Canada the proportion of enrolled of type k in province i, E_{ki}, as:

$$(2) \qquad E_{ki} = \alpha_0 MW_{ki} + \boldsymbol{\beta} X_{ki} + u_{ki},$$

where MW is the ratio of the real level of the provincial minimum wage to the average wage. Specification (2) is more flexible and has been far more frequently applied post 2005. There exist several variants of Equation (2) from the operationalization perspective of both the enrolment and minimum wage variables. It is equally easy to adapt Equation (2) to a difference-in-difference (e.g. Hyslop and Stillman; 2007), regression discontinuity (Dayioglu *et al.*; 2022), or any type of fixed effects specification setting (e.g. Lee; 2020).

There are three broad periods in the evolution of the effects of the minimum wage on educational enrolment. The early period (1980-1986) is populated exclusively by USA-data studies. The reported estimates are based on state-level data or individual survey data and the identification of the minimum wage effect relies on variation in minimum wages across states and time. Due to small sample size, the results of this period are less precise and somewhat contradictory across studies. Ehrenberg and Marcus (1980, 1982) find that larger minimum wages cause asymmetric reaction on enrolment-employment decisions depending on race and income family background. White youth from disadvantaged families move from enrolled-employed category into full time enrolment, while non-white youth shift to full time employment. Cunningham (1981) reports completely opposite results, namely the probability of being in school increases for blacks and decreases for whites of both genders. Using a long time-series data (1947-77) for US states, Mattila (1981; Mattila and Orazem 1986), demonstrate a robust evidence of increased student enrolment when minimum wage increases. Using school level data for Maryland, Mattila and Orazem (1986) report an increase in enrolment into 1-3 years colleges for males and enrolment *decrease* for females. Fleisher (1981) focuses on changes in minimum wages in retail trade sector and its effect on enrolment. He finds a strong positive effect among the 18-19 years old males. Fleisher argues that these young men would not attend school had the employment opportunities in the retail sector not been reduced.

Table 1

Studies included in the meta-analysis of minimum wages and *enrolment*

Study	Country	Dataset	No. of estimates	Period	Estimation model	Estimation method
	(1)	(2)	(3)	(4)	(5)	(6)
Ehrenberg and Marcus (1980)	USA	CP	16	1970	multinomial logit	GLS
Cunningham (1981)	USA	CP	8	1960, 1970	multinomial logit	GLS
Fleisher (1981) book	USA	CPS	22	1947-1978	linear	GLS
Mattila (1981)	USA	CPS	4	1947-1977	linear	OLS
Ehrenberg and Marcus (1982)	USA	NLS	28	1966, 1968	multinomial logit	ML
Mattila and Orazem (1986)	USA	MSBE	7	1951-1969	linear	SURE
Neumark and Wascher (1995a)	USA	CPS	23	1978-1989	conditional logit	ML
Neumark and Wascher (1996)	USA	CPS	23	1979-1992	multinomial logit	ML
Landon (1997)	Canada	Provincial level data	8	1975-1989	linear	OLS
Chaplin *et al.* (2003)	USA	CCD	12	1989-1997	linear	OLS
Neumark and Wascher (2003)	USA	CPS	34	1979-1989, 1980-1998	conditional logit, linear	GLS
Baker (2005)	Canada	LFS	48	1983-2000	linear	OLS
Campolieti *et al.* (2005)	Canada	SLID	3	1993-1999	multinomial logit	ML
Hyslop and Stillman (2007)	New Zealand	HLFS	14	1997-2003	linear	DID
Montmarquette *et al.* (2007)	Canada	SLS	1	1991, 1995	binary probit	ML
Pacheco and Cruickshank (2007)	New Zealand	HLFS	14	1986-2004	linear	synthetic panel LS
Crofton *et al.* (2009)	USA	Maryland counties data	5	1993–2004	linear	panel RE/FE
Rice (2010)	UK	YC9	20	1998-1999	conditional logit	ML
Bakis *et al.* (2015)	Turkey	HBS	6	2003-2006	binary probit	DID
Colombé (2016)	Indonesia	SUSENAS	16	1990-2010	multinomial logit	GLS
Wescher *et al.* (2019)	USA	NLSY	24	1997	probits: ordered & multinomial	ML
Lee (2020)	USA	IPEDS	72	1990-2010	log-linear	matched-pair FE
Pritadrajati (2020)	Indonesia	SUSENAS	15	2000-2018	nested logit	ML
Dayioglu *et al.* (2022)	Turkey	SILC	10	2013-2014	local linear	RDD, diff-in-disc

Alessandrini and Milla (2023)	Canada	SLID	27	1993-2011	log-linear	OLS

Notes: Grey horizontal lines mark the three distinct periods discussed in Section 3.1. Abbreviations in Column (1): CP: Census of Population, CPS: Current Population Survey, NLS(Y): National Longitudinal Survey (of Youth), MSBE: Maryland State Board of Education, CCD: Common Core of Data, LFS: Labor Force Survey, HLFS: Household Labour Force Survey, SLID: Survey of Labour and Income Dynamics, SLS: School Leavers Survey, YC9: 9th Youth Cohort Study, HBS: Household Budget Survey, SUSENAS: National Socio-Economic Survey, IPEDS: Integrated Postsecondary Education Data, SILC: Survey of Income and Living Conditions. Abbreviations in Column (6): GLS: Generalized Least Squares, OLS: Ordinary LS, ML: Maximum Likelihood, SURE: Seemingly Unrelated Regression, DID: Difference in Differences, FE/RE: Fixed/Random Effects, RDD: Regression Discontinuity Design.

The second period (1995-2003) is still largely represented by the USA-based longitudinal studies. Landon (1997) is the single exception, who reports the first account of minimum wage-enrolment relationship for Canada. The overwhelming majority of estimates from this period belong to Neumark and Wascher (1995a, 1996, 2003) who largely report negative or no effects of minimum wages on various combination of enrolment-employment subcategories using both individual and state-year data.

The most recent period, 2005 onwards, is very prolific. Half of the studies and two thirds of all empirical estimates are published during this period. Contributions from five more countries (Canada, Indonesia, New Zealand, Turkey, UK), in most cases even multiple times, become available. Many of the newer studies address endogeneity issues using various approaches as diff-in-diff (e.g. Hyslop and Stillman 2007; Bakis *et al.* 2015), matched pair fixed effects (Lee 2020), or regression discontinuity (Dayioglu *et al.* 2022). Most studies estimate the minimum wage effect on secondary school enrolment. However several papers report minimum wage effects on explicitly college enrolment (e.g. Lee 2020). In Table 1 we offer a chronological overview of the minimum wages-enrolment studies.

We exclude Neumark and Wascher (1995b) as this study contains a subset of estimates reported also in their 1996, more extensive, study, which is part of our meta-data. Furthermore, we do not include Turner and Demiralp (2001) as they only report transition probabilities between employment-enrolment states across time. Three US-data studies report minimum wage effects on schooling-related issues, but do not consider school enrolment as their outcome of interest. (Warren and Hamrock 2010) look specifically at the high school completion and find no effect of minimum wages thereon. McMullen (2011) finds an increase in homework time by students when minimum wage increases. Lastly, Smith (2021) shows that increasing minimum wage substantially increases educational attainment of US teens from low socio-economic backgrounds.

3.2 Minimum wages and on-the-job training

The on-the-job training literature is a smaller strand with only 13 comparable empirical papers over 40 years period. The standard setting is based on regressing training on a minimum wage dummy or a continuous index of minimum wage intensity. The training variable can be a dichotomous variable representing training incidence over a particular time interval, or training intensity, which can be a duration variable of hours, days, or weeks. Studies use either individual level data or firm level data. The specifications used by Neumark and Wascher (2001) and Acemoglu and Pischke (2003) are the most representative of the field:

$$(3) \qquad T_{ijt} = \delta MW_{ijt} + X_{it}\beta + \gamma_i + \theta_j + \tau_t + \epsilon_{ict}$$

$$(4) \qquad \Delta T_{ijt} = \delta \Delta MW_{ijt} + \Delta X_{it}\beta + \Delta\tau_t + \Delta\epsilon_{ijt},$$

where T_{ijt} is a training variable for individual i in state j and year t. MW_{ijt} is a measure of whether (or how much) the minimum wage binds for individuals. Some studies use aggregate state-level data, thus the index i from the above equations does not apply. Three studies use firm level training data (Simpson; 1984; Fairris and Pedace 2004; Bellmann *et al.* 2017). The specification used by Bellmann *et al.* (2017) is similar to Equation (3):

$$(5) \qquad T_{it} = \left(MW_i \cdot D_t^{post}\right)\delta + X_{it}\beta + \theta_i + \tau_t + \epsilon_{it}.$$

In this case T_{it} is a dichotomous variable of whether the ith firm trains in t, or it is a proportion of workers trained within firm.

Similarly to the enrolment literature, there are several distinct time periods of empirical research on the minimum wage effect on training. Each has its unique characteristics. The early studies of the 1980s used USA and Canada individual survey data and identify the minimum wage effect utilizing variation in the minimum wage setting across states. The first empirical study in this literature is Leighton and Mincer (1981), who use data from the National Longitudinal Survey (NLS) and Michigan Panel of Income Dynamics (MID) to show cross-sectional evidence of a negative effect of minimum wages on self-reported training for both white and black males. Hashimoto (1982) used NLS data to model whether the minimum wage was binding in the previous period on the change in training variable. The analysis is limited to young workers (14-24) and shows negative effects of training, albeit the effects are only weakly significant. Simpson (1984) reports the first evidence from Canada. Utilizing the variation in provincial minimum wages, Simpson (1984) finds no significant effect of minimum wages on training duration at the firm level.

Schiller (1994) starts a second wave, characterized by improved econometric specification and modelling of how the minimum wage effects are best identified. Schiller (1994) estimates the effect of minimum wages for workforce entrants on their self-reported training incidence using a NLS data. The analysis reveals an overall negative effect of minimum wages, albeit it was significant only the still-in-school sample of workers. Grossberg and Sicilian (1999) find that the amount of training provided to minimum wage workers is not significantly different to other low-wage workers. The milestone in this research area is Neumark and Wascher (2001) and Acemoglu and Pischke (2003). These papers use the CPS and NLS datasets and set the econometric standards of estimating the effect of minimum wage on training using fixed effects. Neumark and Wascher (2001) regress a training incidence variable on percent by which the state minimum exceeded the federal minimum, i.e. use variation in state minimum wages before the new federal minimum was set. The estimated effects are largely negative, but driven by formal training, while informal training remains unchanged when minimum wage increases. Acemoglu and Pischke (2003) estimate the effect using an equation in levels and in first differences and are the first to use time fixed effects and standard errors adjusted for individual effects. In both cases they find largely mixed effects on training, depending on the competitiveness of industry. The crucial difference lies in the definition of the affected group of workers. In Neumark and Wascher (2001) these are all young workers, while in Acemoglu and Pischke (2003) the treated workers are only those very close to the minimum wage in the previous period.

Commencing in 2004, the last wave in this research reports evidence from Canada, Germany, Japan, and the UK. Arulampalam *et al.* (2004) offer the first analysis of the effects of the UK national minimum wage, finding no training effects for the high-wage group and a weakly positive significant effect on training of low-wage workers. Fairris and Pedace (2004) find no robust negative effect on training using firm-level data for the USA. Baker (2005) uses individual survey data to estimate the effect of varying minimum wages across Canadian provinces on several types of training and finds a consistently negative effect only on job-related training. Bellmann *et al.* (2017) use German establishment data to assess the effect of the 2015 increase in the statutory minimum wages on training incidence and intensity provided by firms. They find no effect on training incidence and a small negative effect on the share of workers trained. Hara (2017) uses the variation in minimum wages across Japanese prefectures to identify the effect on formal and informal on-the-job training of women assuming the treatment group are low educated females only. She finds consistent reduction in training provision, but only for formal training. The most recent study is by Papps (2020) who estimates the effect of a UK regulation which imposed a minimum wage for adult apprentices of age 19 after one year of apprenticeship. Papps finds a reduction of apprentices in this age category among compliant firms.[2] Table 2 offers a chronological overview of this literature.

Table 2

Studies included in the meta-analysis of minimum wages and *on-the-job training*

Study	Country	Dataset	No. of estimates	Period	Estimation model	Estimation method
	(1)	(2)	(3)	(4)	(5)	(6)
Leighton and Mincer (1981)	USA	NLS/ MID	34	1967-1971 1969-1976	linear	OLS
Hashimoto (1982)	USA	NLS	4	1966-1969	log-linear	GLS
Simpson (1984)	Canada	HRS	4	1979	tobit	ML
Schiller (1994)	USA	NLSY	1	1978-1987	logit	ML
Grossberg and Sicilian (1999)	USA	EOPP	8	1980, 1982	tobit	ML
Neumark and Wascher (2001)	USA	CPS	135	1983, 1991	linear	DID
Acemoglu and Pischke (2003)	USA	NLSY	66	1987-1992	linear	GLS
Arulampalam *et al.* (2004)	UK	BHPS	12	1998-2000	linear	DID
Fairris and Pedace (2004)	USA	NES	51	1996-1997	linear, tobit	OLS, DID, IV, GMM, ML
Baker (2005)	Canada	AETS	39	1992, 1994, 1998	logit, linear	ML, OLS
Bellmann *et al.* (2017)	Germany	IAB EP	42	2011-2015	linear	DID, PSM
Hara (2017)	Japan	HRDS/ ESS	14	2004-2009	linear, probit	DID
Papps (2020)	UK	APS	18	2014, 2016, 2018	linear	RDD

Notes: Grey horizontal lines mark the three distinct periods discussed in Section 3.2. Abbreviations in Column 2 are: MID: Michigan Panel of Income Dynamics, HRS: Human Resources Survey, EOPP: Employment Opportunities Pilot Project, BHPS: British Household Panel Survey, NES: National Employer Survey, AETS: Adult Education and Training Surveys, IAB EP: Institut für Arbeitsmarkt und Berufsforschung Establishment Panel, HRDS/ESS: Basic Survey of Human Resources Development/Employment Status Survey, and APS: Apprenticeship Pay Survey. In column 6 PSM stands for propensity score matching. Other abbreviations as in Table 1.

There are two additional studies on training but these use an indirect estimation approach where the training variable is proxied by wage growth. Lazear and Miller (1981) use

[2] We include Papps (2020) here, even if this study discusses the minimum wage effect on apprenticeship training. We limit our collection only to effect estimates related to adult apprentices (age 18-19). In the UK these are contract workers. Thus, they are in an equivalent situation as young low-skilled workers in the USA, or other countries without an apprenticeship system.

NLS data and estimate change in accumulated experience on wage growth in minimum wage covered industries, finding no significant difference in wage growth between covered and non-covered sectors. Fleisher (1981) also uses the Lazear and Miller (1981) approach in a longitudinal analysis of NLS data and finds negative effects on wage growth for minimum-wage covered workers. Haepp and Lin (2017) use a comparable training measure from census data of Chinese establishments. They exploit geographical and intertemporal variations of county-level minimum wages in China and find a significant reduction in training driven mainly by state-owned companies. We exclude this study as its state-owned focus is incompatible to the other studies in our analysis.

4 META-DATA

Empirical studies use a variety of metrics for the minimum wage, enrolment, and training variables. To ensure comparability in the reported estimates, we convert all estimates into partial correlations, r, and underlying standard errors, using the original t-values and degrees of freedom (df) as:

$$(6) \qquad r = \frac{t}{\sqrt{t^2+df}} \quad \text{and} \quad SE(r) = \sqrt{(1-r^2)/df}\,.$$

r is a unitless measure and allows comparisons of effects across studies even with alternate measures of variables. r is interpreted as a correlation coefficient (Stanley and Doucouliagos 2012).[3]

Tables 3 and 4 report descriptive statistics of the variables. t-statistics, standard errors, sample size and degrees of freedom are common to both literatures. For each of the two literatures, we group the moderator variables used to assess heterogeneity in reported estimates into five categories: (i) dataset related, (ii) socio-demographic sample characteristics; (iii)

[3] We attempted to calculate elasticities. However, in most cases, we had low confidence in these calculations due to lack of information in the primary studies.

measurement or specification details; (iv) empirical approach details; and finally (v) outlet details.

4.1 Meta-data: Educational enrolment

The average partial correlation in the enrolment literature is 0.001, effectively zero. However, there is a substantial variation in r spanning from -0.6 to 0.8. The average $SE(r)$ is high compared to the average r signaling that many effects are very imprecisely estimated. The average t-value is negative, -0.685, and denotes statistical insignificance. The degrees of freedom vary substantially and largely depend on whether the study employs region-year data or individual-year data, and furthermore, whether it employs fine grained fixed effects or not.

More than half of the estimates use US data and 10% relate to developing countries. The data spans from 1960 to 2014, but most estimates are based on data from 1990s. Only 20% of estimates are based on data from the 1950s-70s which is our reference category. Studies use either aggregated data on the region-year or individual-year level. Estimates from the latter category make 36% of the total.

The enrolment literature naturally focuses on young people. The average age is 19, but the literature considers ages spanning 14 to 32. Most estimates are not based on gender specific datasets, with only 10% based on female-only and 16% on male-only subsamples. Very few estimates report effects for explicitly white-only individuals (10%) or non-white-only (5%) subsamples. Estimates for individuals from low-income background are distinguished in 7% of cases.

The minimum wage is specified in two broad ways: as a dummy, which happens in 10% of cases, or more commonly as a continuous variable, e.g. as an index, ratio, or directly as a real value or as a natural log. Similarly, there are two ways of specifying the enrolment variable. About one third of the estimates stem from Equation (1) specifications. From these studies we always have a pair of estimates: the enrolment + employment rate or the enrolment + non-employment as dependent variable. The other 70% of estimates refer to *total* enrolment without any further breakdown by employment.[4] 35% of estimates report the minimum wage effect on post-secondary enrolment, while the majority estimate the effect on secondary school enrolment. Only 10% of estimates focus specifically on part-time enrolment, with the other estimates focusing either on full-time enrolment or making no distinction between these two categories. In 35% of cases the original regression controls for compulsory school laws and in almost 70% of cases it controls for unemployment.

Studies differ also in their empirical approach. Non-linear approaches, such as binary, multinomial logit or probit are used in slightly less than half of the cases. The other half of the estimates stem from linear or log-linear specifications. About one quarter of the studies control endogeneity via DID or RD approaches. More than half of the estimates use some fixed effects, but only about one third of estimates apply clustered standard errors. Finally, 32% of estimates are from studies that did not undergo a peer review process, disseminated as working papers or books, and 28% of estimates were published in a labour economics field journals.

Table 3

Descriptive statistics of variables used in the *enrolment* MRA

	Mean	Std. dev.	Min	Max
Effect estimate				
Partial correlation, *r*	0.001	0.139	-0.585	0.802
Standard error of *r*	0.052	0.056	0.002	0.277
Degrees of freedom	14814	37114	13	220477
t-statistics	-0.685	1.971	-6.444	5.324
Dataset				
USA study	0.604	0.49	0	1
Developing country	0.102	0.303	0	1
Mid-year of data	1990.5	13.7	1960	2013.5
1980s data	0.191	0.394	0	1
1990s data	0.402	0.491	0	1

[4] There are some studies that report both types of estimates (e.g. Wescher *et al.* 2019).

2000s data	0.191	0.394	0	1
Individual level data	0.359	0.48	0	1
Socio-demography				
Average age	19.162	3.677	14.5	31.5
Females	0.104	0.306	0	1
Males	0.163	0.37	0	1
Whites	0.096	0.294	0	1
Non-whites	0.052	0.223	0	1
Low-income	0.074	0.262	0	1
Measurement and specification				
Enrolment + employment	0.154	0.362	0	1
Enrolment + non-employment	0.154	0.362	0	1
Min. wage dummy	0.100	0.300	0	1
Post-secondary enrolment	0.354	0.479	0	1
Part-time enrolment	0.091	0.288	0	1
Control for CSL	0.348	0.477	0	1
Control for unemployment	0.685	0.465	0	1
Empirical approach				
Non-linear model	0.45	0.498	0	1
Causal method	0.252	0.435	0	1
Some fixed effects	0.624	0.485	0	1
Clustered SEs	0.354	0.479	0	1
Outlet details				
Not in a journal	0.317	0.466	0	1
Labour economics journal	0.278	0.449	0	1

Notes: $k = 25$ and N = 460. CSL stands for compulsory school law.

4.2 Meta-data: On-the-job training

We report descriptive statistics of estimates of training effects along with relevant moderators in Table 4. This average effect is small and negative, *r* = -0.013. Compared to the enrolment literature, the range is much smaller, varying between -0.10 and 0.10. Similarly, there is less variation in degrees of freedom and underlying *t*-values.

There is less variation in country-specific datasets. There are nine USA studies (Table 2) which translate into 70% of all estimates. Similarly to the enrolment literature, the reported estimates cover five decades from 1968 until 2016. To control the passage of time, we define, based on the mid-year of data, three decades dummies, and use the 1960s/70s as the reference category. Finally, most of the available estimates draw on individual-level data, but 23% of estimates are based on the firm-level data.

There is some variation across socio-economic characteristics of the samples. Half of the samples are younger, below age of 26, workers. Explicit effects on low-skilled workers are reported in 21% of the estimates and male-only subsamples comprise 14%.[5] The remaining estimates use data from both genders which is our reference category.

Again, there is variation in measures of the key variables. 20% of estimates are based on a minimum wage dummy variable instead of a continuous minimum wage. Most studies use a training incidence dummy as a measure of individual or firm training, but 27% of estimates are based on some continuous measure of training intensity, e.g. as training duration or training expenditures, and 11% of estimates assess changes in training. There are multitude of training types. The training the literature studies is in general any type of job-related training. But we have distinguished via a dummy variable an effect on formal and firm-specific training. From a theoretical perspective a stronger effect is expected here. Even if experience and tenure are pivotal variables determining training decisions, only about half of the estimates stem from a specification controlling for it.

Non-linear approaches are less frequently used here than in the enrolment literature. Only 16% of estimates stem from logit or Tobit models, the remaining estimates are based on linear or linear probability models. Contrary to enrolment literature, estimates from studies which control for endogeneity, via using DID, RD, or IV approaches, make up more than one half of the total. Similarly, more than half of the estimates use some fixed effects, but only one quarter of estimates are accompanied by clustered standard errors. Most of the estimates passed a regular journal peer review process, as only 21% of the estimates are only published in a

[5] Only a very small fraction (4%) of the estimates in 2 studies is based on female workers. Due to this insufficient variation, we do not use this moderator.

book, report or working paper. Labour and labour relations journals are the leading publication outlets for this literature.

Table 4

Descriptive statistics of variables used in the *on-the-job training* MRA

	Mean	Std. dev.	Min	Max
Effect estimate				
Partial correlation (r)	-0.013	0.024	-0.1	0.078
Standard error of r	0.017	0.013	0.005	0.072
Degrees of freedom	12084	11711	191	41503
t-statistics	-0.909	1.225	-4.327	2.65
Dataset				
USA study	0.699	0.459	0	1
Mid-year of data	1992.5	11.6	1968	2016
1980s data	0.336	0.473	0	1
1990s data	0.393	0.489	0	1
2000s data	0.173	0.379	0	1
Firm level data	0.227	0.419	0	1
Socio-demography				
Young workers	0.481	0.5	0	1
Males	0.14	0.348	0	1
Low educated/skilled	0.206	0.405	0	1
Measurement and specification				
Training intensity	0.271	0.445	0	1
Change in training	0.112	0.316	0	1
Formal or specific training	0.551	0.498	0	1
Min. wage dummy	0.201	0.401	0	1
Control for experience/tenure	0.456	0.499	0	1
Empirical approach				
Non-linear model	0.157	0.364	0	1
Causal method	0.558	0.497	0	1
Some fixed effects	0.537	0.499	0	1
Clustered SEs	0.245	0.431	0	1
Outlet details				
Not in a journal	0.213	0.41	0	1
Labour economics journal	0.6	0.49	0	1

Notes: $k = 13$ and N = 428.

5 META-REGRESSION METHODOLOGY

We perform the MRA in three consecutive steps. First, we provide an estimate of the overall effect size based on the population of reported research results. This estimate is known as the unconditional meta-average:

(7) $$r_{ij} = \beta_0 + \varepsilon_{ij},$$

where r_{ij} is partial correlation based on ith estimate from the jth study. By unconditional we mean no allowance is made for heterogeneity. In line with most meta-analyses in economics, estimation is with unrestricted weighted least squares (UWLS) using inverse variance weights (Stanley and Doucouliagos 2012; 2015).

In the second step, we correct the evidence base for the effects of publication selection bias. Publication selection bias typically inflates reported estimates and hence biases meta-averages. The most widely used method for correcting the evidence base of publication selection bias involves some variant of the Egger regression (Egger *et al.* 1997; Stanley 2001; Stanley and Doucouliagos 2012), regressing an effect size, which is the partial correlation, *r*, in our case, on a constant and the standard error of the partial correlation, *SE*:

(8) $$r_{ij} = \beta_0 + \beta_1 SE_{ij} + \varepsilon_{ij}.$$

Equation (8) is known as the 'Funnel Asymmetry, Precision Effect Test' (FAT-PET); see Stanley and Doucouliagos (2012). This is also estimated using UWLS. β_1 provides an estimate of the magnitude and direction of publication selection bias, while β_0 provides an estimate of the underlying empirical effect, corrected for publication selection bias (see Stanley and Doucouliagos 2012 and references therein). If researchers prefer statistically significant results, then they will search through datasets, specifications, and estimators until they attain a given level of statistical significance. This would then result in an association between the reported estimated effect size and its estimated standard error. Hence, if there is no publication selection, then $\beta_1 = 0$.

Equation (8) does not identify the factors that may drive heterogeneity in reported estimates and the propensity to differentially report results. Thus in the third step, following Stanley and Doucouliagos (2012) and current strategies for MRA (Irsova *et al.*, 2023), we estimate a more general model, accounting for both heterogeneity and publication selection bias:

(9) $$r_{ij} = \beta_0 + \sum_m \beta_m \boldsymbol{z}_{mij} + \beta_1 SE_{ij} + \sum_n \delta_n \boldsymbol{k}_{nij} \cdot SE_{ij} + v_{ij},$$

where $\boldsymbol{z}$ are variables modelling heterogeneity of the reported estimates and $\boldsymbol{k}$ are variables that influence publication selection. If estimated effects do not vary with an mth component of $\boldsymbol{z}$, the underlying $\beta_m = 0$. Similarly, if an nth vector of $\boldsymbol{k}$ does not cause any asymmetry around the meta-average, its coefficient, $\delta_n = 0$. We use the coefficients from Equation (9) to derive conditional estimates.

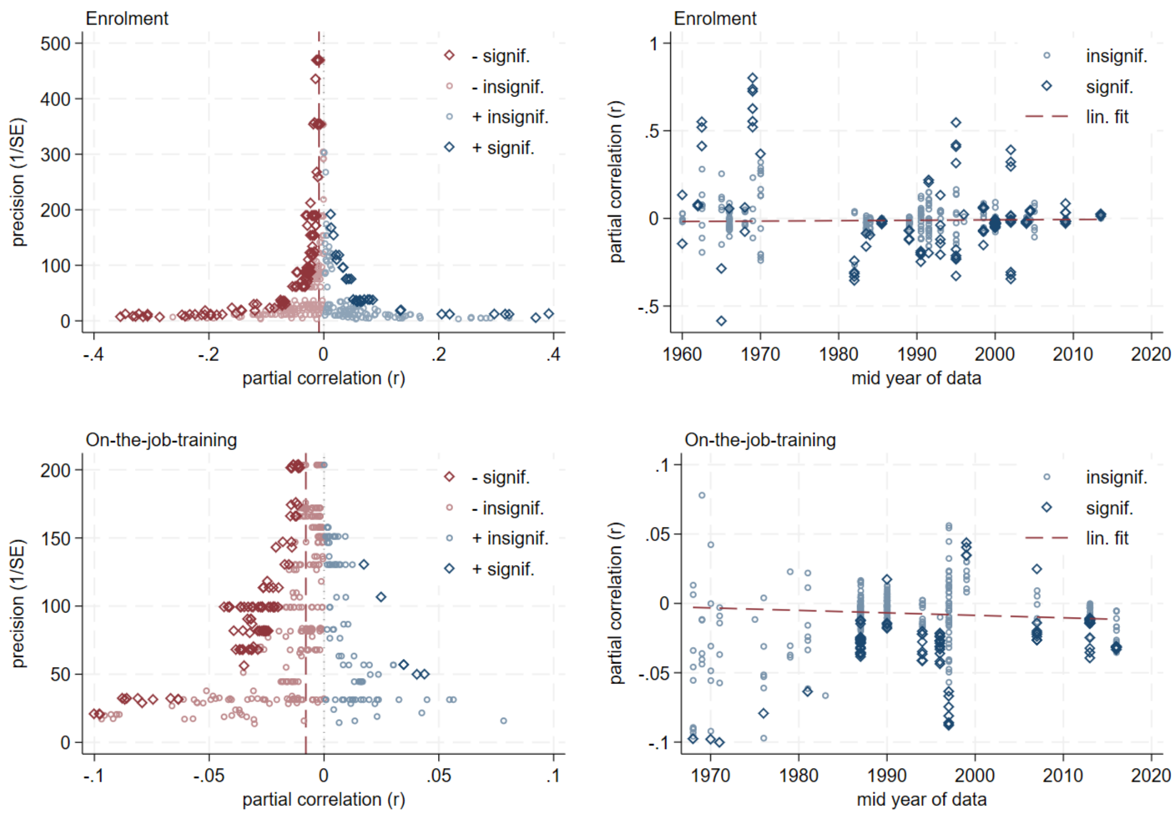
We collected all estimates of minimum wage effects on enrolment and training. Following MAER-Net guidelines and current practice in MRA (Havránek *et al.* 2020, Irsova *et al.*, 2023), we remove outliers and leverage points. To identify outliers, we first estimate Equation (7) using all observations. We then identify as an outlier any estimate with a standardized residual greater than 2.5. With outliers removed, we then identified leverage points as any estimate whose DFBETA was greater than $2/\sqrt{n}$ (see Belsley *et al.* 1980). This procedure identifies 27 estimates as outliers or leverage points in the enrolment literature and 15 in the training literature. We perform our baseline meta-analysis on the estimates without outliers and leverage points; see the Appendix (Table A1) for estimates using the full data sets.

6 RESULTS

Figure 1 (left) depicts ‘funnel plots’, partial correlations against their precision, for both literatures distinguishing them by sign and significance. This illustrates the distribution of reported minimum wage effects and can potentially indicate publication selection bias if there is an asymmetry in the distribution (Stanley and Doucouliagos 2012). Visual inspection suggests asymmetry in the distributions with possibly more asymmetry in the training literature. This may indicate a preference to report negative effects of minimum wages. Figure 1 (right) plots time trends using the mid-year of data. There is hardly any discernible trend; the slope for enrolment is 0.0002 while for training it is -0.0002.

Figure 1

Funnel plots and trends in estimated effects



Notes: <u>Left side:</u> Funnel plots of N = 460 and N = 428 partial correlations of minimum wage effects on enrolment (top) and on training (bottom), respectively. The vertical dashed lines depict the underlying meta-averages weighted by squared precision, which are in both cases about -0.008. 13 correlations of the effect on enrolment where abs(r) > 0.4 are not shown. Precision is calculated as 1/standard error of the partial correlation. Right side: Linear trends in partial correlations of enrolment (top-right) and training (bottom-right). Dashed line depicts the trends in the mid-year of data.

6.1 Unconditional meta-averages

In this section we report meta-averages of the full sample and various subsamples. We estimate Equations (7) and (8), i.e. we report averages without and with correction for publication bias. Table 5 reports six different unconditional meta-averages. These are estimates of the mean of the distribution of reported effects of minimum wage on enrolment (or training) without taking heterogeneity into account. The weighted average partial correlation is about -0.01 for both literatures. According to Cohen (1988), a correlation of 0.1 or less is small. Hence, Table 5 suggests that the overall effect of minimum wages on human capital investment is negative, but on average negligible. Minimum wage policies have only a very small adverse effect on individual enrolment decisions and workers' training.

The meta-averages for both literatures remain stable when limiting the sample to only main estimates, i.e., excluding robustness and sensitivity estimates (Column (2)), excluding estimates from unpublished studies (Column (3)), and using the more precise estimates only (Column (4)). The FAT-PET test suggests no publication bias in the enrolment literature (Panel A, Column (5)). For the training literature, there is evidence of publication bias with a preference for reporting adverse effects on training. Correcting for this bias reduces the meta-average which then becomes statistically zero (Panel B, Column (5)). Nevertheless, the coefficient on publication bias (-0.623) suggests that bias is not substantial in this literature. The PET-PEESE conditional estimator gives a less biased estimate of the meta-average if there is an underlying effect. These results are reported in Column (6).[6]

[6] To explore the robustness of publication bias assessment, in the Appendix (Table A2) we report several alternative models or weighting (FE, RE, WAAP, double weighting).

Table 5

Unconditional meta-average effect of minimum-wage on *enrolment* and *training*

	All estimates	Main estimates	Estimates published in journals	Top 10% most precise estimates	FAT-PET	PET-PEESE
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Enrolment literature						
Meta-average	-0.008	-0.008	-0.009	-0.008	-0.008	-0.009
	(-6.54)***	(-6.36)***	(-6.28)***	(-7.79)**	(-7.45)***	(-6.55)**
SE					-0.086	
(pub. bias)					(-0.35)	
SE^2						1.572
						(0.72)
I^2 (%)	98.61	96.85	97.87	97.53		
N / k	460 / 25	218 / 25	314 / 16	46 / 3	460 / 25	460 / 25
Panel B: On-the-job training literature						
Meta-average	-0.008	-0.008	-0.006	-0.008	-0.003	-0.007
	(-4.31)***	(-3.34)***	(-4.82)***	(-12.52)*	(-1.19)	(-3.65)***
SE					-0.623	
(pub. bias)					(-2.39)**	
SE^2						-13.632
						(-3.33)***
I^2 (%)	98.06	95.54	97.52	0		
N / k	428 / 13	181 / 13	337 / 10	43 / 2	428 / 13	428 / 13

Notes: The dependent variable is the partial correlation between minimum wage and enrolment (Panel A), or between minimum wage and training (Panel B). All estimations use unrestricted weighted least squares with inverse variance weights (Equation 7). Figures in parentheses are *t*-statistics, using standard errors adjusted for clustering of estimates within studies. N and k denote the number of estimates and studies, respectively. I^2 measures the percentage of variation in reported estimates attributed to heterogeneity. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. In the Appendix (Table A1) we report the same set of meta-averages, but using full sample, i.e., including outliers and leverage points. Column (5) reports FAT-PET estimates of the meta-mean and publication bias, Equation (8).

6.2 *Accounting for heterogeneity and publication bias*

Even if the overall meta-mean is negligible, the funnel plots (Figure 1) for both literatures reveal substantial heterogeneity in reported partial correlations. Such heterogeneity may arise naturally in empirical economics where researchers have different datasets at hand. As time passes, authors naturally employ newer data to study more recent minimum wage legislations. Datasets also differ by aggregation. In the enrolment literature some scholars employ individual level data, while others work with more aggregated datasets on a region-year breakdown. Similarly, in the training literature, most scholars work with individual survey data, but some authors assess firm-level data. Some researchers use data only for a specific age, gender, income background, or racial groups. Further heterogeneity arises from alternate measures of the relevant variables, i.e. how enrolment and training are operationalized and what is then their underlying meaning. Similarly, the core variable of interest, the minimum wage, varies across studies and this determines how the effect of minimum wages is identified. Two broad formats are clearly recognizable in both literatures. The first type uses a continuous measure of minimum wages which has in its core a real minimum wage level, sometimes further indexed by the mean or median wages for a subcategory of interest. In this case the minimum wage effect is identified due to variation in the minimum wage strength, sometimes called "bite''. The second type, however, defines the minimum wage as a change from zero to 1. In such cases identification is driven by changes from no to a binding minimum wage policy. We show below that these definitional distinctions cause significant heterogeneity among the reported estimates. Lastly, studies differ in their empirical approaches, e.g. the chosen econometric model, linear vs. non-linear, or applying a causal vs. correlational approach, and they differ in terms of control variables, fixed effects, or clustering of standard errors. We use this last group of moderators for modelling both effect heterogeneity and bias heterogeneity.

All these factors may create heterogeneity in the reported effects. The multivariate meta-regression model, Equation 9, helps to identify which differences are significant sources of heterogeneity. After close examination of the literature, we are confident that the moderator variables listed in Tables 3 and 4 cover the overwhelming majority of observable differences in these two literature strains: (i) data, (ii) socio-demographic, (iii) specification and measurement, and (iv) modelling and outlet specific moderators. This approach expands the FAT-PET model (Table 5, Column (5)) so that we can further assess the relative contribution of moderators to overall heterogeneity. While most specifications only assume heterogeneity in the reported estimates ($\boldsymbol{z}$ moderators), we also allow publication bias to have a multivariate format (via ***k*** moderators), i.e. a more complex structure of publication bias. The meta-analysis literature offers little guidance on which ***k*** variables should be included. Here, we focus on four variables that may be employed at the discretion of authors: estimate nonlinear models, estimate causal models, include fixed effects, and/or cluster adjust standard errors.

Table 6 reports estimates of these models for the minimum wage–enrolment literature. Columns (1) to (4) report estimates of Equation (9) with expanding sets of moderator variables (***z***). In the fifth column we include a multivariate treatment of publication bias. For brevity of exposition, Tables 6 and 7 report only those moderators that are statistically significant in at least one specification. The full set of results are reported in the Appendix, Tables A3 and A4. Given the *ex-ante* model uncertainty regarding the choice of moderator variables to include in Equation (9), we also use Bayesian model averaging (BMA) procedure to identify significant variables (Havránek, 2015). We report the ratio of estimated posterior means and standard deviations. When this ratio is at least 1.3, then the variable can be regarded to be statistically significant at least at the 10% level. These results are reported in Column (6) of Tables 6 and 7.

The MRA explains about 26% of the total variation in reported estimates (Table 6, Column (5)). A positive (negative) coefficient in Tables 6 and 7 means that the moderator variable has a smaller negative (positive) or larger positive (negative) correlation relative to the reference group.

With regard to data, we find differences in reported effects by country, time, and level of data aggregation. The minimum wage effect on enrolment is larger for students from low-income families. This effect is also large in relative terms; taking the meta-average effect of -0.01 into account (recall Table 5), it turns positive for this subgroup if we ignore all other factors. The operationalization of the enrolment variable also matters. Estimates using enrolment combined with non-employment are larger compared to enrolment only measures, which is the reference category. The use of a minimum wage dummy significantly affects the reported estimates, suggesting larger and on average positive effects, compared to studies identifying via variation over minimum wage ``bite´´. From the empirical approach moderators, only the causal method dummy shows a robust effect on reported estimates. The estimates are on average more negative when using a causal econometric approach. Clustering of standard errors seems to matter; the dummy variable remains significant as part of both ***z*** and ***k*** moderators using the BMA procedure. Even if the enrolment does not show an overall publication bias, there is a pocket of bias in the use of clustered standard errors and causal models.

Table 6

Heterogeneity and bias models in the minimum wage and *enrolment* literature

	Dataset	Socio-demography	Measurement and specification	Empirical approach / Outlet	Bias	BMA
	(1)	(2)	(3)	(4)	(5)	(6)
SE of *r*	0.261	0.202	0.506	0.149	0.367	**0.205**
	(1.26)	(0.86)	(1.78)*	(0.37)	(0.60)	**[2.217]**
Developing country	0.008	0.004	0.003	0.035	0.050	**0.048**
	(1.02)	(0.59)	(0.28)	(2.48)**	(2.88)***	**[4.662]**
Data decade 80s	-0.005	-0.005	0.004	-0.020	-0.042	**-0.042**
	(-1.75)*	(-1.25)	(0.47)	(-1.56)	(-2.32)**	**[4.044]**
Data decade 90s	0.003	0.002	0.006	0.007	-0.014	**-0.022**
	(0.38)	(0.33)	(0.56)	(0.51)	(-1.04)	**[2.110]**
Data decade 2000s	-0.002	-0.005	0.008	-0.014	-0.027	**-0.029**
	(-2.59)**	(-1.15)	(0.97)	(-0.48)	(-1.01)	**[1.873]**
Individual level data	0.018	0.019	0.008	-0.033	-0.043	**-0.042**
	(2.51)**	(2.37)**	(0.86)	(-1.38)	(-2.25)**	**[3.335]**
Males		0.012	0.006	0.003	0.001	0.000
		(2.01)*	(1.25)	(0.86)	(0.23)	[0.058]
Nonwhites		0.003	0.006	0.008	0.006	0.001
		(0.61)	(4.09)***	(2.89)***	(3.28)***	[0.304]
Low income		0.021	0.018	0.029	0.029	**0.030**
		(1.92)*	(1.86)*	(2.66)**	(2.85)***	**[4.575]**
Enrolment+ non-employment			0.008	0.009	0.012	**0.013**
			(1.74)*	(1.76)*	(2.63)**	**[4.630]**
Min. wage dummy			0.017	0.063	0.096	**0.087**
			(2.21)**	(1.99)*	(3.21)***	**[5.584]**
Post-secondary			-0.006	-0.005	-0.003	0.000
			(-2.09)**	(-1.40)	(-1.31)	[0.107]
Compulsory school			-0.033	-0.062	-0.024	-0.013

laws			(-2.56)**	(-2.15)**	(-0.81)	[0.798]
Unemployment			0.004	0.003	0.003	0.001
			(2.42)**	(1.24)	(2.25)**	[0.553]
Non-linear model				-0.004	-0.003	-0.001
				(-2.03)*	(-1.42)	[0.319]
Causal method				-0.066	-0.124	**-0.121**
				(-2.03)*	(-3.13)***	**[5.207]**
Clustered SEs				-0.007	0.046	**0.056**
				(-0.50)	(1.64)	**[4.789]**
Not in journal				-0.029	-0.001	0.001
				(-2.21)**	(-0.06)	[0.148]
Labor econ journal				-0.004	0.046	**0.052**
				(-0.12)	(1.42)	**[2.667]**
Causal method*SE					1.634	**1.707**
					(2.06)*	**[3.349]**
Clustered SEs*SE					-1.448	**-1.690**
					(-1.26)	**[4.461]**
Constant	-0.025	-0.032	-0.052	0.010	-0.000	**0.012**
	(-3.38)***	(-2.45)**	(-2.28)**	(0.26)	(-0.01)	**[2.502]**
Adjusted R2	0.091	0.112	0.201	0.232	0.257	

Notes: The dependent variable is the partial correlation between minimum wages and enrolment. N = 460 and k = 25. Table reports results of estimating the heterogeneity and selection bias model, Equation (9). A further nine moderators are included but were never statistically significant. These are not reported here for the brevity of exposition. We report the full results in the Appendix). All estimations are based on weighted least squares with inverse variance weights. Figures in parentheses are *t*-statistics, using standard errors adjusted for clustering of estimates within studies. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Column (6) reports the estimated coefficients and the absolute posterior Mean/SD ratio in brackets from Bayesian model averaging with univariate prior and g-prior being $\sqrt{N}$. Significant coefficients, with Mean/SD ratio>1.3, are marked bold.

In Table 7 we report the meta-analysis for the 428 estimates of minimum wage–on-the-job training effects.[7] In this literature, the total number of reported estimates is of similar size as in the enrolment literature, but there are fewer studies and less overall heterogeneity (c.f. Figure 1) and we also found fewer moderators for exploring heterogeneity in the training literature. Altogether the moderators explain almost 40% of the total variation in reported estimates (Column (5)).

USA estimates tend to be more positive, on average (+0.092). Estimates based on younger workers are only slightly smaller (-0.007), however not necessarily when the estimates

[7] Table 7 reports only the subset of at-least-once-significant, moderator estimates. See the Appendix, Table A4, for the full results.

are based on low educated or low skilled workers. The minimum wage effects are slightly (-0.003) more detrimental in estimations that could distinguish the formalized trainings, from other types of training. As is the case in the enrolment literature, the measurement of the minimum wage variable as dummy is related to somewhat larger effects. The minimum wage effect on training is smaller in models that control for tenure and experience. The estimates are on average more positive when using a nonlinear econometric model as tobit or logit/probit.

Using the FAT-PET model and some variants (c.f. Table 5 and Table A2) the training literature robustly exhibits a moderate negative bias, while there is small pocket of bias in the enrolment literature. Multiplying all four empirical approach variables with standard errors we study whether the bias is related to some of these choices. We identify clustered standard errors and fixed effects dummies as significant bias moderators. Our results suggest a small degree of bias in preference for positive effects on enrolment (0.266), that is effectively zero, and a modest to substantial degree of bias in preference for negative effects on training (-1.19).[8]

Table 7

Heterogeneity and bias models in the minimum wage and *training* literature

	Dataset	Socio-demography	Measurement and specification	Empirical approach / Outlet	Bias	BMA
	(1)	(2)	(3)	(4)	(5)	(6)
SE of *r*	-0.590	-0.682	-0.550	-0.930	-1.424	**-0.887**
	(-2.21)**	(-3.60)***	(-1.55)	(-5.25)***	(-1.16)	**[3.672]**
USA study	0.013	0.008	0.006	0.084	0.092	**0.079**
	(2.18)**	(1.16)	(0.40)	(2.90)**	(3.02)**	**[4.779]**
Data decade 80s	0.015	0.010	0.020	-0.029	-0.046	**-0.034**
	(1.54)	(1.35)	(1.83)*	(-2.15)*	(-1.12)	**[2.687]**
Data decade 90s	0.018	0.008	0.014	-0.008	0.007	0.010
	(1.98)*	(1.20)	(1.13)	(-0.57)	(0.44)	[0.857]
Data decade 2000s	0.019	0.003	0.011	0.068	0.104	**0.086**
	(1.89)*	(0.35)	(0.52)	(1.84)*	(2.51)**	**[3.722]**
Firm level data	0.004	0.004	0.008	-0.033	-0.053	**-0.046**
	(1.80)*	(1.82)*	(0.71)	(-1.80)*	(-2.62)**	**[4.382]**
Young workers		-0.007	-0.005	-0.007	-0.007	**-0.007**

[8] These estimates are derived by factoring all the *SE* terms in Columns (5) of Tables 6 and 7. Using the BMA coefficients gives estimates of bias of +0.037 and -0.760, for enrolment and training, respectively.

		(-1.93)*	(-1.59)	(-5.21)***	(-6.40)***	**[3.958]**
Males		-0.003	0.003	-0.001	0.000	0.000
		(-2.59)**	(0.71)	(-0.61)	(0.00)	[0.167]
Low educated/skilled		0.006	0.006	0.005	0.001	0.000
		(2.18)*	(1.91)*	(2.47)**	(0.39)	[0.111]
Training intensity			-0.004	-0.007	-0.005	-0.002
			(-0.94)	(-2.06)*	(-1.77)	[0.736]
Formal/specific training			-0.003	-0.003	-0.003	**-0.002**
			(-2.31)**	(-2.85)**	(-3.22)***	**[1.730]**
Min. wage dummy			0.002	0.001	0.002	0.001
			(2.56)**	(1.90)*	(2.75)**	[0.633]
Experience/tenure			0.000	-0.058	-0.068	**-0.059**
			(0.01)	(-2.83)**	(-3.13)***	**[4.859]**
Non-linear model				0.012	0.011	**0.011**
				(2.57)**	(0.66)	**[2.582]**
Some FEs				0.033	-0.017	-0.001
				(5.39)***	(-0.37)	[0.085]
Clustered SEs				-0.018	0.011	0.001
				(-2.00)*	(0.64)	[0.191]
Not in a journal				-0.030	-0.028	**-0.019**
				(-1.31)	(-1.42)	**[1.749]**
Labor econ journal				-0.054	-0.049	**-0.038**
				(-2.44)**	(-2.26)**	**[3.533]**
Some FEs*SE					1.705	**1.182**
					(1.84)*	**[4.049]**
Clustered SEs*SE					-2.764	**-2.072**
					(-2.85)**	**[4.022]**
Constant	-0.029	-0.013	-0.022	0.009	0.030	0.004
	(-2.74)**	(-1.37)	(-1.33)	(0.41)	(0.60)	[0.259]
Adjusted R2	0.187	0.239	0.274	0.367	0.383	

Notes: The dependent variable is the partial correlation between minimum wages and training. N = 428 and k = 13. See *Notes* of Table 6 for further details.

6.3 Conditional meta-averages

We use coefficients from the estimated MRA models to estimate the conditional average minimum wage effect after considering publication bias and accounting for heterogeneity. We use only those variables that are statistically significant and confirmed by both UWLS and BMA in Tables 6 and 7. Following the recent recommendations of the meta-regression analysis in economics we search for baseline 'best practice' in both literatures (Irsova *et al.*, 2023)). We report such meta-averages in Table 8.

Using the UWLS estimates for enrolment (Table 6, Column (5)), and assuming a causal model that uses individual level data, we get a correlation of -0.117 for developing countries and -0.167 for developed countries. These correlations become -0.074 and -0.124 for aggregate level data. These negative effects are smaller for low-income workers. Equivalently, using the UWLS estimates confirmed by BMA for training (Table 7, Column (5)), we assume the best practice is the use of a nonlinear model that controls for experience or tenure. For the averages below we also impose that such model uses the most recent individual level data and assesses an effect on formal training. In this combination we get a correlation of 0.137 for the US data and 0.044 for other countries data. Using firm level data, these correlations become 0.084 and -0.009, respectively. The correlations become only little reduced, for young workers.[9]

Table 8

Conditional meta-averages

	Panel A. *Enrolment*			
	Developed countries		Developing countries	
	All workers	Low-income background	All workers	Low-income background
	(1)	(2)	(3)	(4)
Individual level data	-0.168	-0.139	-0.117	-0.088
	(-2.95)***	(-2.49)**	(-2.52)**	(-1.96)*
Aggregate level data	-0.124	-0.095	-0.074	-0.045
	(-3.13)***	(-2.40)**	(-2.50)**	(-1.51)
	Panel B. *Training*			
	USA		Other countries	
	All workers	Young workers	All workers	Young workers
	(1)	(2)	(3)	(4)
Individual level data	0.137	0.129	0.044	0.037
	(2.53)**	(2.41)**	(1.56)	(1.33)
Firm level data	0.084	0.076	-0.009	-0.016
	(1.95)*	(1.81)*	(-0.31)	(-0.57)

Notes: Panels A and B use UWLS estimates from Columns (5), Table 5 and Table 6, respectively. Panel A assumes the use of a causal model and continuous measure of the minimum wage. Panel B assumes a use of nonlinear model that control for experience/tenure and with the most recent data decade (2000s). Figures in parentheses are *t*-statistics; *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[9] If we instead use the BMA estimates (rather than the UWLS coefficients), we get broadly similar meta-averages.

7 CONCLUSIONS

Our MRA shows that, on average, minimum wages *reduce* education enrolment. This adverse effect is smaller for developing countries and for individuals from low-income backgrounds, but it is more pronounced when using individual enrolment data. The estimated correlation of -0.17 for developed countries using individual enrolment data is of small to moderate size and may be of practical significance. In contrast, we find that minimum wages *increase* training of US workers, with a correlation of 0.14 and has a small positive effect on training elsewhere (0.044). The adverse effect on enrolment appears to be larger than the positive effect on training. We find no evidence of publication bias in the education enrolment literature and a modest negative bias in the on-the-job training literature.

Our analysis also identifies several drivers of heterogeneity in reported estimates, in particular, data differences and the measurement of core variables and specification appear to be important. Other relevant sources of heterogeneity relate to the econometric approach, namely the use of a causal identification, clustered standard errors, nonlinear model, and inclusion of region and/or time fixed effects. These findings suggest that modelling choices can lead to different quantitative and qualitative findings. The only demographic characteristic that has an effect on heterogeneity is low-income background in the enrolment literature. In contrast with some theoretical predictions, educational enrolment of these individuals is less affected by minimum wages and minimum wages appear not to have a differentially large effect on the training of low-skilled workers.

Theory specifies a range of minimum wage effects, from reducing inequality (Krueger 2015) to reducing employment prospects and job quality features like training (Neumark and Wascher 2008). Prior studies show that minimum wages do not have a large adverse effect on employment. Our findings suggest that, on average, minimum wages reduce formal education, and increase training. The size of the enrolment effect appears to be larger than that for training.

The magnitude of these effects depends on the level of data aggregation and level of economic development (developed vs. developing and US vs other nations). In line with previous quantitative evidence on minimum wage effects, based on our meta-analysis we can exclude large adverse effects of minimum wages on human capital investment. An assessment of the overall effect of minimum wages requires quantitative reviews of the evidence on other outcomes, such as prices, productivity, and inequality.

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Online Appendix

A Meta-analysis of Minimum Wage Effects on Human Capital Investment

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Table of contents

Table A1

UWLS and FAT-PET meta-average effect of minimum-wage on enrolment and training including outliers and leverage points

	All estimates	Main estimates	Estimates published in journals	Top 10% most precise estimates	FAT-PET
	(1)	(2)	(3)	(4)	(5)
Panel A: Enrolment literature					
Constant	-0.004	-0.004	-0.004	-0.002	-0.003
	(-1.87)*	(-2.86)***	(-1.79)*	(-1.39)	(-1.27)
SEpartial					-0.344
					(-1.10)
I^2 (%)	99.2	97.95	98.85	64.53	
N / k	487 / 25	229 / 25	336 / 16	49 / 3	487 / 25
Panel B: On-the-job training literature					
Constant	-0.008	-0.006	-0.006	-0.007	-0.002
	(-3.73)***	(-1.69)	(-3.54)***	(-3.99)*	(-0.89)
SEpartial					-0.751
					(-3.08)***
I^2 (%)	98.74	96.82	98.58	0	
N / k	443 / 13	189/13	350/10	45/3	443 / 13

Notes: See Table 5 notes of the main text

Table A2

Effect beyond bias: FAT-PET and further alternatives

	FAT-PET	FE MRA	RE MRA	WAAP	FAT-PET double weighting
	(1)	(2)	(3)	(4)	(5)
*Panel A: **Enrolment** literature*					
Constant	-0.008	-0.011	-0.010	-0.013	-0.007
(effect beyond bias)	(-7.45)***	(-10.36)***	(-8.91)***	(-5.90)***	(-5.41)***
SE	-0.086	0.125	0.341	0.052	0.168
(publication bias)	(-0.35)	(1.60)	(1.32)	(0.08)	(0.59)
N	460	460	460	121	460
*Panel B: **On-the-job training** literature*					
Constant	-0.003	0.001	0.0003	0.003	-0.004
(effect beyond bias)	(-1.19)	(0.47)	(0.22)	(1.58)	(-1.16)
SE	-0.623	-0.978	-0.986	-3.148	-0.749
(publication bias)	(-2.39)**	(-6.66)***	(-3.17)***	(-7.36)***	(-1.98)*
N	428	428	428	55	428

Notes: The dependent variable is the partial correlation between minimum wage and enrolment (Panel A), or training (Panel B). Figures in parentheses are t-statistics, using standard errors adjusted for clustering of estimates within studies. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. Column 1 repeats the FAT-PET estimation of column 5 of Table 5 in the main text. See discussion below for the columns 2 to 5.

The meta-average from the FAT-PET regression (eq. 8) does not show any significant publication bias (Table A2, Panel A, column 1). Accordingly, the publication bias is not significant. On the contrary, the bias in the training literature is significantly negative and turns the meta-average to zero when accounted for it. To increase robustness of this finding we show additional models which accounts for publication bias (Table A2, Panel B, column 1). To probe robustness of this finding, we repeat the calculation of meta-averages acounting for publication bias, but using further methods (Table A2, columns 2 to 5). In columns 2 and 3 we report FAT-PET models with fixed and random study effects panel models, using the unbalanced panel structure of the meta data. Next we apply the WAAP approach, which includes only subset of adequately powered estimates, with power larger than 0.7, into the FAT-PET regression (Ioannidis et al. 2017). Lastly, we use in the FAT-PET regression with a double weighting procedure, where each estimate is weighted, additionally to squared precision, also by the inverse number of reported estimates per study, in order to scale down the weight of studies with many reported estimates. The conclusions on bias and effect beyond bias remain unchanged across models for both, enrolment and training literature.

Table A3

Heterogeneity and bias models in the minimum wage and *enrolment* literature

	Dataset	Socio-demography	Measurement and specification	Empirical approach / Outlet	Bias	BMA
	(1)	(2)	(3)	(4)	(5)	(6)
SE of *r*	0.261	0.202	0.506	0.149	0.367	**0.205**
	(1.26)	(0.86)	(1.78)*	(0.37)	(0.60)	**[2.217]**
USA study	-0.001	-0.000	0.002	0.011	0.009	0.001
	(-0.54)	(-0.13)	(0.22)	(0.96)	(1.16)	[0.275]
Developing country	0.008	0.004	0.003	0.035	0.050	**0.048**
	(1.02)	(0.59)	(0.28)	(2.48)**	(2.88)***	**[4.662]**
Data decade 80s	-0.005	-0.005	0.004	-0.020	-0.042	**-0.042**
	(-1.75)*	(-1.25)	(0.47)	(-1.56)	(-2.32)**	**[4.044]**
Data decade 90s	0.003	0.002	0.006	0.007	-0.014	**-0.022**
	(0.38)	(0.33)	(0.56)	(0.51)	(-1.04)	**[2.110]**
Data decade 2000s	-0.002	-0.005	0.008	-0.014	-0.027	**-0.029**
	(-2.59)**	(-1.15)	(0.97)	(-0.48)	(-1.01)	**[1.873]**
Individual level data	0.018	0.019	0.008	-0.033	-0.043	**-0.042**
	(2.51)**	(2.37)**	(0.86)	(-1.38)	(-2.25)**	**[3.335]**
Average age		0.000	0.001	0.001	0.001	0.000
		(0.91)	(1.38)	(1.25)	(1.24)	[0.194]
Males		0.012	0.006	0.003	0.001	0.000
		(2.01)*	(1.25)	(0.86)	(0.23)	[0.058]
Females		-0.002	0.001	0.000	-0.001	0.000
		(-0.36)	(0.20)	(0.11)	(-0.21)	[0.013]
Whites		-0.006	0.009	0.013	0.008	0.001
		(-0.72)	(1.27)	(1.25)	(1.03)	[0.216]
Nonwhites		0.003	0.006	0.008	0.006	0.001
		(0.61)	(4.09)***	(2.89)***	(3.28)***	[0.304]
Low income		0.021	0.018	0.029	0.029	**0.030**
		(1.92)*	(1.86)*	(2.66)**	(2.85)***	**[4.575]**
Enrolment+ employment			-0.005	-0.004	-0.001	0.000
			(-1.18)	(-1.01)	(-0.23)	[0.008]
Enrolment+ non-employment			0.008	0.009	0.012	**0.013**
			(1.74)*	(1.76)*	(2.63)**	**[4.630]**
Min. wage dummy			0.017	0.063	0.096	**0.087**
			(2.21)**	(1.99)*	(3.21)***	**[5.584]**
Post-secondary			-0.006	-0.005	-0.003	0.000
			(-2.09)**	(-1.40)	(-1.31)	[0.107]
Part-time enrolment			-0.001	-0.000	-0.000	0.000
			(-0.31)	(-0.08)	(-0.06)	[0.003]
Compulsory school laws			-0.033	-0.062	-0.024	-0.013
			(-2.56)**	(-2.15)**	(-0.81)	[0.798]
Unemployment			0.004	0.003	0.003	0.001
			(2.42)**	(1.24)	(2.25)**	[0.553]
Non-linear model				-0.004	-0.003	-0.001
				(-2.03)*	(-1.42)	[0.319]

Causal method				-0.066	-0.124	**-0.121**
				(-2.03)*	(-3.13)***	**[5.207]**
Some FEs				-0.000	0.002	0.000
				(-0.15)	(0.64)	[0.110]
Clustered SEs				-0.007	0.046	**0.056**
				(-0.50)	(1.64)	**[4.789]**
Not in journal				-0.029	-0.001	0.001
				(-2.21)**	(-0.06)	[0.148]
Labour econ journal				-0.004	0.046	**0.052**
				(-0.12)	(1.42)	**[2.667]**
Non-linear model*SE					-0.150	-0.036
					(-0.33)	[0.291]
Causal method*SE					1.634	**1.707**
					(2.06)*	**[3.349]**
Some FEs*SE					-0.356	-0.111
					(-0.87)	[0.586]
Clustered SEs*SE					-1.448	**-1.690**
					(-1.26)	**[4.461]**
Constant	-0.025	-0.032	-0.052	0.010	-0.000	**0.012**
	(-3.38)***	(-2.45)**	(-2.28)**	(0.26)	(-0.01)	**[2.502]**
Adjusted R2	0.091	0.112	0.201	0.232	0.257	

Notes: This is the full Table 6 of the main text. See Table 6 notes of the main text.

Table A4

Heterogeneity and bias models in the minimum wage and *training* literature

	Dataset	Socio-demography	Measurement and specification	Empirical approach / Outlet	Bias	BMA
	(1)	(2)	(3)	(4)	(5)	(6)
SE of *r*	-0.590	-0.682	-0.550	-0.930	-1.424	**-0.887**
	(-2.21)**	(-3.60)***	(-1.55)	(-5.25)***	(-1.16)	**[3.672]**
USA study	0.013	0.008	0.006	0.084	0.092	**0.079**
	(2.18)**	(1.16)	(0.40)	(2.90)**	(3.02)**	**[4.779]**
Data decade 80s	0.015	0.010	0.020	-0.029	-0.046	**-0.034**
	(1.54)	(1.35)	(1.83)*	(-2.15)*	(-1.12)	**[2.687]**
Data decade 90s	0.018	0.008	0.014	-0.008	0.007	**0.010**
	(1.98)*	(1.20)	(1.13)	(-0.57)	(0.44)	**[0.857]**
Data decade 2000s	0.019	0.003	0.011	0.068	0.104	**0.086**
	(1.89)*	(0.35)	(0.52)	(1.84)*	(2.51)**	**[3.722]**
Firm level data	0.004	0.004	0.008	-0.033	-0.053	**-0.046**
	(1.80)*	(1.82)*	(0.71)	(-1.80)*	(-2.62)**	**[4.382]**
Young workers		-0.007	-0.005	-0.007	-0.007	**-0.007**
		(-1.93)*	(-1.59)	(-5.21)***	(-6.40)***	**[3.958]**
Males		-0.003	0.003	-0.001	0.000	0.000
		(-2.59)**	(0.71)	(-0.61)	(0.00)	[0.167]
Low educated/skilled		0.006	0.006	0.005	0.001	0.000
		(2.18)*	(1.91)*	(2.47)**	(0.39)	[0.111]
Training intensity			-0.004	-0.007	-0.005	-0.002
			(-0.94)	(-2.06)*	(-1.77)	[0.736]
Change in training			0.008	0.001	0.002	0.001
			(1.01)	(1.06)	(1.24)	[0.488]
Formal/specific training			-0.003	-0.003	-0.003	**-0.002**
			(-2.31)**	(-2.85)**	(-3.22)***	**[1.730]**
Min. wage dummy			0.002	0.001	0.002	0.001
			(2.56)**	(1.90)*	(2.75)**	[0.633]
Experience/tenure			0.000	-0.058	-0.068	**-0.059**
			(0.01)	(-2.83)**	(-3.13)***	**[4.859]**
Non-linear model				0.012	0.011	**0.011**
				(2.57)**	(0.66)	**[2.582]**
Causal method				-0.002	-0.020	-0.004
				(-0.17)	(-0.84)	[0.597]
Some FEs				0.033	-0.017	-0.001
				(5.39)***	(-0.37)	[0.085]
Clustered SEs				-0.018	0.011	0.001
				(-2.00)*	(0.64)	[0.191]
Not in a journal				-0.030	-0.028	**-0.019**
				(-1.31)	(-1.42)	**[1.749]**
Labour econ journal				-0.054	-0.049	**-0.038**
				(-2.44)**	(-2.26)**	**[3.533]**
Non-linear model*SE					-0.009	-0.040
					(-0.01)	[0.168]
Causal method*SE					0.620	0.030
					(0.50)	[0.171]

Some FEs*SE					1.705	**1.182**
					(1.84)*	**[4.049]**
Clustered SEs*SE					-2.764	**-2.072**
					(-2.85)**	**[4.022]**
Constant	-0.029	-0.013	-0.022	0.009	0.030	0.004
	(-2.74)**	(-1.37)	(-1.33)	(0.41)	(0.60)	[0.259]
Adjusted R2	0.187	0.239	0.274	0.367	0.383	

Notes: This is the full Table 7 of the main text. See Table 7 notes of the main text.