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DISCUSSION PAPER SERIES

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ABSTRACT

Education Quality, Green Technology, and the Economic Impact of Carbon Pricing*

Carbon pricing is increasingly used by governments to reduce emissions. The effect of carbon pricing on economic outcomes as well as mitigating factors has been studied extensively since the early 1990s. One mitigating factor that has received less attention is education quality. If technological change that reduces the reliance of production on emissions is skill-biased, then carbon pricing may increase the skill premium of earnings and subsequent wage inequality; however, a more elastic skill supply through better education quality may mitigate adverse economic outcomes, including wage inequality, and enhance the effect of carbon pricing on technological change and subsequently emissions. A general equilibrium, overlapping-generations model is proposed, with endogenous skill investment in which the average skill level of the workforce can affect the need for emissions in an aggregate production function. This study uses data on industrial emissions linked to the Organisation for Economic Co-operation and Development's Programme for International Assessment of Adult Competencies dataset for European Union countries. The findings show that, within countries, cognitive skills are positively associated with employment in industries that rely less on emissions for production and in industries that, over time, have been able to reduce their reliance on emissions for production. In the estimated general equilibrium model, higher cognitive skills reduce an economy's reliance on emissions for production. Having higher quality education—defined as the level of cognitive skills attained by workers per unit of cost—increases the elasticity of skill supply and, as a result, mitigates a carbon tax's economic costs including output loss and wage inequity, and enhances its effect on emissions reduction. The implication is that investments in education quality are needed for better enabling green technological innovation and adaptation and reducing inequality that results from carbon pricing.

JEL Classification: Q43, O47, Q56, O41
Keywords: carbon pricing, education, skills, learning outcomes

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INTRODUCTION

It is argued that carbon pricing allows reaching the internationally accepted temperature targets at minimal cost (Gollier and Tirole 2015; Borissov, Brausmann and Bretschger 2019). The report of the Commission on Carbon Pricing explains the role of education and skilled labor for the transition to green growth (Stiglitz et al. 2017). It explains that production using clean technologies is human capital intensive so that education decisions become closely interlinked with the energy transition. At the same time, shortages of skilled labor may constrain the decarbonization process of an economy (Faye 2012). The OECD (2017) argues that the path to a green economy can only be made by developing the right skills. Carbon pricing - by its impact on human capital accumulation - may not only be the cornerstone of climate policy but may also act as a development policy, fostering technology switches and education of the labor force (Borissov, Brausmann and Bretschger 2019). Yet, one mitigating factor that has received less attention is education quality. If technological change that reduces the reliance of production on emissions is skill-biased, then carbon pricing may increase the skill premium of earnings and subsequent wage inequality; however, a more elastic skill supply through better education quality may mitigate adverse economic outcomes including wage inequality and enhance the effect of carbon pricing on technological change and subsequently emissions. This paper explores the role of skills as measured through cognitive achievement on emissions through carbon pricing in European Union countries.

Many governments are enacting policies to place a price on greenhouse gas emissions, including the establishment of carbon taxes and cap-and-trade systems, to reduce emissions. For example, 31 high income OECD countries have one or more carbon pricing schemes, including 14 countries with carbon or emissions taxes and 25 countries with an emissions trading system (Yunis and Aliakbari 2020). According to the World Bank's Carbon Pricing Dashboard (World Bank 2021), 27 countries have implemented a carbon tax nationally, and nine countries have implemented an emissions trading system; these figures exclude sub-national entities including provinces and states that have also implemented carbon pricing.

The economic impact of carbon taxes has been of considerable concern to policy makers, and a large body of literature has emerged on carbon taxes in particular since the early 1990s. The bulk of the literature estimates effects of a hypothetical carbon tax using computable general equilibrium models or input-output models, and these studies generally find a negative effect on output as measured, for example, by GDP, in the absence of the quantification of benefits of reduced emissions or specific methods of redistributing carbon tax revenues (for a review, see Timilsina 2018). A number of studies have predicted that carbon taxes will be regressive because lower income earners tend to allocate more of their expenditure towards goods and services more prone to carbon taxes (Fremstad and Paul 2017; Grainger and Kolstad 2010; Mathur and Morris 2014). The mechanism to redistribute the revenue of carbon taxes has emerged as a well-studied mitigating factor, as a means to make carbon taxes progressive (Goulder et al. 2019), have a lower effect on inequality (Liang and Wei 2012), and as a way to offset existing tax regimes that are distortionary, known as the double dividend, either reducing output loss (for example, Goulder et al. 1997; Parry 1997; Goulder 1998; Timilsina and Shrestha 2002; Meng et al. 2013; Allan et al. 2014; Alton et al. 2014; Mahmood and Marpaung 2014; Orlov and Grethe 2014; Tuladhar et al. 2015; Benavente 2016) or reversing the effect and increasing output (e.g.: McKitrick 1997; Jorgenson et al. 2015; McKibbin et al. 2015).

As Metcalf and Stock (2020a) note in their review, there is now, increasingly, long enough time-series data to empirically evaluate actual carbon taxes, and few negative economic effects have been found. For example, Metcalf (2019) found no negative effective of British Columbia's carbon tax on GDP using a difference-in-differences approach and no negative effect for European countries' GDP using panel data. Bernard, Kichian and Island (2018) applied a vector auto-regression approach and found no negative effect of British Columbia's carbon tax on GDP, while Yamazaki (2017) found this carbon tax increased employment in aggregate. Metcalf and Stock (2020b), using a similar methodology, found a non-negative effect for European countries' carbon taxes.

Part of the motivation of carbon pricing is to induce technological change, for example, by creating new industries that emit less carbon or by existing industries using different technology to produce the same goods with fewer emissions. A number of studies have developed endogenous technological change models to study how carbon taxes affect endogenous investment in R&D, which in turn affects economic outcomes and emissions, either as partial equilibrium models (for example, Gerlagh et al. 2009; Baker and Shittu 2006; Gerlagh and Lise 2005) or general equilibrium models (for example, Grimaud and Lafforgue 2008). This extends more general research on induced technological change in the environmental sector (Goulder and Mathai 2000; Nordhaus 2002; Buonanno 2003; Sue Wing 2003; Popp 2004).

The effect of carbon pricing on economic outcomes through technological change induced by carbon pricing and how this technological change interacts with workers' skills has received little attention in the literature so far, but it is potentially an important pathway for two reasons. First, skills have been shown to be a critical determinant of innovation and a potential enabling factor for technological change in general (see OECD 2011 for a review). A number of studies at the firm level, for example, have found that having higher human capital increases the likelihood that a firm will change production practices to reduce emissions and comply with environmental protection regulation (Blackman and Kildegaard 2010; Dasgupta et al. 2000; Gangadharan 2006; Lan and Munro 2013; Pargal and Wheeler 2006). Second, technological change has been characterized as skill-biased by a large body of literature (for example, Katz and Murphy 1992; Autor, Katz and Kearney 2008), and given this trend it is a reasonable hypothesis that technological change induced by carbon pricing is also skill-biased. Yao et al. (2020), for example, find that higher education is associated with reductions in emissions at the country level; though, the effect of higher education through technological change cannot be distinguished from changes in attitudes or beliefs and subsequently environmental policies.

If carbon pricing induces technological change that increases the productivity of higher skill workers relative to lower skilled workers or, to put it differently, if carbon pricing requires innovation that in turn increases demand for higher skilled workers relative to lower skilled workers, then carbon pricing has an economic impact through increased wage inequality. The elasticity of skill supply in the economy may act as mitigating factor both for the impact of carbon pricing on emissions reduction and on economic outcomes including wage inequality and output. This argument is parallel to skills and automation: if automation complements higher skilled workers' productivity, then the elasticity of skill supply, for example through the quality of education, enhances the economic benefits and mitigates costs of automation (Bentaouet Kattan, Macdonald and Patrinos 2020).

In this study, we test the hypothesis that cognitive skills, as an indicator of human capital overall, are associated with a lower reliance on emissions in aggregate production technology and estimate the subsequent mitigating effect of education quality on the carbon pricing's effectiveness and economic consequences including wage inequality. We propose a general equilibrium, overlapping-generations model in which: (1) agents are heterogeneous and their choice of skills is endogenous and (2) the average skill level of an economy affects the share of capital relative to carbon-emitting inputs in the aggregate production function. We then present two empirical applications. First, we test how workers' cognitive skills associate with their industries' emissions per output using the OECD's PIAAC data set with industrial emissions from the EU's environmental accounts data set. We find that cognitive skills are associated with lower emissions per output and lower or negative growth in emissions per output. This finding is consistent with the hypothesis that a higher skilled workforce is not only associated with industries that are able to produce output with less emissions but also able to innovate over time and reduce the amount of emissions required to produce output.

Second, we estimate: (1) our overlapping-generations model's aggregate production function parameters using industry level data on output, capital, emissions, and literacy skills from the same two sources and (2) our model's skills cost function conditional on household wealth using the OECD's PISA data. We find that higher literacy skills are associated with production technology in which capital has a larger contribution relative to emissions in production. In this sense, capital can substitute emissions through more highly skilled labor. This is consistent with technology imbedded in capital (for example, machines) that can produce output with fewer emissions requiring more highly skilled labor.

One result of this finding is that green technology—technology that enables production with fewer emissions—is skill-biased, in that workers with a higher level of literacy skills contribute more to reducing the production function's reliance on emissions relative to capital. We then estimate the marginal effects of a carbon tax based on our model's steady state variables and find that, like other general equilibrium models which do not quantify the direct benefits of reduced emissions for output (such as the benefits to health, agricultural production, and so on), carbon taxes reduce output and increase wage inequality. However, we also find that better education quality mitigates a carbon tax's negative effect on output and positive effect on wage inequality and, to a small extent, increases the impact of a carbon tax on emissions reduction.

These findings contribute to at least three areas of research. First, the finding that cognitive skills are associated not only with reduced emissions but also with technology that relies less on emitting-inputs relative to capital contributes evidence to the literature on human capital and climate change (for example, Yao et al. 2020) that education, specifically skills, has an effect on climate change through technological change. Second, the finding that cognitive skills are associated with these technological differences is consistent with green technology being skill-biased, which adds also to the literature on skill-biased technological change (see Autor, Katz and Kearney 2008 for a review). Third, that education quality is associated with reduced output loss and inequality resulting from carbon tax increases as well as higher emissions reduction adds another potential mitigating factor to the literature on carbon taxes and factors that mitigate economic cost and inequality (see Timilsinas 2018 for a review of research on mitigating factors).

THEORETICAL MODEL

The objective of our general equilibrium, overlapping-generations model is both to capture and allow estimation of the fundamental relationships between emissions, output, cognitive skills, capital, and the decisions to invest in cognitive skills by individuals, conditional on household wealth. Because our interest is in the interaction, demand and supply of skills, our starting point for our model is the typical overlapping generation models with endogenous choice in investment in skills (e.g.: Heckman, James, Lochner and Taber 1998), which typically comprise of an aggregate production function in which skills are rewarded.

Our aggregate production function, equation (1), maps inputs labor, L_t, capital, K_t, and carbon emitting-inputs measured by carbon emissions, E_t to output Y_t, at time *t*. Technology consists of exogenous total factor productivity, A_t, and capital augmenting technology, $A_{K,t}$. The functional form is Cobb-Douglas with the addition of an endogenous component to technology, $\alpha ln\left(\frac{H_t}{L_t}\right)$, in which the average cognitive skill level of the labor stock, $\frac{H_t}{L_t}$, determines the production share of capital relative to emissions. This functional form is relatively simple, and its parameters can be estimated using available data. It captures the hypothesis that capital that relies less on emissions requires a higher level of skills than capital that relies more on emissions for production.

$$Y_t = A_t(L_t)^{\beta}\left(\left(A_{K,t}K_t\right)^{\alpha ln\left(\frac{H_t}{L_t}\right)}(E_t)^{1-\alpha ln\left(\frac{H_t}{L_t}\right)}\right)^{1-\beta} \qquad (1)$$

A single-good aggregate production function, while typical in models of endogenous skill investment and skill-biased technology change, differs from the literature studying the effect of carbon taxes on endogenous technology change where R&D investment or demand for R&D is endogenous (e.g.: in Grimaud and Lafforgue 2008).

Labor in our model is heterogeneous and defined by skill level, h. The total number of workers with skill level h is given by distribution function $L_t(h)$, and the total stock of skills, H_t is given by $H_t = \int hL_t(h)dh$ and the total stock of labor by $L_t = \int L_t(h)dh$. It is assumed that $\alpha ln\left(\frac{H_t}{L_t}\right)$ remains within 0 and 1 for the range of H_t and L_t of interest and that β is also between 0 and 1. Wages for a given a worker with skill level h are given by $w_t(h)$; the rental rate of capital is $1+r_t$ and the price of carbon, for example a carbon tax, is denoted τ and assumed to be exogenous.

As for the consumer's problem, agents are heterogeneous and defined by an initial endowment of wealth, $k{\sim}f^k(k)$, and an exogenous level of ability, $\theta{\sim}\int f^{\theta}(\theta)$. We treat the labor stock as fixed at L. Because we do not have data on household or individual consumption and savings decisions with measures of individual skills, we model the consumer's problem as follows. Agents live for two periods and choose a level of skills in the first period which determine their wage earnings in the second period. They choose first and second period consumption, c_1 and c_2 and skills h to maximize utility $u(c_1, c_2)$. Choosing h is costly and this cost is reduced by having higher exogenous level of initial ability, θ, and having higher initial endowment k. By modeling education cost as a function of initial endowment, we get a reduced form version of the typical credit constraint model in which individuals with less initial endowment underinvest in education.

The advantage of this approach is that while we do not have data on savings and consumption choices with skills, we do have data on household wealth and skills acquisition from, for example PISA to estimate the skills cost function. How this is estimated is discussed below. The disadvantage is that the capital stock, K, is fixed; here we define it as the sum of all endowments, $K = L \int k f^k(k) dk$.

By modeling education cost as a function of initial endowment of wealth, we can remove credit constraints and assume the following budget constraint: $c_{1,t} + c_{2,t} \leq (1 + r_t)k + \tau \frac{E_t}{L} + w_t(h) - e(h, k, \theta)$ where $w_t(h)$ is the wage for a unit of labor with skill level h, $e(h, k, \theta)$ is the skills cost function, $\tau \frac{E_t}{L}$ is the redistribution of revenue from emissions tax receipts, and L is the total stock of labor which is assumed to be fixed. Because there is no credit constraint, the solution to the consumer problem can be characterized by the choice of h alone where h : $\frac{\partial e(h,k,\theta)}{\partial h} = \frac{\partial w(h)}{\partial h}$; optimal choices for c_1, c_2 follow from h.

Education cost, $e(h, k, \theta)$, is defined as $e(h, k, \theta) = \gamma_a \frac{(h-\gamma_b)^2}{2} (\gamma_0 + \gamma_1 ln(k) + \gamma_2 ln(k)^2 + \gamma_3 \theta)^{-1}$. In equilibrium, $\frac{\partial e(h,k,\theta)}{\partial h} = \frac{\partial w(h)}{\partial h}$, and as a result, $h(\theta, k) = \frac{\partial w(h)}{\partial h} \frac{1}{\gamma_a} (\gamma_0 + \gamma_1 ln(k) + \gamma_2 ln(k)^2 + \gamma_3 \theta) + \gamma_b$ which is a linear function with wealth and wealth squared as independent variables, In other words, the functional form of the skills cost function is based on typical, linear cognitive production function estimated with data on test scores (Todd and Wolpin 2003). Parameters γ_a and γ_b are changed to provide a counterfactual skills cost function as described below. They are assumed to be equal to 1 and 0, respectively, in the baseline case.

This education cost is the monetized cost of an individual investing in skills. It might represent tuition payments or foregone earnings from attaining a higher level of education, but it would also reflect intangible costs including the disutility of effort invested by an individual into studying, for example. This cost whether tangible or intangible is monetized because of the equilibrium condition requiring that the marginal cost of skills equals the marginal benefits, which is the wage skill premium. As discussed below, in steady state, the skills cost function represents the efficiency of the education system to produce skills conditional on an individual's level of family wealth and consequently represents, at the same time, equity of the education system.

Competitive and steady state equilibrium

A competitive equilibrium is defined as the infinite set, $\{E_t, L_t(h), h_t(\theta,k), c_{1,t}(\theta,k), c_{2,t}(\theta,k), w_t(h), r_t\}_{t=0}^{\infty}$. In equilibrium, wages are equal to the marginal product of labor for each skill type, h, that is,

$$\frac{\partial Y_t}{\partial L_h} = Y_t(1-\beta)\alpha\big(ln(A_{Kt}K) - ln(E_t)\big)\frac{1}{H_t}h + Y_t\left(\frac{\beta}{L} - (1-\beta)\alpha\big(ln(A_{Kt}K) - ln(E_t)\big)\frac{1}{L}\right)$$

Let $w_{h,t}$ be the marginal wage rate of skills, $\frac{\partial w_t(h)}{\partial h}$. It follows that

$$w_{h,t} = Y_t(1-\beta)\alpha\big(ln(A_{Kt}K) - ln(E_t)\big)\frac{1}{H_t} \tag{2}$$

The marginal products of capital and emissions equal their respective prices, the rental rate of capital and carbon tax.

$$\frac{\partial Y_t}{\partial K} = Y_t(1-\beta)\left(\alpha ln\left(\frac{H_t}{L}\right)\right)\frac{1}{K} = (1+r_t)$$

and

$$\frac{\partial Y_t}{\partial E} = Y_t(1-\beta)\left(1 - \alpha ln\left(\frac{H_t}{L}\right)\right)\frac{1}{E_t} = \tau \tag{3}$$

For consumers, the optimal choice of skills, h, satisfies $h_t(\theta,k)$: $\frac{\partial e(h,k,\theta)}{\partial h} = \frac{\partial w_{t+1}(h)}{\partial h}$ which is

$h_t(\theta,k) = w_{h,t}\frac{1}{\gamma_a}(\gamma_0 + \gamma_1 ln(k) + \gamma_2 ln(k)^2 + \gamma_3\theta) + \gamma_b$. From this, the total skills in the economy, H_t, is $\iint \left(w_{h,t}\frac{1}{\gamma_a}(\gamma_0 + \gamma_1 ln(k) + \gamma_2 ln(k)^2 + \gamma_3\theta) + \gamma_b\right) dk d\theta$ which yields,

$$H_t = L\left(w_{h,t}\frac{1}{\gamma_a}\left(\gamma_0 + \gamma_1\mu_k + \gamma_2({\sigma_k}^2 + {\mu_k}^2)\right) + \gamma_b\right) \tag{4}$$

From equation (4), it is clear that the skills cost function parameters with exception of γ_b control the elasticity of skill supply in the economy with respect to changes in demand through the skill premium, $w_{h,t}$.

In steady state, there are four equations, (1) to (4), and four endogenous variables, the total stock of skills, H, output, Y, emissions, E, and wage rate for skills, w_h.

Of interest to this study is the marginal effect of the carbon price, τ, on these endogenous variables as well as on wage inequality, under different skills cost functions. The marginal effects of the price of carbon can be specified through implicit differentiation of equations (1) to (4) and solving for the respective total derivatives. In the analysis, parameters γ_a and γ_b can be set to create a counterfactual skills cost function. One counterfactual of interest is a skills cost function that is more efficient and subsequently results in a more elastic supply of skills, all things being equal. This counterfactual can be achieved by reducing the cost of skills through γ_a while increasing γ_b to leave H and the equilibrium values for the other endogenous variables, unchanged. Comparing the marginal effects between a baseline skills cost function and a more efficient, counterfactual cost function provides an estimate of how the more efficient skills cost function can mitigate the economic impacts of an increase in the price of carbon. Another counterfactual is to examine the marginal effects of the price of carbon with a counterfactual, out-of-equilibrium level of skills, H. This can be achieved by changing γ_a and H to a counterfactual level. This provides estimates of the mitigating effect of having a higher level of skills, all other variables being equal.

DATA

For the two empirical exercises presented in this paper, (1) testing the assumptions of the model around skills and industrial carbon emissions and (2) estimating the model's predictions, three data sets were used.

Individual-level skills and industrial emissions

To test the hypothesis that skills of employees in an industry are associated with lower emissions per unit of output of the industry, the first data set was created by merging the OECD's Programme for International Assessment of Adult Competencies (PIAAC) data sets with industry-level data from the EU's air emissions accounts (EUROSTAT 2021a) and national accounts aggregates and employment by industry (EUROSTAT 2021b, 2021c). PIAAC is a nationally representative household survey of individuals aged 15 to 64 which collected data on individual literacy, numeracy and problem solving skills based on a standardized test as well as background data on employment including earnings, education and on other demographics. Included in the employment data is the industry employment for those employed using the ISIC Rev 4 coding. PIAAC data for the EU countries used in this study were conducted in 2012. The EU emissions accounts data set provides data on various types of emissions by industry based on the NACE rev 2 coding system. There were values for approximately 60 industries per country, depending on the country. For this study, carbon emissions were used. The EU's national account aggregates and employment data sets provide data on output in terms of value-added and employment numbers for each industry also coded using the NACE rev 2 system. Both the level for 2012, to match the PIAAC year was used as well as the annualized growth from 2010 to 2019.

Merging the EUROSTAT data to the OECD PIAAC data by industry was conducted by aggregating the EUROSTAT data to ISIC Rev 4 coding using a NACE rev 2 and ISIC Rev 4 mapping data set provided by European Commission (2021a). This was used to map values for the variables of interest derived from the EUROSTAT datasets for the four types of ISIC Rev 4 coding, the 4-, 3-, 2- and 1- digit levels. In cases where NACE Rev 2 value mapped to more than one ISIC code, particularly at the 4- and 3- digit levels, the same value was used for each ISIC code. In cases where more than NACE Rev 2 value mapped to a single ISIC code, then the average of the values from the NACE Rev 2 codes was applied. Values at the 4-, 3-, 2- and 1- digit ISIC coding were then merged with PIAAC country datasets based on the finest ISIC coding reported by the individual (e.g., in some cases the 4- and 3- digit ISIC code was missing for an individual but a 2- digit level was reported). Table 1 presents summary statistics from the resulting skills and industrial emissions data set.

Industry-level data set

Industry-level data was used to estimate the model's production function. This data was derived from aggregating the individual-level skills and industrial emissions dataset to the industry level after adding industry level data on employment and fixed assets from EUROSTAT (2021c, 2021d), mapped to ISIC in the same way as described above. The aggregates were averages for each ISIC 2 digit industry weighted by the PIAAC sample weights and converted to per worker terms. Summary statistics for this data set are presented in Table 2.

OECD's PISA 2000 and 2012 data sets

The final data sets used in this study were the OECD PISA data sets for 2000 and 2012. OECD PISA is a nationally representative, school-based assessment of 15 year-old students' reading, mathematics, and science skills. The 2012 data set was used to estimate the baseline steady-state of the model while the 2000 data set was used in one of the counterfactuals.

Table 1. Descriptive statistics of the skills and industrial emissions dataset

Variable	mean	SD	obs.	countries
Literacy skills (standardized)	0.16	0.95	81,265	22
Numeracy skills (standardized)	0.17	0.95	81,265	22
Problem solving skills (standardized)	0.02	0.97	55,146	18
Log CO2 per real value-added (industry of employment), log tonnes per million euros	4.05	1.67	81,278	22
Annual percent growth in CO2 per real value-added (industry of employment)	-3.25	5.57	81,278	22
Female	0.48	0.5	81,277	22
Age	40.51	12.31	73,635	20
Highest level of education:				
None	0.01	0.1	75,107	21
Primary	0.03	0.18	75,107	21
Lower secondary	0.1	0.31	75,107	21
Upper secondary (vocational)	0.16	0.37	75,107	21
Upper secondary (general)	0.32	0.47	75,107	21
Post-secondary (technical)	0.11	0.31	75,107	21
Post-secondary (academic)	0.26	0.44	75,107	21

Means and standard deviations are weighted by sampling weights that have been adjusted to give equal weight to each country; for literacy, numeracy, and problem-solving skills, mean and SD are estimated using plausible values.

Table 2. Descriptive statistics of the industry-level dataset

Variable	mean	SD	obs.	countries
Cog. skills per worker (literacy skills, 2nd percentile set as zero)	127.98	18.55	373	22
Output per worker (euros 2012)	67,820	140,618	356	21
Capital per work (euros 2012)	471,920	1,661,381	319	19
Emissions per worker (tonnes)	24.80	81.74	356	21

SKILLS AND INDUSTRIAL EMISSIONS

To test whether higher cognitive skills are associated with production technology that relies less on emissions for production, several linear regression models were estimated using our individual-level skills and industrial emissions data sets. Two outcome variables were examined: emissions per output in 2012 and annualized growth in emissions per output between 2010 and 2019. These models were estimated using pooled data for all countries (see descriptive statistics above); models were estimated following OECD (2013) using plausible value estimates for cognitive skills and the Jackknife 2 method. Jackknife replicate weights were provided for each country by the OECD based on either the "delete-one" Jackknife or "paired" Jackknife method; however, the paired Jackknife method was applied because the data was pooled (using the paired Jackknife aggregation formula with delete-one jackknife weights results in an overestimate of the standard error). Stata routines by Macdonald (2008) were used in implementing the estimation method.

Table 3 presents estimates from the first set of models, looking at the association between cognitive skills and emissions per output in 2012 and annualized growth in emissions per output from 2010 to 2019 within a Mincerian type model. All three measures of cognitive skills, literacy, numeracy, and problem solving, are negatively associated with the level of emissions per output in 2012 as well as growth between 2010 and 2019. Country fixed effects were added to this model and presented in Table 4 showing that cognitive skills negatively associate with emissions and growth in emissions per output within countries, across industries. Table 5 presents the same model with highest level of education added; higher levels of education generally associate with lower emissions and growth in emissions per output. Finally, Table 6 introduces an interaction term between whether the individual was employed in a managerial or professional occupation (ISCO-08 categories 1 and 2). The association between cognitive skills and lower emissions per output and lower growth in emission per output is strong for individuals employed in these two occupational categories[1]; for the other occupations, no statistically significant association is found except for a positive association between emissions per output and numeracy skills.

[1] The association between cognitive skills and the dependent variable for individuals in managerial or professional occupations is measured as the coefficient for *Manager or professional occupation + Manager or professional occupation x skill*.

That cognitive skills are associated with industries that rely less on emissions for production is consistent with less polluting technology requiring workers with a higher level of cognitive skills. That this association is within countries suggests that link between skills and lower pollution is not through country-level factors that are associated with skills, for example, policies or values but rather through industry-level factors including technology. The link between cognitive skills and technology that relies less carbon emissions is further suggested by the association between cognitive skills and reductions in emissions per output at the industry level. Variation in the reduction of reliance on emissions across industries and within countries is likely the result of technological change either through innovation or adaption, and the association between cognitive skills and reduction in reliance on emissions by industries is consistent with skill-level being an enabler of this innovation or technology adoption. This is further supported by the association between skills and reduced reliance on emissions being predominantly through managerial and professional occupations which are the occupations most involved in innovation and driving technological change.

Table 3. Linear regression model estimates

Dependent variable:	Log CO_2 emissions per millions of industry real value-added (2012 euro)			Average annual growth ratio in CO_2 emissions per industry real value-added (2010-2019), % point		
Skill measure domain	Literacy	Numeracy	Problem solving	Literacy	Numeracy	Problem solving
Skill measure (standardized)	-0.11***	-0.088***	-0.123***	-0.434***	-0.439***	-0.255***
	(0.006)	(0.005)	(0.007)	(0.025)	(0.025)	(0.03)
Female	-0.65***	-0.667***	-0.616***	-0.369***	-0.445***	-0.496***
	(0.008)	(0.008)	(0.011)	(0.034)	(0.035)	(0.043)
Other controls: age, age square, ln GDP pc	yes	yes	yes	yes	yes	yes
Constant	15.372***	15.412***	15.077***	107.092***	107.036***	110.881***
	(0.094)	(0.094)	(0.104)	(0.535)	(0.536)	(0.56)
Observations	73621	73621	48673	73686	73686	48735
R^2	0.17	0.17	0.18	0.02	0.02	0.03
countries	21	21	17	21	21	17

Estimated using ten plausible values for each skill measure following OECD (2013); jackknife standard errors reported in parentheses. Statistical significance at the 1, 5 and 10 percent levels denoted by ***, **, and * respectively.

Table 4. Linear regression model estimates (with country fixed effects)

Dependent variable:	Log CO2 emissions per millions of industry real value-added (2012 euro)			Average annual growth ratio in CO2 emissions per industry real value-added (2010-2019), % point		
Skill measure domain	Literacy	Numeracy	Problem solving	Literacy	Numeracy	Problem solving
Skill measure (standardized)	-0.17***	-0.16***	-0.17***	-0.17***	-0.17***	-0.19***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Female	-0.65***	-0.68***	-0.61***	-0.24***	-0.27***	-0.4***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)
Other controls: age, age square, country fixed effects	yes	yes	yes	yes	yes	yes
Constant	4.94	4.93	3.94	4.71	4.69	-7.93
	(6.86)	(6.84)	(6.65)	(92.42)	(92.38)	(86.38)
Observations	73621	73621	48673	73686	73686	48735
R2	0.26	0.26	0.28	0.21	0.21	0.23
countries	21	21	17	21	21	17

Estimated using ten plausible values for each skill measure following OECD (2013); jackknife standard errors reported in parentheses. Statistical significance at the 1, 5 and 10 percent levels denoted by ***, **, and * respectively.

Table 5. Linear regression model estimates (education level and country fixed effects)

Dependent variable:	Log CO2 emissions per industry real value-added (2012)			Average annual growth in CO2 emissions per industry real value-added (2010-2019), % point		
Skill measure domain	Literacy	Numeracy	Problem solving	Literacy	Numeracy	Problem solving
Skill measure	-0.05***	-0.03***	-0.05***	-0.12***	-0.13***	-0.11***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
female	-0.6***	-0.6***	-0.55***	-0.12***	-0.15***	-0.28***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)
Education level (relative to no education)						
Primary	-0.12**	-0.13**	-0.11	-1.21***	-1.21***	-1.88***
	(0.06)	(0.06)	(0.07)	(0.15)	(0.15)	(0.24)
Lower secondary	-0.12**	-0.13***	-0.14***	-0.03	-0.03	-0.51***
	(0.05)	(0.05)	(0.05)	(0.14)	(0.14)	(0.15)
Vocational upper secondary	-0.12**	-0.14***	-0.18***	0.37***	0.38***	-0.11
	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.13)
General upper secondary	-0.33***	-0.35***	-0.39***	0.07	0.08	-0.47***
	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.12)
Technical post-secondary	-0.57***	-0.6***	-0.66***	0.25*	0.27*	-0.37***
	(0.05)	(0.05)	(0.05)	(0.15)	(0.14)	(0.12)
General post-secondary	-0.79***	-0.83***	-0.85***	-0.21	-0.19	-0.77***
	(0.05)	(0.05)	(0.05)	(0.15)	(0.14)	(0.12)
Other controls (age, age square, dummy variables for each country)	yes	yes	yes	yes	yes	yes
Constant	13.88***	14.01***	13.85***	73.29***	73.28***	82.86***
	(0.2)	(0.2)	(0.22)	(0.96)	(0.95)	(1.08)
obs	67812	67812	44446	67877	67877	44508
r2	0.25	0.25	0.26	0.21	0.21	0.23
Countries	21	21	17	21	21	17

Estimated using ten plausible values for each skill measure following OECD (2013); jackknife standard errors reported in parentheses. Statistical significance at the 1, 5 and 10 percent levels denoted by ***, **, and * respectively.

Table 6. Linear regression model estimates (education level, country fixed effects and interaction for managers and professionals)

Dependent variable:	Log CO2 emissions per industry real value-added (2012)			Average annual growth in CO2 emissions per industry real value-added (2010-2019), % point		
Skill measure domain	Literacy	Numeracy	Problem solving	Literacy	Numeracy	Problem solving
Skill measure	-0.01	0.02***	-0.01	0	-0.02	-0.02
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
female	-0.61***	-0.61***	-0.56***	-0.1***	-0.12***	-0.24***
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.04)
Manager or professional occupation	-0.41***	-0.41***	-0.42***	-0.15***	-0.17***	-0.26***
	(0.01)	(0.01)	(0.01)	(0.05)	(0.05)	(0.05)
Manager or professional occupation x skill measure	-0.08***	-0.1***	-0.07***	-0.45***	-0.4***	-0.25***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.06)
Education level (relative to no education)						
Primary	-0.13**	-0.14**	-0.11	-1.2***	-1.21***	-1.8***
	(0.06)	(0.06)	(0.07)	(0.15)	(0.15)	(0.25)
Lower secondary	-0.12**	-0.14***	-0.14***	-0.09	-0.09	-0.53***
	(0.05)	(0.05)	(0.04)	(0.14)	(0.14)	(0.14)
Vocational upper secondary	-0.14***	-0.16***	-0.18***	0.27**	0.28**	-0.13
	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.13)
General upper secondary	-0.31***	-0.35***	-0.37***	-0.03	-0.02	-0.49***
	(0.05)	(0.05)	(0.05)	(0.13)	(0.13)	(0.12)
Technical post-secondary	-0.46***	-0.51***	-0.54***	0.2	0.23	-0.33***
	(0.05)	(0.05)	(0.05)	(0.14)	(0.14)	(0.12)
General post-secondary	-0.56***	-0.61***	-0.63***	-0.1	-0.08	-0.62***
	(0.05)	(0.05)	(0.05)	(0.15)	(0.14)	(0.12)
Other controls (age, age2, dummy for country)	yes	yes	yes	yes	yes	yes
Constant	14.15***	14.29***	14.12***	73.02***	73.12***	82.89***
	(0.2)	(0.2)	(0.22)	(1.03)	(1.02)	(1.11)
Manager or professional occupation + Manager or professional occupation x skill	-0.09***	-0.08***	-0.08***	-0.45***	-0.41***	-0.27***
	(0.01)	(0.01)	(0.01)	(0.04)	(0.04)	(0.05)
obs	66665	66665	43701	66726	66726	43759
r2	0.26	0.26	0.28	0.21	0.21	0.22
Countries	19	19	15	19	19	15

Estimated using ten plausible values for each skill measure following OECD (2013); jackknife standard errors reported in parentheses. Statistical significance at the 1, 5 and 10 percent levels denoted by ***, **, and * respectively.

MODEL ESTIMATION

Estimating the parameters of the production function

The log transformation of the production function in per worker terms, equation (1), is a linear function in parameters. A country-industry specific productivity factor, $ln(A_{K,i})$, has been added here that is assumed to be independently and identically distributed, with mean zero, while the log of total factor productivity, $ln(A)$, is also assumed to be i.i.d but not necessarily mean zero. One challenge is that the measure of cognitive skills is not a tangible quantity unlike tonnes of emissions or euro value of capital and output. Arbitrary rescaling of the skills measure can result in different parameters. As a result, a scaling factor, A_H, was added to the definition of skills. The resulting parameters of the model, α, β, $ln(A_K)$, and $ln(A_H)$ can be estimated by the following linear regression model, which was estimated using the industry-level data set.

$$\begin{aligned} ln\left(\frac{Y}{L}\right) - ln\left(\frac{E}{L}\right) \\ &= ln(A) + \beta\left(-ln\left(\frac{E}{L}\right)\right) + (1-\beta)\alpha ln\left(\frac{H}{L}\right)\left(ln\left(\frac{K}{L}\right) - ln\left(\frac{E}{L}\right)\right) \\ &+ (1-\beta)\alpha ln\left(\frac{H}{L}\right) ln(A_K) + (1-\beta)\alpha ln(A_H)\left(ln\left(\frac{K}{L}\right) - ln\left(\frac{E}{L}\right)\right) \\ &+ (1-\beta)\alpha ln\left(\frac{H}{L}\right) ln(A_{K,i}) \end{aligned}$$

Table 7 presents the estimates of the coefficients of this model from which the parameters are derived as described below. The skills scaling factor, A_H, is then used to rescale the measure of skills.

Table 7. Linear regression model estimates for the aggregate production function parameters (dependent variable: log output per worker - log emissions per worker)

	skills measure not rescaled	skills and capital measure rescaled
log emissions per worker (negative)	0.24***	0.24***
	(0.04)	(0.03)
log skills per worker x (log capital per worker - log emissions per worker)	0.07	0.07***
	(0.09)	(0.003)
log capital per worker - log emissions per worker	0.30	
	(0.46)	
log skills per worker	-0.37	
	(1.01)	
Industry fixed effects included	yes	yes
Constant	4.07	5.63***
	(4.83)	(0.19)
Observations	317	317
R-square	0.96	0.96

Standard errors denoted in parentheses. Statistical significance at the 1, 5, and 10 percent levels denoted as ***, **, and *, respectively.

Estimating the skill premium

In steady state, the skill premium, w_h, is constant. This was estimated for each country using the PIAAC data set with a simple, univariate linear regression model with earnings as the dependent variable and literacy skills, rescaled as described above, as the independent variable. This estimate of w_h is used to determine the country-specific capital augmenting technology factor, $A_{K,i}$, by setting $A_{K,i}$such that equation (2) holds.

Estimating the skills cost function

In equilibrium, individual cognitive skills is determined by $h(\theta, k) = w_h(\gamma_0 + \gamma_1 ln(k) + \gamma_2 ln(k)^2 + \gamma_3 \theta)$ where γ_a and γ_b are set to one and zero, respectively, which is cognitive skills expressed as a linear function of the individual's endowment and endowment squared; $\gamma_3 \theta$ is the mean zero error term. This function was estimated using PISA for each country, with the following rescaling of the variables. First, each plausible value of reading achievement was rescaled such that their means equaled the mean of the skills per worker for the country, calculated from the industry-level data set, and the standard deviation equaled the standard deviation of literacy skills in the country's original PIAAC data set. Second, PISA provides a household wealth index based on students' assets at home. This wealth index was treated as the log of the individual endowment, $ln(k)$; however, the mean and standard deviation of the wealth index was rescaled such that (1) the mean of k was equal to the average capital stock per worker for the country, calculated from the industry-level data set, and (2) the mean-median difference matched the mean-median difference in the OECD's Wealth Inequality Dataset (2021). Three countries did not have data in the OECD's Wealth Inequality Dataset and as a result, the mean median wealth difference was imputed based on the relationship between this and the variance in the PISA wealth index for countries with data.

Two skills cost functions were estimated. The baseline skills cost function for 2012 was estimated as described using PISA 2012 data. A counterfactual skills cost function was also estimated for 2000 using the PISA 2000 data which was the earliest round of PISA. For this counterfactual skills cost function, the plausible values of reading skills were scaled using the same factors as used for the PISA 2012 data set; this results in a different mean and standard deviation which is used below to compare how the marginal effects of a carbon price increase differ between the two skills cost functions implied by the 2000 and 2012 PISA.

MODEL PREDICTIONS: MITGATING EFFECTS OF EDUCATION QUALITY

With the above estimates, we use the model to predicts the marginal effects of an increase in the price of carbon on the endogenous variables, the total stock of skills, H, output, Y, emissions, E, and wage rate for skills, w_h as well as wage inequity. Wage inequity was defined as the difference in wages that children from wealthy and poorer households earn when they reach adulthood. In our model, the randomly distributed endowment, k, defines whether the individual comes from a poor or wealthy household. Wage inequity is therefore defined as the log difference in the average steady state wages between an individual from a wealthy household, defined as having endowment, k, at the 75th percentile and from a poor household, defined as having an endowment at the 25th percentile. There is variation in future wages for individuals with the 25th and 75th percentiles of endowment due to variation in exogenous ability, θ; hence, the expected value of the log wages of individuals at these two percentiles is used in the calculation of the wage gap. The parameterization of the mean and standard deviation of the log of the endowment for each country was described above.

Estimation method for marginal effects of an increase in the carbon price

The marginal effects of an increase in the carbon price on the endogenous variables using implicit differentiation of equations (1) to (4) and was computed for each country based on the parameter estimates and endogenous and exogenous variable values for each country from a country-level data set derived from aggregating the industry-level data set. However, because the parameter estimates are estimates, each with a sampling distribution, the marginal effects were computed following a Bayesian approach. One thousand draws were drawn from the estimated parameters' sampling distributions including estimates for w_h with the exception of α which was held fixed. For each of these draws, the marginal effects of an increase in the carbon tax were calculated. The resulting 1,000 marginal effects computations form the posterior distribution for the marginal effects; the point estimate of the marginal effects are the means of the posterior distribution while the standard errors were the standard deviations of the posterior distributions. P-values were also computed from these posterior distributions.

Marginal effects of an increase in carbon price

Table 8 presents the estimated marginal effects of an increase in the price of carbon in terms of elasticity with respect to the impact on carbon emissions. For all countries, the marginal effect on carbon emissions is negative, which is essentially a result of the parameterization of the production function. A carbon price increase negatively affects output, positively affects the stock of skills and the skills wage premium, and positively affects (widens) the wage gap between rich and poor. To quantify these effect sizes, Table 8 presents them in terms of elasticity, the percent change in the endogenous variable resulting from a percent change in carbon emissions. For example, a 1 percent decrease in carbon emissions results in a 0.08 percent decrease in output, a 0.14 percent increase in skills, a 0.14 percent increase in the skills wage premium, and 0.01 percent increase in the wage gap between rich and poor. The carbon price's effect on output and wage inequality represent the economic costs of carbon pricing in other models when the benefits of emissions reduction are not monetized and the distribution of carbon tax revenue is not targeted. The increases in the stock of skills and wage premium characterize carbon reducing technology as being skill-biased in our model.

Table 8. Marginal effects of an increase in carbon price

Country	Marginal effect on carbon emissions	Elasticities: marginal effect expressed as a percent change in endogenous variable per percent change in emissions (effect on emissions is negative; negative elasticity implies the effect on the variable is positive & vice versa)			
		Output	Skills	Marginal product of skills	Log difference in wages between high and low wealth
Average of countries	-0.031***	0.0846*	-0.1383***	-0.1383***	-0.0129***
	(0.0163)	(0.0396)	(0.0642)	(0.0646)	(0.0036)
Belgium	-0.0285***	0.0802*	-0.1021***	-0.1021***	-0.0199***
	(0.0157)	(0.0401)	(0.0114)	(0.0114)	(0.0042)
Czech Republic	-0.0734***	0.0822*	-0.1166***	-0.1166***	-0.0104***
	(0.0369)	(0.0392)	(0.0047)	(0.0047)	(0.0039)
Denmark	-0.0366***	0.0826*	-0.1044***	-0.1044***	-0.0126***
	(0.0188)	(0.0399)	(0.0094)	(0.0094)	(0.0037)
Spain	-0.0122***	0.0919***	-0.1481***	-0.1481***	-0.0171***
	(0.0051)	(0.0386)	(0.0053)	(0.0053)	(0.0037)
Estonia	-0.1038***	0.0821*	-0.0909***	-0.0909***	0.0008
	(0.0533)	(0.0401)	(0.0075)	(0.0075)	(0.0027)
Finland	-0.0427***	0.0706*	-0.1396***	-0.1396***	0.0026
	(0.0317)	(0.039)	(0.0043)	(0.0042)	(0.0023)
France	-0.0084***	0.0861***	-0.1529***	-0.153***	-0.0209***
	(0.0041)	(0.0388)	(0.0096)	(0.0095)	(0.0048)
United Kingdom	-0.0144***	0.0913*	-0.0368***	-0.0368***	-0.0093***
	(0.0069)	(0.0442)	(0.0171)	(0.0171)	(0.003)
Greece	-0.0066**	0.0924***	-0.4788***	-0.4792***	-0.026***
	(0.0047)	(0.0359)	(0.9597)	(0.9656)	(0.0062)
Italy	-0.0111***	0.0926***	-0.1985***	-0.1985***	-0.0255***
	(0.0043)	(0.0374)	(0.0238)	(0.0238)	(0.0044)
Netherlands	-0.0278***	0.0743*	-0.1044***	-0.1044***	-0.0066**
	(0.0183)	(0.0402)	(0.0107)	(0.0107)	(0.0034)
Norway	-0.0204***	0.0745*	-0.1609***	-0.1609***	0.0095***
	(0.0138)	(0.0388)	(0.0082)	(0.0082)	(0.0029)
Poland	-0.0449***	0.09***	-0.0751***	-0.0752***	-0.0198***
	(0.0197)	(0.0406)	(0.0096)	(0.0096)	(0.0048)
Slovak Republic	-0.012***	0.0818*	-0.0944***	-0.0945***	-0.0264***
	(0.0062)	(0.0399)	(0.0064)	(0.0064)	(0.0051)
Slovenia	-0.0221***	0.0964***	-0.0702***	-0.0702***	-0.0122***
	(0.0088)	(0.041)	(0.0126)	(0.0126)	(0.0038)

What if countries had better education quality?

The skills cost function reflects the quality of education: if more skills can be acquired given a level of investment in skills, or put differently, if more skills can be acquired for a given skills premium, then this increases both skill supply and elasticity of skill supply overall. Finland had the highest measure of skills in the model based on PIAAC; to demonstrate the impact of better quality education on the marginal effects of an increase in carbon price, we compared the estimated marginal effects of an increase in carbon prices for each country under (1) a skills cost function calibrated to match that of Finland and (2) each country's originally estimates skills cost function. Using Finland to calibrate the counter-factual skills cost functions provides a "real world" example: what would be the effect if a country's education system were as efficient as Finland's?

Higher quality education influences the marginal effects of an increase in carbon prices by (a) increasing the elasticity of skill supply and (b) by increasing the overall level of skills in an economy. As a result, two comparisons were made to understand how higher education quality through these two channels affects the marginal effects of a carbon price. For both comparisons, a counter-factual skills cost function was parameterized calibrated to Finland. First, for both counter-factual skills cost functions, parameter γ_a was changed from 1 and set such that $L\left(w_h \frac{1}{\gamma_a}\left(\gamma_0 + \gamma_1\mu_k + \gamma_2({\sigma_k}^2 + {\mu_k}^2)\right) + \gamma_b\right)$, from equation (4), equaled the average level of skills in Finland. For the first counter-factual skills cost function, that measuring the education quality through increased elasticity of skill supply alone, parameters γ_b was adjusted such that $L\left(w_h \frac{1}{\gamma_a}\left(\gamma_0 + \gamma_1\mu_k + \gamma_2({\sigma_k}^2 + {\mu_k}^2)\right) + \gamma_b\right)$ equaled the country's own average level of skills. As a result, the equilibrium is not affected by this counter-factual skills cost function because the same values for the endogenous variables satisfy the steady-state equilibrium equations (1) to (4). For the second counter-factual skills cost function, parameter γ_b was not adjusted and left at 0, and as a result the skill level, H, was higher. It is likely that the endogenous variable values no longer satisfy a steady state equilibrium, but it offers a measure of impact on the marginal effects of a carbon price if skills were increased, all things being equal, to better understand the magnitude that skills play.

Table 9 presents the comparison of the marginal effects for each country between the higher quality, counterfactual skills cost function and the original, estimated skills cost function. These comparisons are presented as ratios with a value greater than one implying a stronger marginal effect in the same direction and a value less than one implying a weaker marginal effect in the same direction. Statistical significance is indicated for a difference from one rather than zero. Higher education quality through increased elasticity in skill supply alone (Scenario 1a in Table 9) in a marginal increase in carbon prices having (1) a stronger effect on reducing emissions, (2) a weaker effect on reducing output, (3) a stronger effect on the level of skills, and (4) a weaker effect on widening the wage gap. For example, on average, a marginal increase in the carbon price under the high education quality scenario results in a reduction in emissions that is 1.01 that of the marginal effect with the original skills cost function. When the level of skills is also increased to match that of Finland (Scenario 1b in Table 9), then the marginal effect of an increase in carbon price on emissions increases more while the that on output decreases more. For example, on average, a marginal increase in the carbon price under the high education quality scenario is 1.14 times higher than under the original scenario. Note that the higher level of skills implies a higher wage premium for skills and as a result the effect on skills' premium and wage inequality is not comparable. The ratios of marginal effects vary by country and depend on the baseline levels of endogenous variables, the difference in education quality between each country and Finland, and, for the effect on the wage gap, the relationship between wealth and skills in the skills cost function.

Table 9. How many times stronger would the marginal effect of an increase in carbon price be if each country's education quality were calibrated to match Finland's?

	Note: value of 1 implies no difference in marginal effect and statistical significance is indicated for a difference from 1 not 0					
	Scenario 1a: Same skills but higher elasticity of skill supply due to higher education quality				Scenario 1b: Higher skills and higher elasticity of skills supply due to higher education quality	
	Emissions	Output	Skills	Wage gap (log diff.)	Emissions	Output
Average of ratios	1.0105** (0.0142)	0.9922* (0.6113)	1.1001*** (0.0168)	0.8827*** (0.0184)	1.1415*** (0.1225)	1.0194 (2.5202)
Belgium	1.0038*** (0.0036)	0.9538* (0.9176)	1.0573*** (0.0043)	0.9045*** (0.0158)	1.0835*** (0.0677)	0.8808* (3.4765)
Czech Republic	1.0059*** (0.0045)	0.9888* (0.6202)	1.0814*** (0.0058)	0.8854*** (0.0115)	1.119*** (0.096)	1.0446 (2.6973)
Denmark	1.005*** (0.0044)	1.2645 (8.4159)	1.0769*** (0.0054)	0.878*** (0.0173)	1.1118*** (0.09)	2.1999 (35.522)
Spain	1.0144*** (0.009)	0.9386*** (0.0962)	1.1698*** (0.0116)	0.8334*** (0.0249)	1.2513*** (0.2169)	0.8472*** (0.4765)
Estonia	1.0036*** (0.0033)	0.9855* (0.1346)	1.0657*** (0.0044)	0.8785*** (0.0125)	1.0939*** (0.0727)	1.0061 (0.5539)
Finland	1	1	1	1	1	1
France	1.0122*** (0.009)	0.9255*** (0.211)	1.1263*** (0.0106)	0.8794*** (0.0262)	1.1903*** (0.1729)	0.7487*** (1.1116)
United Kingdom	1.0015*** (0.0023)	0.9959* (0.1794)	1.0754*** (0.0037)	0.7654*** (0.033)	1.0963*** (0.0702)	1.0212 (0.7252)
Greece	1.0704** (0.2049)	0.9784 (0.2141)	1.2655** (0.2401)	1.0369 (0.2355)	1.3429** (0.3816)	0.8706** (0.3832)
Italy	1.0216*** (0.0089)	0.9413*** (0.0819)	1.1937*** (0.0126)	0.8765*** (0.0067)	1.2851*** (0.2512)	0.8617*** (0.4021)
Netherlands	1.001*** (0.001)	0.9977* (0.1256)	1.0124*** (0.0011)	0.9784*** (0.0038)	1.0182*** (0.0149)	1.0027 (0.3951)
Norway	1.0046*** (0.0043)	1.091 (3.4195)	1.0374*** (0.0046)	0.9661*** (0.0094)	1.0575*** (0.0546)	1.3577 (12.061)
Poland	1.0045*** (0.0041)	0.8964*** (0.4146)	1.1148*** (0.0064)	0.775*** (0.0217)	1.1594*** (0.1202)	0.6122*** (1.9485)
Slovak Republic	1.0038*** (0.0033)	0.9855* (0.136)	1.0656*** (0.0044)	0.8832*** (0.0108)	1.094*** (0.0729)	1.0067 (0.5598)
Slovenia	1.0054*** (0.005)	0.9399*** (0.1116)	1.1593*** (0.0077)	0.7005*** (0.0339)	1.219*** (0.165)	0.8307*** (0.5068)

Implied changes in marginal effects due to changes in education quality from 2000 to 2012

The impact of education quality on the marginal effects of an increase in carbon prices was also demonstrated by estimating the impacted of the changes in education quality implied between PISA 2000 and PISA 2012. We compared the marginal effects of a carbon price increase between the original skills cost function estimated using PISA 2012 and a skills function estimated using

PISA 2000. Because the PISA 2012 rescaling was applied to the PISA 2000 data before estimating the skills cost function (see above), the PISA 2000 skills cost function implies a different level of education quality and subsequently a different elasticity of skill supply and a different level of skills in the economy. Some countries saw increases in PISA scores between the 2000 and 2012 rounds, notably Poland, while others saw decline. In reality, the change in education quality between 2000 and 2012 would not be instantaneous and affect all workers simultaneously; rather, the PISA results provide a measure of the skills that a single-aged cohort of students possess. However, by estimating the implication of the change in the quality of education for the marginal effects of a carbon price, we provide a value, in terms of marginal effects, of the change in quality.

Table 10 presents the comparison of the marginal effects for each country between the education quality implied by 2012 and 2000 rounds of PISA. A value greater than one implies that the quality of education in 2012 results in a stronger marginal effect in the same direction and a value less than one implies a weaker marginal effect in the same direction. As before, statistical significance is indicated for a difference from one rather than zero.

Changes in education quality through changes in the elasticity of skill supply alone (Scenario 2a in Table 10) result, on average for the countries in the sample, in no change in the marginal effects of a carbon price. However, the marginal products are found to be both higher and lower depending on the country. For example, Poland's PISA scores increased substantially between 2000 and 2012. The implied increase in the elasticity of skill supply results in a marginal increase in carbon prices having a slightly larger effect on emissions reduction, a lower effect on reducing output, and a stronger effect on skills supply. Another example is Italy. Italy experienced minor improvements in its PISA reading scores between 2000 and 2012. In our model this implies a slightly higher effect on reducing emissions, slightly lower effect on reducing output, and slightly higher effect on increasing skill supply, all statistically insignificant. However, this slight increase in PISA reading scores was accompanied by a change in the relationship in household wealth and scores resulting in carbon prices having a larger rather than smaller effect on increasing wage inequity. Table 10 also demonstrates cases when education quality decreased from 2000 to 2012. Overall, we see the predicted link between changes in education quality and equity and the resulting marginal effects of an increase in carbon prices.

Table 10. How would the changes in education quality implied by PISA from 2000 to 2012 affect the marginal effect of an increase in carbon price?

	Note: value of 1 implies no difference in marginal effect and statistical significance is indicated for a difference from 1 not 0					
	Scenario 2a: Same skills but different elasticity of skill supply implied by changes in quality from 2000 to 2012				Scenario 2b: Different skills and elasticity of skills supply implied by changes in quality from 2000 to 2012	
	Emissions	Output	Skills	Wage gap (log diff.)	Emissions	Output
Average of ratios	0.9999 (0.0014)	1.0005 (0.0631)	1.0004 (0.0095)	0.2324 (11.783)	0.996 (0.0109)	0.9906 (0.3104)
Belgium	1.0002 (0.0007)	0.9985 (0.0276)	1.0032 (0.0083)	1.6657 (0.6586)	1.004 (0.0106)	0.9994 (0.0459)
Czech Republic	1.0002 (0.0007)	1.0037 (0.0952)	1.0027 (0.0079)	0.6893 (0.2707)	1.0033 (0.0072)	1.005 (0.1025)
Denmark	0.9999 (0.0007)	0.9997 (0.0337)	0.998 (0.008)	0.8471 (0.2956)	0.9974 (0.0078)	0.9998 (0.0516)
Spain	0.9991 (0.0009)	1.0039 (0.008)	0.9894 (0.0078)	0.6195** (0.1235)	0.9883* (0.0098)	1.0067 (0.02)
Estonia	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Finland	0.9951*** (0.0049)	1.0204* (0.2833)	0.9575*** (0.0083)	-0.3115*** (0.3895)	0.9333*** (0.0591)	1.0621 (1.5171)
France	1.0003 (0.001)	0.9981 (0.0124)	1.0037 (0.0084)	0.6902** (0.1385)	1.0043 (0.0078)	0.9968 (0.0242)
United Kingdom	0.9989*** (0.0018)	1.0281* (0.4839)	0.9458*** (0.0095)	0.6199* (0.1984)	0.9355*** (0.0393)	0.9248 (3.1876)
Greece	1.0034 (0.0105)	0.9991 (0.0111)	1.0134 (0.0213)	1.0243 (0.3658)	1.0117 (0.0172)	0.9969 (0.0101)
Italy	1.0009 (0.0011)	0.9976 (0.0049)	1.0084 (0.0095)	1.7298*** (0.4326)	1.0086 (0.0098)	0.9966 (0.0086)
Netherlands	0.9968*** (0.0036)	1.0058* (0.504)	0.9604*** (0.0098)	-3.8441 (120.07)	0.941*** (0.0477)	0.9734 (0.8435)
Norway	0.9999 (0.0012)	1.0004 (0.0401)	0.9996 (0.0083)	-1.6975 (74.485)	0.9995 (0.0092)	0.9999 (0.0411)
Poland	1.0043*** (0.0038)	0.95*** (0.1108)	1.1222*** (0.0192)	0.7566 (0.2842)	1.1253*** (0.0702)	0.9265*** (0.1355)
Slovak Republic	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.
Slovenia	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.

CONCLUSIONS

Our estimated model predicts that better education quality can reduce the negative economic effects of an increase in carbon prices as well as increase the emissions benefits. While the magnitudes of the examples of counter-factual education quality regimes used in our study are quite small at the margin, they are expected to be much larger considering the size of emissions reduction targets. For example, on average in our model a carbon tax increase that reduces emissions by 1 percent would reduce output by 0.08 percent; however, the European Commission's target in its 2030 Climate and Energy Framework (2021b) is to reduce greenhouse gasses by 55 percent. Projecting our model's predicted marginal effects would imply that if the United Kingdom, France, and Italy had education quality equivalent to Finland, the increased skill supply elasticity would reduce GDP loss by around 0.3 percent per year. For Poland, the increase in education quality from 2000 and 2012, would imply a savings of 0.25 percent of GDP per year if carbon prices were increased to reduce emissions by 55 percent. These benefits are quite substantial given that reforms to improve learning outcomes in the EU countries are more likely to increase the efficiency of recurrent expenditure in education, for example through advancements in pedagogy and governance reform, given that the predominant recurrent cost of education, teacher salaries, is already being incurred. In our model, the monetary benefits of reduced emissions are not quantified and the recycling of carbon price revenue is not targeted to poorer households or to offset existing distortionary taxes. In this sense, our finding that education quality can reduce the economic cost of carbon pricing is applied to a pessimistic model compared to previous studies. This highlights the importance of education quality as a mitigating factor.

The European Green Deal (EGD) is a growth strategy aimed at achieving carbon neutrality by 2050 in the EU by decoupling economic growth from natural resource use, where the transition within the EGD is based on the "no person and no place left behind" principle (European Commission 2019). Actions required within the EGD will have significant economic and social impact across the sectors, which will affect different groups and territories in different ways. The European Commission estimates that transition to a climate-neutral EU economy by 2050 will have a positive net impact of 1.5 to 2 million jobs with an insignificant impact on GDP. However, this impact will vary considerably between sectors and countries. For example, the move away from carbon intensive industries (auto industry, mining, and extraction) is expected to eliminate

4.7 million low-skilled and middle-skilled jobs by 2030, with the coal sector being one of the worst affected. The EGD lays out a prominent role for the education sector to help achieve the ambitious emissions reduction goals. New skills will be needed for future workers for "green" jobs.

Our findings that cognitive skills associate with industries that are more efficient in terms of emissions per output, and subsequently the mitigating role of education quality, is consistent with greener technology requiring a higher level of skills than existing technology. This echoes previous literature showing that firm level human capital improves environmental compliance and practices as well as literature showing higher education's association with reduced emissions at the macro level. The resulting characterization is that green technology is skill-biased. However, our model is not intended to explain why this would be case, and this deserves further research. For example, O*NET's report on the skill requirements of green jobs (Kochhar 2020) suggests that green jobs are associated with higher-order skills ranging from advanced technical skills to analytical skills. One explanation may be that green jobs involve a high level of innovation to develop new technologies, adapt existing technologies or optimize newer green technologies. It is not clear that there is anything inherent in green technology that requires a higher level of skills, unlike, for example, automation which requires skills that machines and artificial intelligence cannot replicate (Brynjolfsson and McAfee 2014). It may just be the case that the current vintage of capital being produced is skill-biased, resulting from a more general trend in technological development.

Our model could be extended in a number of ways in future research. First, labor mobility could be added to understand how the variation in education quality across the EU may affect the impact of carbon pricing. For example, countries with lower quality education systems may have higher elasticity in skill supply by attracting foreign trained labor; however, the presence of low quality education systems within the EU may lower the elasticity of skill supply for the EU as a whole. A second extension of the model would be to include other mitigating factors including progressive or otherwise targeted redistribution of a carbon tax and compare the strength of the mitigating effect with increased education quality. Finally, a third extension is to transform the framework into a growth a model and examine steady state growth outcomes includes to better understand how elasticity of skill supply affects carbon pricing impacts on the annual change in carbon emissions and other macroeconomic outcomes including output. Data from the next round of PIAAC would help provide comparable measure of how cognitive skills have changed since 2012.

The policy implication of our work is that carbon pricing that is accompanied by improvements in education quality will result in better environmental and economic outcomes when carbon pricing is used to reduce emissions. The resulting motivation for investing in education quality is not to change values or behaviors of consumers but rather to enable technological change that can reduce emissions, and this is a different motivation than the reasoning behind a lot of policy literature on how education can help benefit climate change. Indeed, the EU's Green Deal includes investment in human capital as a complement to emissions targets; our model suggests that this human capital investment should be utilized to improve cognitive skills and help enable technological change to mitigate the costs and enhance the benefits of increased carbon pricing.

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