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## Article

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ORIGINAL ARTICLE

Open Access



# The green potential of occupations in Switzerland

Michael Lobsiger<sup>1\*</sup>  and Christian Rutzer<sup>2</sup>

## Abstract

We use a data-driven methodology to quantify the importance of different skills in performing green tasks, aiming to estimate the green potential of occupations in Switzerland. By this we mean the potential of an occupation to be able to perform green tasks on the basis of the skills attributed to it, whereby it is irrelevant whether the occupation already bundles green tasks or not. The results show that occupations with a high green potential are predominantly those with an engineering and technical background. In order to substantiate our green potential measure, we provide evidence of a positive association between demand of employment in occupations with high green potential and an increase in the implicit tax rate on greenhouse gas emissions. The share of employment in occupations with a green potential above a reasonable threshold in the total Swiss labour force is 16.7% (number of persons employed) and 18.8% (full-time equivalents). These employed persons are, on average, younger, more often men, have a higher level of educational attainment and a higher probability of having immigrated than employed persons in occupations with low green potential.

**Keywords:** Green potential, Green transition, Labour market

**JEL Classification:** J23, J24, Q52

## 1 Introduction

Environmental awareness has increased in the population in recent years, especially against the background of climate change. These developments have also led to regulatory activities at the political level.<sup>1</sup> Strategies and action plans are aimed, among other things, at increasing the resource efficiency of production and achieving a more sustainable economy.<sup>2</sup> As recognized by research

and practice alike, such a transformation towards a more sustainable economy may also have strong effects on the labour market (e.g. Vona et al., 2018). Specifically, the labour market asks for employees with specific skills (knowledge, abilities, skills in the narrower sense and attitudes) that are necessary to perform green tasks—that is work activities that make a positive contribution to the green economy. These tasks will be increasingly demanded on the path to a more sustainable economy (Rutzer et al., 2020; Janser, 2018).

Against this background, it is important to know which Swiss occupations have a high potential to perform green tasks. By this we mean the potential of an occupation to be able to perform green tasks on the basis of the skills attributed to it, whereby it is irrelevant whether the occupation already bundles green tasks or not (Rutzer

<sup>1</sup> Based on country case studies Strietska-Ilina et al. (2011) identify other drivers of greening economies such as changes in the physical environment, technological development, developments of markets for green products and services, and changing consumer habits.

<sup>2</sup> In this paper, green economy and sustainable economy are used as synonyms. Footnote 6 provides a definition of the concept *green economy*. For Switzerland, the Federal Councils Sustainable Development Strategy 2016–2019 (Bundesrat, 2016) can be mentioned in this context. The strategy sets out a number of objectives, one of which aims at improving resource effi-

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Footnote 2 (Continued)

ciency in production. Specific measures to achieve better resource efficiency are set out in the 2013 Green Economy Action Plan and its development for the period 2016–2019 (BAFU, 2013, 2016).

et al., 2020). An electrical engineer, for example, can put her skills to work both overseeing a nuclear reactor at a nuclear power plant or researching renewable energy. Only in the second case does she perform a green task, but in any case she brings the potential to perform green tasks. Therefore, information about the green potential of occupations seems central to us, e.g. for education and training policy: The need to align education and training with green transformation will be less urgent if many workers are employed in occupations with high green potential. This is because one can assume that, to a certain extent, they have the necessary skills to carry out green tasks and are thus well prepared for a green transformation.

In order to quantify the green potential of occupations in Switzerland, we follow a novel approach developed by Rutzer et al. (2020). The approach relies on machine-learning algorithms to quantify the importance of different skills in performing green tasks. The results show that occupations with a high green potential are predominantly those with an engineering and technical background. Once the green potential of different Swiss occupations is determined, we aim at finding empirical support for our measure of the green potential of occupations. In particular, we follow a recent strand of the literature examining heterogeneous demand responses in labour markets (measured at the occupational level) with respect to changes in environmental policy stringency (Niggli & Rutzer, 2020; Vona et al., 2018). In particular, we investigate whether occupations with high green potential are in higher demand relative to other occupations when environmental policy stringency proxied by green emission taxes increases. The results provide evidence of a positive association between demand of occupations with high green potential and an increase in the implicit emission tax. Although we do not claim a causal relationship, we interpret this result as empirical support for the estimated green potential of occupations in Switzerland.

Next, we use our green potential estimates at the occupational level to determine the proportion of employees in Switzerland working in occupations considered to have a high green potential. Furthermore, we describe their socio-economic background. In particular, we characterize employment in occupations with high green potential along different dimensions such as age, sex, migration status and level of education as well as a set of labour market indicators (rate of job vacancies, rate of unemployment). For that, we divide the occupations into two groups based on a particular threshold for the green potential (which we will justify later). According to our estimates, in Switzerland in the year 2017, 739,000 persons and 670,000 full-time equivalents (FTE) have

been employed in occupations with high green potential. Measured relative to the total number of persons employed and FTE, this is around 16.7% and 18.8%, respectively. Employed persons in occupations with high green potential are, on average, younger, more often men, have a higher level of educational attainment and a higher probability of having immigrated than employed persons in other occupations. Moreover, the group of occupations with high green potential has a lower unemployment rate and a higher job vacancy rate.

The rest of the paper is structured as follows: Next, we review the literature (1) assessing the extent of greenness of occupations based on task level information, (2) relating the extent of greenness of occupations to skills and (3) analysing heterogeneous demand responses of the labour market due to green economy measures. Afterwards, we describe our methodology to estimate the green potential of occupations and the estimates thereof. We then outline our empirical strategy to analyse possible heterogeneous labour market effects in response to changes in environmental policy stringency and provide the respective estimation results. Consequently, we characterize employment in occupations with high green potential along different dimensions. Finally, we summarize our main findings and conclude.

## 2 Literature

Our paper can be attributed to the growing literature analysing the impact of a green economy on the labour market by applying a task-based approach. This approach is conceptually related to a rich literature that analyses how labour market outcomes (such as employment and wages) are shaped by skills and tasks (Acemoglu & Autor, 2011).<sup>3</sup> In particular, our approach to estimating the green potential of occupations is based on two strands of the literature:

First, there is the literature that assesses the extent of greenness of occupations based on task level information. Consoli et al. (2016) use occupation and task level information provided by O\*NET<sup>4</sup> to classify occupations as green or non-green in order to elaborate on the differences between both occupational groups in terms of skill content and human capital. As Bowen et al. (2018) point out, there is considerable heterogeneity among the occupations considered as green with respect to the

<sup>3</sup> According to Acemoglu and Autor (2011, p. 1045), "[...] a task is a unit of work activity that produces output (goods and services). In contrast, a skill is a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output."

<sup>4</sup> The Occupational Information Network (O\*NET) is a US American database that holds various job-related information. More information about O\*NET will follow in Sect. 3.

“greenness”—that is the use of green tasks within occupations. Again relying on O\*NET, Vona et al. (2018) exploit this variation in the use of green tasks within occupations to compute a continuous greenness measure for each occupation. An alternative approach to measure the greenness of occupations based on tasks has been developed by Janser (2018). Based on job requirements stated in the German occupations database BERUFENET and applying a text mining approach, they identified green tasks in Germany. On this basis, they computed a greenness-of-jobs index per occupation by relating the identified green tasks (that is job requirements that contain key words form a pre-defined green tasks dictionary) to all job requirements.<sup>5</sup> This approach is interesting because it shows a way to identify green tasks apart from using the O\*NET database. It has the advantage that country-specific occupational information databases can be used for task identification and do not require a diversion via O\*NET. However, identifying green tasks is only one step towards estimating the green potential of occupations. In order to estimate the potential for all occupations (including those without green tasks), detailed occupation-specific information on skills is necessary.

This is where the second strand of the literature on which our approach is based comes in, namely the research relating the extent of greenness of occupations to skills. Vona et al. (2018) use the continuous greenness measure (see above) to assess the importance of green skills for the exercise of green tasks. Their analysis is based on O\*NET that provides, apart from information about green tasks within occupations, detailed information about skills on the level of occupations. A recent approach by Rutzer et al. (2020) starts here and offers a method to estimate the green potential of occupations based on skills in a continuous way. Rutzer et al. (2020) define the green potential of an occupation based on the skills which are required to perform green tasks. It is not important whether an occupation bundles green tasks or not, but whether the skills needed to perform those work activities would in principle allow green tasks to be performed. Essentially, the idea is that a set of skills can be applied to different (green or non-green) tasks. In this respect, there are no green skills, but skills that are better suited than others to exercise green tasks. While following Vona et al. (2018) in terms measuring the greenness of occupations and using information of skills provided by O\*NET, Rutzer et al. (2020) use a different estimation approach that delivers (from a statistical point of

view) more accurate predictions of the green potential of occupations. In particular, the method of Rutzer et al. (2020) relies on machine learning and not on a principal component analysis on the top of OLS estimations as Vona et al. (2018) do. The statistical superiority of the former method is probably mainly due to the fact that it also makes it possible to use information of skills that are highly needed for non-green tasks. In contrast, Vona et al. (2018) only exploits information from skills that are important for green tasks.

The concept of green potential contrasts strongly with current methods of identifying so-called *green jobs* and determining employment in these occupations on this basis. A uniform definition of green jobs is missing (Bowen et al., 2018; Janser, 2018; Esposito et al., 2017). The literature therefore provides different definitions based on industry affiliation or the production methods used (Martinez-Fernandez et al. 2010; Consoli et al., 2016; Bowen et al., 2018). A frequently used approach to identify green jobs starts at the industry level and identifies those sectors that produce goods and services that contribute to the protection of the environment or the conservation of natural resources. In particular, the efforts of statistical offices to define the so called *Environmental Goods and Services Sector (EGSS)* and describe it in terms of employment and value added are to be mentioned here (Eurostat, 2016; ILO, 2018). This approach has, however, some drawbacks: As noted in ILO (2018) and Esposito et al. (2017), it neglects jobs that improve production processes with respect to their environmental impact, irrespective of the goods that are produced. Furthermore, it does not shed light on the skills necessary to carry out an activity that is expected to contribute to a sustainable economy and therefore says nothing in terms of an occupation's potential to bundle green tasks. But precisely this information is of interest to education policy and practice in order to, for example, gear training courses to the needs of a sustainable economy.

While there are estimates of employment in green industries in Switzerland (according to the definition of the EGSS, covering employment in industries that produce goods and services contributing to the protection of the environment or the conservation of natural resources), there are no estimates based on the concept of green potential. Here we make a contribution by applying the approach of Rutzer et al. (2020) to determine the green potential of Swiss occupations. To the best of our knowledge, a database that allows both the identification of green tasks and provides information on skills at the occupational level is not available in Switzerland. For this reason, we will follow Rutzer et al. (2020) and rely our analysis on O\*NET data.

<sup>5</sup> Janser (2018) differentiates between core and additional job requirements, the former being essential to the practice of the profession. In 2016, 190 job requirements (2.6% of all job requirements) were green tasks. 19.9% of all occupations (according to the *Klassifikation der Berufe 2010—KldB2010*) contained at least one of these 190 green tasks.

Once the green potential of different occupations is determined, we aim to find empirical support for our measure of the green potential of occupations. For that, we follow a recent strand of the literature examining heterogeneous demand responses in labour markets (measured at the occupational level) with respect to changes in environmental policy stringency (Niggli & Rutzer, 2020; Vona et al., 2018). The execution of occupations with high green potential requires skills that allow to perform green tasks. A central hypothesis is that these tasks and the skills associated with them will be in greater demand in case of a green shift of an economy (e.g. Vona et al., 2018). In such a case, one would accordingly expect a higher demand for occupations that require these tasks and skills compared to other occupations: On the one hand, occupations that already bundle green tasks benefit from the increased demand due to environmental policy becoming more stringent. On the other hand, occupations that do not yet bundle green tasks, but already require skills that are necessary to perform these tasks, are predestined to include green tasks in their activity bundle as a result of a development towards a green economy (Niggli & Rutzer, 2020). Niggli and Rutzer (2020) provide a recent empirical contribution with respect to heterogeneous labour market effects on the occupational level. They estimate the green potential of occupations for 19 European countries following Rutzer et al. (2020). On this basis, they then analyse the effect of increased environmental policy stringency on the occupation-level manufacturing employment for the period 1992 to 2010. In line with other literature (Vona et al., 2018; Marin & Vona, 2019), they provide evidence for heterogeneous employment changes in response to an increase in environmental policy stringency. In particular, they document a decrease in labour demand for occupations with relatively low green potential and an increase in labour demand for occupations with relatively high green potential. We add to this literature by providing further evidence of heterogeneous labour demand responses associated with increased greenhouse gas emission taxes as a proxy for environmental policy stringency, using Switzerland as an example.

After this brief review of the literature, the next section deals with the methodological approach and the data we use to estimate the green potential of occupations in Switzerland.

### 3 Quantifying and testing the green potential of occupations

In the following, we first provide detailed information about the measurement of the green potential of occupations in Switzerland and the respective results. Afterwards, we inform about the methodological approach to analyse heterogeneous labour market effects to green economy measures and describe the data needed for this analysis. Finally, we provide the respective results.

#### 3.1 Measurement of the green potential of occupations

The measurement of the green potential of occupations in Switzerland draws on the recent contribution of Rutzer et al. (2020). This work estimates the green potential of occupations in the US labour market, that is, for occupations classified according to the Standard Occupational Classification (SOC). This approach can be adapted so it can be used to estimate the green potential of occupations in Switzerland (and other countries) relying on a different classification system for occupations, namely the International Standard Classification of Occupations (ISCO). The following section briefly discusses this approach and highlights the modifications that need to be made to apply it to Swiss data. Here we follow the approach of Niggli and Rutzer (2020) and refer to this article for a detailed description of the procedure.

The estimates of Rutzer et al. (2020) of the green potential for SOC occupations are based on data from O\*NET. This database provides information about the tasks and skills contained in occupations and classifies tasks as green or non-green. The classification of tasks according to green or non-green is carried out by experts. A green task is a work activity that makes a positive contribution to the green economy<sup>6</sup> (e.g. the development of a method for measuring water quality).

Table 1 provides four examples of different O\*NET occupations. For the solar photovoltaic installer, O\*NET lists a total of 26 tasks, where 26 tasks are classified as “green new tasks”. The environmental engineer bundles a total of 28 tasks, three of which are green new tasks and 25 that are existing green tasks. An example of an “existing green task” is *designing or supervising of the design of systems, processes, or equipment for control, management, or remediation of water, air, or soil quality*. An example of a “new green task” is *writing reports or articles for Web sites or newsletters related to environmental engineering issues*. Architects have seven new green tasks and 18

<sup>6</sup> According to Dierdorff et al. (2009, p. 3), “[t]he green economy encompasses the economic activity related to reducing the use of fossil fuels, decreasing pollution and greenhouse gas emissions, increasing the efficiency of energy usage, recycling materials, and developing and adopting renewable sources of energy.”



**Table 1** Examples of green jobs and tasks according to O\*NET

Title	# of tasks			Greenness $\eta$
	Green		Other	
	New	Existing		
Solar photovoltaic installer (47-2231.00)	26	0	0	1.0
Environmental engineer (17-2081.00)	3	25	0	1.0
Architect (17-1011.00)	7	0	18	0.3
Electrician (47-2111.00)	0	0	21	0.0

Source: O\*NET

non-green tasks. *Designing or constructing plans of green buildings projects to minimize adverse environmental impact or conserve energy* is an example of a “new green task”. Tasks such as *preparing scale drawings or architectural designs, using computer-aided design or other tools* that has no obvious impact on the green economy are examples of “non-green tasks”. 21 tasks can be attributed to the electrician occupation, none of which are considered green.

On that basis Rutzer et al. (2020) calculate the greenness of an occupation  $i$  as  $\eta_i = \#green\ tasks_i / \#total\ tasks_i$ . In the examples provided by Table 1 (last column), two occupations have a  $\eta = 1.0$  (solar photovoltaic installer, environmental engineer), one a  $\eta = 0.3$  (architect) and one a  $\eta = 0$  (electrician). It is important to note that there are occupations that do not perform any green tasks, that is jobs with  $\eta = 0$ , but demand skills similar to occupations that perform green tasks. While these occupations do not bundle green tasks, they nevertheless have the *potential* to perform green tasks based on the skills required. The calculation of this potential is what is at the heart of the measurement strategy used in this analysis. For example, it is not a-priori clear that electricians that perform, according to the O\*NET classification, no green tasks (cf. Table 1) have a low green potential. Indeed, as the calculations later will show, electricians are assigned to an occupational group that has a relatively high green potential, because it is associated with skills that are similar to occupations that perform green tasks. In other words, employees that work as electricians are thought to

be equipped with skills that are a prerequisite to perform green tasks.

Besides information about tasks, O\*NET provides detailed information about job-specific skills for every occupation. Following Vona et al. (2018), skills are understood as knowledge, skills (in the narrower sense) and work activities.<sup>7</sup> O\*NET provides, for each occupation, a quantitative rating for the importance ( $IM$ ) and the level ( $LV$ ) of a total of 114 skills. For each skill  $s$ , this information is aggregated into a single value by applying a weighting scheme of importance and level. Following Rutzer et al. (2020), the value of a skill  $s$  of occupation  $i$  is calculated as  $skill_{i,s} = IM_{i,s}^\alpha LV_{i,s}^{1-\alpha}$  with  $\alpha = 0.7$ . Afterwards, the value of each  $skill_{i,s}$  is normalized between 0 and 1 by computing  $(skill_{i,s} - \min(skill_s)) / (\max(skill_s) - \min(skill_s))$ .

Using machine-learning algorithms, it is possible to predict the potential of SOC occupations to perform green tasks on a continuous scale. For that, a prediction model is trained to predict the greenness of an occupation depending on the values of different skills using data from O\*NET. According to the analysis of Rutzer et al. (2020), the Ridge algorithm performs best compared to alternative estimation models (OLS, Lasso, Random forest) in terms of prediction quality (measured by the mean squared error and the multiclass receiver operating characteristic curve (Mroc) on a holdout dataset).<sup>8</sup> For this reason, the estimation of the green potential for SOC occupations is based on the Ridge regression model. The model uses the information on skills described above as explanatory variables and the greenness  $\eta_i$  of an occupation  $i$ , that is the share of green tasks within the total number of tasks, as the dependent variable. The result is a coefficient  $\hat{\beta}_s^{ridge}$  for each skill  $s$ , which can be used to predict the green potential  $\hat{\eta}_i$  of an occupation  $i$ :

<sup>7</sup> It is important to note that there is no uniform definition of skills in the literature (OECD, 2017). We stick to the definition used by O\*NET as we will base our analyses strongly on this database. For detailed information on the database, see <https://www.onetcenter.org/database.html#individual-files>. The following definitions were taken from <https://www.onetcenter.org/reports/Related.html> (Volume I: Report): **Knowledge** is defined as a “[...] collection of discrete but related and original facts, information, and principles about a certain domain that is acquired through education, training, or experience” (such as “Administration and Management” or “Design”), **skills** (basic and cross-functional) is defined as “[...] capabilities of individuals that are acquired through experience and practice, and are used to facilitate knowledge acquisition” (such as “Mathematics” or “Writing”), **work activities** is defined as an “[...] aggregation of similar job activities/behaviors that underlie the accom-

Footnote 7 (Continued)

plishment of major work functions” (such as “Analyzing Data or Information” or “Developing and Building Teams”).

<sup>8</sup> In comparison to OLS, the Ridge regression endogenously shrinks some coefficients towards zero in order to reduce overfitting to the training data.

$$\hat{\eta}_i = \hat{\beta}_0 + \sum_{s=1}^p \text{skill}_{i,s} \hat{\beta}_s^{\text{ridge}}. \quad (1)$$

Table 6 in the “Appendix 1” shows, for each considered skill  $s$ , the coefficient  $\hat{\beta}_s^{\text{ridge}}$ . On the one side, there are skills associated with a high predicted greenness as “Building and Construction”, “Geography” and “Physics” with coefficients of 0.15 and 0.08, respectively. On the other side are skills such as “Support”, “Fine Arts” and “Foreign Language” that are associated with a low predicted greenness carrying the coefficients of  $-0.13$ ,  $-0.09$  and  $-0.08$ , respectively. When interpreting the coefficients, however, it is important to note that they are not unbiased, since the Ridge regression shrinks coefficients of skills with low prediction power towards zero.

O\*NET provides information on the value of a skill  $s$  of occupation  $i$  ( $\text{skill}_{i,s}$ ) according to the SOC on an 8-digit level. In order to estimate the green potential for occupations according to the ISCO 08 on the 3-digit level based on Eq. (1), the values of the skills must accordingly be transferred. Here we follow Niggli and Rutzer (2020) (and the work cited therein) and carry out the following three steps:

1. The values of a particular skill  $s$  of all occupations  $i$  belonging to the same 6-digit SOC occupation are transferred to that 6-digit level SOC occupation by taking a simple (unweighted) average.
2. The  $\text{skill}_{i,s}$  is then transferred to ISCO occupations, where a conversion table (provided by the US Bureau of Labor Statistics (BLS)) informs about the relations between SOC occupations on the 6-digit level and ISCO occupations on the 4-digit level. In the case of multiple matches, a simple (unweighted) average is used. The transfer of job information prepared for the US labour market to the European context in this second step can be seen as a limitation of this approach. However, following research of other scientists (e.g. OECD, 2017), we assume that this transfer is by and large permissible. Firstly, environmental issues arise not only in Switzerland, but internationally. Secondly, we assume that a skilled worker in both the USA and Switzerland must, with a few exceptions (e.g. in terms of nomenclature), has the same skills in order to be able to carry out the tasks assigned to her. For example, electricians must have the skills to estimate the necessary material quantities on the basis of planning documents and to install switches and sockets, no matter where they work.
3. The  $\text{skill}_{i,s}$  for ISCO occupations on the 3-digit level are computed by taking simple (unweighted) averages of all values of a particular skill  $s$  of all 4-digit occupations that belong to a 3-digit occupation.

On that basis, it is then possible to apply the trained model (see Eq. 1) to predict the potential of 3-digit ISCO occupations to perform green tasks. Finally, we normalize the green potential of occupations on a scale between 0 and 1, whereby the value of 1 (0) is attributed to the occupation with the highest (lowest) estimated green potential. The values for the other occupations  $i$  are then calculated relative to the values of the occupations with the highest and lowest green potential:  $(\hat{\eta}_i - \min(\hat{\eta})) / (\max(\hat{\eta}) - \min(\hat{\eta}))$ .

A summary of the results is shown in Table 2. It lists the ten occupations with the highest green potential estimates. As one can see, Engineering professionals have the highest green potential with a value of 1, followed by Physical and earth science professionals with a value of 0.76 and Production managers in agriculture, forestry and fisheries with a value of 0.76. The green potential of all occupations used in this study are shown in Table 7 in the “Appendix”.

### 3.2 Emission tax, green potential and employment

In the previous section, we determined the green potential of ISCO occupations. In doing so, we argued that such occupations have skills needed to perform green tasks. Therefore, in case of a green shift of an economy one would expect a relatively high demand for such jobs compared to jobs that do not have such skills. In the following, we would like to examine whether we find signs of such a heterogeneous demand response in the Swiss labour market. Specifically, we use changes in the implicit tax rate on greenhouse gas emissions at a two-digit industry level to investigate whether this is associated with a heterogeneous change in the demand for workers with higher green potential relative to those with lower green potential. For this purpose, we estimate the following empirical model

$$\log \text{emp}_{i,j,t} = \beta_1 \hat{\eta}_i \tau_{j,t} + \gamma X_{j,t} + \delta_t + \epsilon_i + \nu_j + u_{i,j,t}, \quad (2)$$

where our left-hand side variable  $\log \text{emp}_{i,j,t}$  consists of the log of employment of occupation  $i$  in industry  $j$  at time  $t$ ,  $\tau_{j,t}$  stands for the implicit emission tax of industry  $j$  at time  $t$ . We interact the implicit emission tax with our previous determined green potential level  $\hat{\eta}_i$  of an occupation  $i$  in order to analyse possible heterogeneous labour market responses. In addition, the matrix  $X_{j,t}$  contains control variables, such as the non-interacted implicit emission tax  $\tau_{j,t}$  and the labour productivity at the industry level. In addition, we use time fixed effects ( $\delta_t$ ), occupational fixed effects ( $\epsilon_i$ ) and industry fixed effects ( $\nu_j$ ).<sup>9</sup> For example, the fixed effects take into

<sup>9</sup> Our specification does not include a term  $\hat{\beta}_3 \hat{\eta}_i$ , because it is completely captured by the occupational fixed effect  $\epsilon_i$ .

**Table 2** Occupations with highest green potential

ISCO	Occupation	Green potential
214	Engineering professionals (excluding electrotechnology)	1.00
211	Physical and earth science professionals	0.76
131	Production managers in agriculture, forestry and fisheries	0.76
210	Science and engineering professionals, nos	0.75
312	Mining, manufacturing and construction supervisors	0.75
215	Electrotechnology engineers	0.73
132	Manufacturing, mining, construction, and distribution managers	0.72
216	Architects, planners, surveyors and designers	0.71
112	Managing directors and chief executives	0.68
314	Life science technicians and related associate professionals	0.68
...	...	...

Own calculations based on Rutzer et al. (2020)

account unobserved heterogeneity among different ISCO occupations that may affect the level of employment and industry-specific employment differences. Finally,  $u_{i,j,t}$  is the error term.

To summarize, our estimation strategy relies on analysing variations in the number of employed persons over time within industry-specific occupational groups that differ according to their green potential. It is important to note that our specification only shows an association and not a causal relationship. Since the aim of this analysis is to empirically support our measure of the green potential of occupations, we consider establishing a controlled correlation as sufficient.

### 3.3 Data

Next, we provide an overview of the data used to estimate equation (2). Our analysis is based on different data sources: Firstly, we use data from the O\*NET database (v21.2). We have already described it in Chapter 3.1 when discussing the measurement of the green potential of occupations. Secondly, for the number of employed persons we use data from the Swiss Labour Force Survey (SLFS) for the years 2008–2017. The SLFS provides information on the structure of the labour force and employment behaviour patterns. Specifically, in addition to general socio-economic information, the SLFS contains information on the job currently exercised, according to the ISCO nomenclature and the industry where the person is employed, which corresponds to the six digit NOGA-2008 nomenclature.<sup>10</sup> Thirdly, we use data on expenditures on greenhouse gas emissions (measured in millions of Swiss Francs) and greenhouse gas emissions (measured in thousand tons of CO<sub>2</sub> equivalent emissions) from the Federal Statistical Office (FSO).

This information is available at the two digit NOGA-2008 industry level—and for some industries for a grouping of several two digit industries—from 2008 onwards and allows us, for each industry and year, to calculate an implicit tax rate by dividing the environmental expenditures through the greenhouse gas emissions. Afterwards, we multiply the result by 1000 to get an implicit emission tax measured as Swiss Franc per one ton of CO<sub>2</sub> equivalent emission. A list of industries and their corresponding change in the implicit emission tax between our first year 2008 and last year 2017 can be found in the “Appendix 3”. In total, we have data for 37 different industries of the second (manufacturing) and third sector (services). Fourthly, we use data from the FSO to calculate the labour productivity at the industry level (value added at the industry level divided by the number of employment). Having outlined the data, we now turn to the empirical results.

### 3.4 Empirical results

Table 3 shows the main results. The first row captures whether there exists a heterogeneous association between implicit emission tax and labour demand.

The variable is highly significant with a positive sign in all of our four specifications either above or almost at the 99% level. In particular, the first column shows our baseline specification. This specification controls only for general economic conditions and time-invariant occupation- and industry specific effects, such as the routine intensity of occupations. Therefore, we add year-industry fixed effects and, additionally, year-occupation fixed effects to capture time varying effects at the most disaggregated level. As one can see in columns (2) and (3), the coefficient remains very stable. Note that, in this case, the implicit emission tax without interaction is completely absorbed by the fixed effects. In a last step,

<sup>10</sup> The NOGA nomenclature is identical to the NACE classification up to a four-digit level.



**Table 3** Association between Implicit Emission Tax and Employment

	<i>Dependent variable</i>			
	$\log(\text{employment}_{i,j,t})$			
	(1)	(2)	(3)	(4)
Implicit emission tax $x_{j,t} \times$	0.0626**	0.0649***	0.0655***	0.0573**
Green potential $\hat{\eta}_i$	(0.0245)	(0.0247)	(0.0251)	(0.0240)
Implicit emission tax $x_{j,t}$	✓			✓
Occupation fixed effects	✓	✓	✓	
Industry fixed effects	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Year-industry fixed effects		✓	✓	
Year-occupation fixed effects			✓	
$\log(\text{labour productivity})$				✓
3-digit ISCO time trends				✓
Observations	22,642	22,642	22,642	22,642
Pseudo- $R^2$	0.0691	0.0698	0.0422	0.0695

The sample is an unbalanced panel covering 37 Swiss industries between 2008 and 2017. The dependent variable in all columns is the log of occupational employment. All model specifications include fixed effects for industries and years. Columns (1), (2) and (3) further include occupation fixed effects. Columns (1) and (4) additionally include the implicit emission tax. Columns (2) and (3) additionally contain yearly occupation and industry fixed effects. Furthermore, column (4) contains the labour productivity at the industry level in logarithmic form and occupation time trends. Data are from the FSO and the SLFS. Standard errors in parentheses are clustered at the industry level. Significance levels for the coefficients are indicated as: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

we use the labour productivity at the industry level and 3-digit ISCO time trends to control for major structural changes such as digitization and the increasing globalization. Again, the coefficient of our variable of interest remains almost the same (column 4). Moreover, in order to check the robustness of our results, we varied the time period, excluded the most and least polluting industries and also the most and least affected ISCO occupations. The results can be found in “Appendix 4” and generally confirm the heterogeneous association demonstrated in Table 3.

So far, the estimates are based on a continuum of green potential. However, for our subsequent descriptive characterization of employment in occupations with high green potential, it is necessary to divide occupations into discrete groups. For this purpose, we divide the ISCO occupations into two groups based on their green potential. In particular, we classify all ISCO occupations with a green potential larger or equal to 0.5 as occupations with high green potential and the rest as occupations with low green potential. The choice of the threshold is further

**Table 4** Association between Implicit Emission Tax and Employment: Binary case

	<i>Dependent variable:</i>			
	$\log(\text{employment}_{i,j,t})$			
	(1)	(2)	(3)	(4)
Subset of green potential:	Full sample	< 0.5	≥ 0.5	Full sample
Implicit emission tax $x_{j,t} \times$	0.0381***			
$\mathbb{I}_{\hat{\eta} \geq 0.5}$	(0.0147)			
Implicit emission tax $x_{j,t} \times$	0.0071			
$\mathbb{I}_{\hat{\eta} < 0.5}$	(0.0106)			
Implicit emission tax $x_{j,t} \times$		0.0368	0.00402	0.0626**
Green potential $\hat{\eta}_i$		(0.0407)	(0.0350)	(0.0245)
Implicit emission tax $x_{j,t}$		✓	✓	✓
Occupation fixed effects	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Observations	22,642	17,580	5062	22,642
Pseudo- $R^2$	0.0693	0.0696	0.1052	0.0691

The sample is an unbalanced panel covering 37 Swiss industries between 2008 and 2017. The dependent variable in all columns is the log of occupational employment. All model specifications include fixed effects for occupations, industries and years. Columns (2), (3) and (4) additionally include the implicit emission tax. It is not included in column (1) as otherwise one of the two green potential group dummies are fully absorbed. Data are from the FSO and the SLFS. Standard errors in parentheses are clustered at the industry level. Significance levels for the coefficients are indicated as: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

explained in Sect. 4.1, but can also be justified empirically. For this purpose, Table 4 again shows the estimations of our previously determined baseline specification. But instead of considering a continuum of green potential, jobs are now divided into two groups with high and low green potential, respectively.<sup>11</sup>

In the first column, we interact the implicit emission tax with the binary green potential dummy. The results show a highly significant positive association between an increase in the implicit emission tax and demand for occupations of the high green potential group. Instead, for the occupation group with low green potential, the association is insignificant. Thus, our previous results based on a continuum of green potential also transfers to a binary case.<sup>12</sup> In columns (2) and (3), we further analyse whether there exists some within-group heterogeneity. In both cases, the coefficient of the implicit emission

<sup>11</sup> Due to reasons of high collinearity between the binary green potential dummy and time varying occupational fixed effects, we stick to the baseline specification.

<sup>12</sup> In Table 10 in the “Appendix”, we show additional estimations for a binary grouping based on a threshold of 0.45 and 0.55, which we also use as robustness checks in our subsequent descriptive characterization of the green potential of the Swiss labour market. The results remain stable.

tax interacted with the green potential remains insignificant. For reasons of better comparison, we also show the previous result of the full sample (column 4). Together with the result of column (1), this suggests high between-group but not much within-group heterogeneity. This, in turn, empirically supports our subsequent partitioning of occupations into two groups based on their green potential in order to characterize the Swiss labour market.

In summary, our empirical results show that there exists a heterogeneous association between labour demand of occupations with high and low green potential and changes in emission taxes. This supports our initial claim that—when an economy becomes greener—occupations with a high green potential are in relative terms in higher demand than occupations with a low green potential. The result is in line with other work, for example, by Niggli and Rutzer (2020) or Vona et al. (2018). The first study uses a panel dataset of different manufacturing occupations of various European countries to analyse the labour market response to changes in environmental regulations. The latter exploits exogenous variations in environmental regulations among different US labour market regions. Both studies find heterogeneous labour demand responses qualitatively equivalent to this paper.

Having established a heterogeneous association between emission taxes and labour demand of Swiss occupations with high and low green potential, we now take a detailed look at the green potential of the Swiss labour market. This helps us to better understand how well the Swiss labour market is prepared for a transformation towards a green economy.

#### 4 Characterization of employment in occupations with high green potential

In the following sections, we will characterize employment in occupations with high green potential along different dimensions. In order to do that, it is necessary to divide occupations into discrete groups. Particularly, we divide the ISCO occupations into two groups based on the estimated green potential of the occupations. For that, we set a threshold at 0.5. Occupations with a green potential equal or above this threshold are considered as occupations with high green potential, the other occupations as occupations with low green potential. The determination of a threshold value is arbitrary to a certain degree. Nevertheless, the chosen value can be justified as follows: First, the choice of the threshold value is empirically supported by the results from Table 4, showing a highly significant

positive association between an increase in the implicit emission tax and demand for occupations with a green potential equal to or above 0.5, whereas the estimated effect for occupations with a green potential below 0.5 is insignificant. Second, the mean green potential (measured by the median) is 0.27. The threshold value at 0.5 thus indicates that the group of occupations with high green potential includes occupations that have more than one and a half times the median green potential. These are thus occupations with a green potential that is well above average.

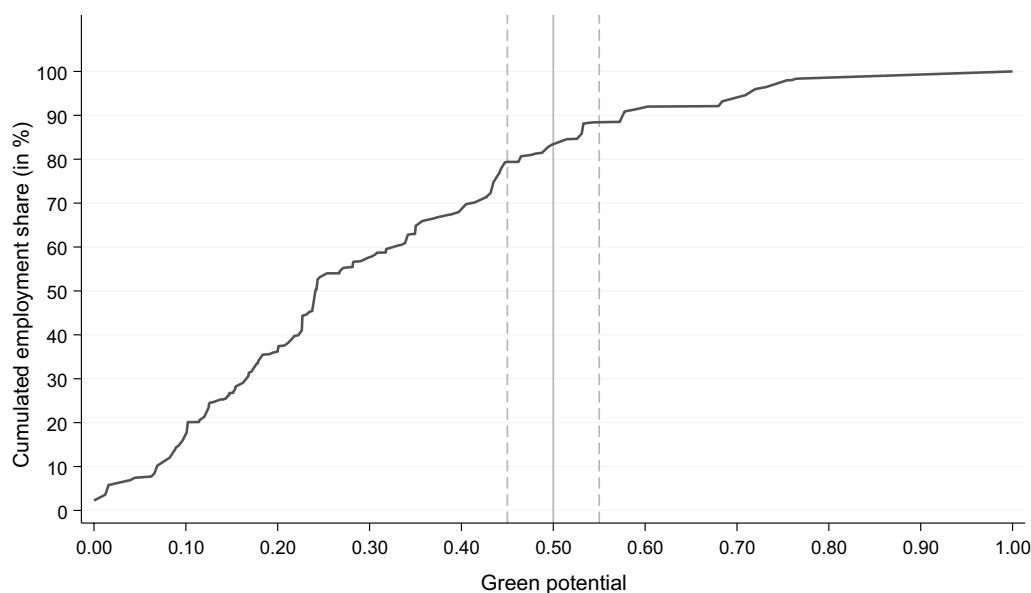
##### 4.1 Size and development

Given the threshold value of 0.5, we calculate the number of employees and FTE in occupations with high green potential for Switzerland in the year 2017 of about 739,000 persons and 670,000 FTE. Measured in terms of total employment, the number of people employed and FTE in occupations with high green potential was around 16.7% and 18.8%, respectively. Figure 1 shows the cumulative employment share (in %) in dependency of the green potential. If the threshold value is increased (decreased) by 0.05 to 0.55 (0.45), the share of employed persons in the total employed population increases (decreases) to 11% (20%).

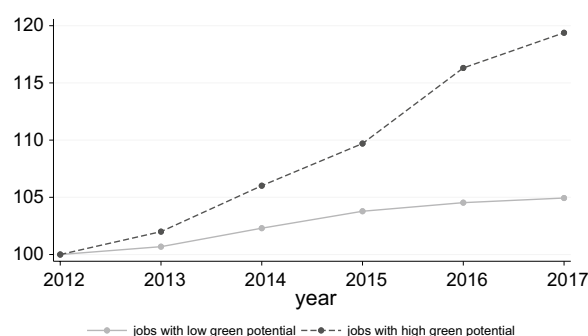
As Fig. 2 shows, employment growth in the group of occupations with high green potential was stronger in the time period 2012–2017 than in the group occupations with low green potential: While the number of employees in the group of occupations with high green potential grew by 19.4% in 2012–2017, the growth in employment in the group of occupations with low green potential over the same period was only 5.1%. It is worth noting that in absolute terms, growth in the group of occupations with low green potential was significantly higher at 179,363 than in the group of occupations with high green potential at 119,938.

##### 4.2 Industry share

The employment share of occupations with high green potential is distributed differently across industries. In 2017, the highest shares of employees in jobs with high green potential to the total labour force are found for energy, construction, manufacturing and professional, scientific and technical activities (with shares above 20%) (see Fig. 3). On the other hand, accommodation and food service activities, financial and insurance as well as human health and social work activities have the lowest shares, being well below 10%.



**Fig. 1** Cumulated employment share (in %). Source: Own calculations based on SLFS 2017 (FSO)



**Fig. 2** Employment growth in jobs with low and high green potential, 2012–2017, index: 2012=100. Source: Own calculations based on SLFS (FSO)

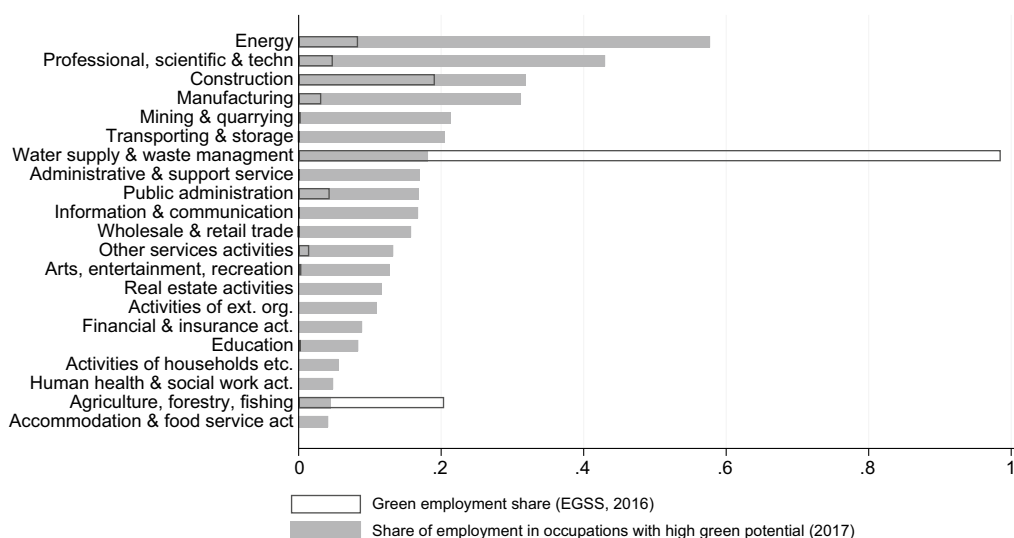
For the sake of comparison, Fig. 3 shows the shares of green employment when using the definition of the EGSS, covering employment in industries that produce goods and services contributing to the protection of the environment or the conservation of natural resources. As described in the literature review in Sect. 2, such an industry approach is often used to quantify green employment. Using this definition produces quite different results: Three sectors dominate, namely water supply and waste management, agriculture, forestry and fishing, and construction. In comparison, the shares for three sectors that were still among

the four most important sectors (energy, manufacturing, professional, scientific & technical activities) in terms of green potential are now significantly lower. These differences reveal the impact of the two different approaches. The approach used in this study differs from the EGSS approach in two important aspects: First, it is occupation based and therefore not dependent on the industry to which it belongs. Second, an occupation is classified as one with high green potential if it is associated with skills that are important for the exercise of green tasks; regardless of whether green tasks are already being performed or not and whether the job being carried out already contributes to a green economy or not. What counts is the potential of the occupations to perform green tasks.

### 4.3 Socioeconomic characteristics and labour demand indicators

We have also compared those employed in jobs with high green potential with those employed in jobs with low green potential in terms of age structure, gender, level of education and migratory status<sup>13</sup> (see Table 5): Employed persons in occupations with high green potential are, on average, younger, more often men, have a higher level of educational attainment and a higher probability of having immigrated than employed persons in occupations with low green potential.

<sup>13</sup> We differentiate between employed people that immigrated in the last 10 years (no matter what nationality) and people that have not immigrated or immigrated over 10 years ago.



**Fig. 3** Employment in jobs with high green potential and green employment as a percentage of total employment by industry. Note: The figure indicates for each industry **a** the share of employment in occupations with high green potential as a percentage of total employment (measured in FTE) and **b** the share of jobs (filled) in industries belonging to the Environmental Goods and Services Sector (EGSS) as a share of the job base (measured in FTE). Source: SLFS 2017 (FSO), EGSS 2016 (FSO)

**Table 5** Characterization of jobs with high and low green potential

Variable	Occupations with	
	High green potential (%)	Low green potential (%)
<i>Age</i>		
15–34	31.6	30.6
35–49	37.0	34.5
50+	31.4	34.9
<i>Sex</i>		
Male	76.0	48.7
Female	24.0	51.3
<i>Education</i>		
Primary	3.6	11.9
Secondary	33.4	50.1
Tertiary	63.0	38.0
Migration rate	15.4	13.1
Rate of job vacancies	3.6	2.9
Rate of unemployment	3.6	4.6

Own calculations based on x28 (job vacancies rate) and SLFS 2017 (all other variables). The migration rate is defined as the number of immigrant workers in the labour force (immigrated in the last 10 years) divided by the employed persons. The rate of job vacancies is defined as the number of job vacancies divided by the employed persons plus the number of job vacancies. The rate of unemployment is defined as the number of unemployed persons (as defined by ILO) divided by the economically active persons (that is employed and unemployed persons)

Finally, we have computed two commonly used labour demand indicators, namely the rate of job vacancies and the unemployment rate (see Table 5).<sup>14</sup> There are differences in both indicators between the two occupational groups. The group of occupations with high green potential shows a higher rate of job vacancies and a lower rate of unemployment compared to the group of occupations with low green potential.

## 5 Discussion

We have estimated the green potential of occupations in Switzerland based on a data-driven methodology that allows quantifying the importance of different skills in performing green tasks. The results show that occupations with a high green potential are predominantly those with an engineering and technical background. We further provide evidence in support of our green potential measure: We have investigated whether we find signs of a heterogeneous demand response in the Swiss labour market due to green economy measures. Specifically, we use changes in the implicit tax rate on greenhouse gas emissions at a two-digit industry level to investigate whether this is associated with a heterogeneous change in the demand for workers with higher green potential relative to those with lower green potential. Our empirical results show a positive association between the demand of occupations with higher

<sup>14</sup> The results for the two groups of occupations are computed as a weighted average of the values on the 3-digit level of ISCO occupations, where the number of employees are used as weights.

green potential and an increase in the implicit tax rate on greenhouse gas emissions. In contrast, for occupations with lower green potential, we do not find such an association. This substantiates our measure of green potential. Afterwards, we characterized employment in occupations with high green potential. For that, we divided the ISCO occupations into two groups by applying a particular threshold value. On that basis, we estimate the share of employment in occupations with high green potential to the total labour force to 16.7% (number of persons employed) and 18.8% (FTE). Employed persons in occupations with high green potential are, on average, younger, more often men, have a higher level of educational attainment and a higher probability of having immigrated than employed persons in occupations with low green potential. Furthermore, the group of occupations with high green potential has a higher job vacancy rate and a lower unemployment rate compared to the group with low green potential.

At about 20%, a considerable part of the workforce in Switzerland works in occupations with a high green potential and thus presumably also has the corresponding skills. Nevertheless, it can be assumed that a transformation towards a green economy is likely to be accompanied by increased demand for occupations with high green potential, and the availability of suitably trained workers is important for this transformation to take place. How can the relevant skilled workers be provided? Since occupations with high green potential are primarily those with an engineering and technical background, i.e. occupations for which there are already indications of a shortage of skilled workers today, there are already initiatives to increase the number of skilled workers in these fields.<sup>15</sup> These initiatives address the problem primarily through the recruitment of skilled workers through four approaches: (1) education and training, (2) the utilization of existing skilled labour potential by increasing the level of employment, (3) the retention of existing skilled workers by reducing the migration to other occupations or early career departures, and (4) employment beyond the normal retirement age. Not all of these measures seem equally relevant for occupations with high green potential: As the analyses show, workers in occupations with high green potential have a younger labour force structure than those in other occupations. In this respect, retirements of skilled workers are not as relevant as in other occupations.

Furthermore, there is evidence that the labour potential in occupations with high green potential is already being exploited to an above-average extent, leaving little room to increase the level of employment.<sup>16</sup> For these reasons, the education and training of appropriate professionals seems to be the indicated way to meet an increased future demand due to a development towards a green economy.<sup>17</sup>

Our findings are far from exhaustive. We see three directions for advancing research in this field: The estimation of the green potential of occupations is based on a set of general skills. Building a deeper knowledge about what specific skills (for particular occupations and countries) will be needed for a transformation towards a sustainable economy is a first avenue for future research. A second axis of future research could focus on the development of green tasks within occupations over time. In this context, the approach of Janser (2018) (see Sect. 2 for more details) could be applied to job advertisements in Switzerland. Against the background of a possible increased future demand for occupations with high green potential, research on a third axis could be devoted to the topic of skills mismatches in general and skills shortages in particular, even more so as there is already some evidence of skill shortages for occupations with high green potential.

## Appendices

### Appendix 1: Coefficients of the ridge regression

See Table 6

<sup>16</sup> The exploitation of the labour force potential can be estimated on the basis of the employment rate and the level of employment. It was not possible to calculate the employment rate for the present analysis on the basis of the available data. Since occupations with high green potential are often technical occupations and accordingly trained persons have an above-average employment rate according to other studies (Degen et al., 2016), we assume that this is also the case for occupations with high green potential. Our own analysis based on the SLFS 2017 shows that employed persons in occupations with high green potential have an above-average level of employment (93% compared to the overall economic value of around 80%).

<sup>17</sup> Another potential option could be international migration. However, since the share of migrants in occupations with high green potential is already above average, the possibilities of covering the (additional) demand for skilled labour through migration already seems to be heavily exploited.

<sup>15</sup> One such initiative is the federal government's initiative for skilled workers (FKI), that aims to improve the development and exploitation of existing domestic skilled labour potentials (Bundesrat, 2018).



**Table 6** List of the coefficients of the ridge regression

General skill from O*NET	Ridge coefficient
Achievement	0.07
Active learning	– 0.01
Active listening	– 0.03
Administration and management	0.01
Analyzing data or information	0.04
Assisting and caring for others	– 0.05
Biology	0.05
Building and construction	0.15
Chemistry	0.06
Clerical	0.01
Coaching and developing others	– 0.01
Communicating with persons outside organization	0.04
Communicating with supervisors peers or subordinates	0.03
Communications and media	0.01
Complex problem solving	– 0.03
Computers and electronics	– 0.02
Controlling machines and processes	– 0.07
Coordinating the work and activities of others	0.05
Coordination	– 0.02
Critical thinking	– 0.01
Customer and personal service	– 0.04
Design	0.02
Developing and building teams	0.06
Developing objectives and strategies	0.01
Documenting recording information	0.03
Economics and accounting	0.07
Education and training	– 0.01
Engineering and technology	0.07
English language	– 0.02
Equipment maintenance	0.02
Equipment selection	– 0.03
Establishing and maintaining interpersonal relationships	– 0.02
Estimating the quantifiable characteristics of products events or information	0.02
Evaluating information to determine compliance with standards	0.04
Fine arts	– 0.09
Food production	– 0.03
Foreign language	– 0.08
Geography	0.08
Handling and moving objects	– 0.04
History and archeology	– 0.02
Identifying objects actions and events	– 0.05
Independence	– 0.03
Inspecting equipment structures or material	0.01
Installation	0.05
Instructing	– 0.01
Interacting with computers	0.01
Interpreting the meaning of information for others	0.02
Judging the qualities of things services or people	– 0.03
Judgment and decision making	– 0.01

**Table 6** (continued)

General skill from O*NET	Ridge coefficient
Law and government	0.05
Learning Strategies	– 0.03
Making Decisions and Solving Problems	– 0.04
Management of Financial Resources	0.05
Management of Material Resources	0.03
Management of Personnel Resources	0.01
Mathematics	0.01
Mechanical	0.05
Medicine and Dentistry	– 0.06
Monitor Processes Materials or Surroundings	0.02
Monitoring	0.01
Monitoring and Controlling Resources	0.03
Negotiation	0.05
Operating Vehicles Mechanized Devices or Equipment	0.04
Operation and Control	0.01
Operation Monitoring	0.01
Operations Analysis	– 0.07
Organizing Planning and Prioritizing Work	– 0.02
Performing Administrative Activities	– 0.04
Performing General Physical Activities	0.02
Personnel and Human Resources	– 0.03
Persuasion	0.05
Philosophy and Theology	– 0.04
Physics	0.08
Production and Processing	– 0.02
Programming	0.06
Provide Consultation and Advice to Others	0.06
Psychology	– 0.03
Public Safety and Security	0.07
Quality Control Analysis	0.01
Reading Comprehension	0.02
Recognition	0.01
Relationships	– 0.03
Repairing	0.01
Repairing and Maintaining Electronic Equipment	– 0.02
Repairing and Maintaining Mechanical Equipment	– 0.01
Sales and Marketing	0.01
Scheduling Work and Activities	0.01
Science	0.03
Selling or Influencing Others	0.05
Social Perceptiveness	– 0.05
Sociology and Anthropology	– 0.02
Speaking	– 0.02
Staffing Organizational Units	– 0.02
Support	– 0.13
Systems Analysis	0.06
Systems Evaluation	0.05
Technology Design	– 0.01
Telecommunications	– 0.06

**Table 6** (continued)

General skill from O*NET	Ridge coefficient
Therapy and Counseling	– 0.05
Thinking Creatively	– 0.02
Time Management	– 0.03
Training and Teaching Others	– 0.03
Transportation	0.01
Troubleshooting	0.02
Updating and Using Relevant Knowledge	– 0.01
Working Conditions	0.05
Writing	0.04

## Appendix 2: Green potential of ISCO occupations

See Table 7

**Table 7** List of ISCO occupations and their predicted green potential

ISCO	Job title	Predicted greenness
214	Engineering professionals (excluding electrotechnology)	1.00
211	Physical and earth science professionals	0.76
131	Production managers in agriculture, forestry and fisheries	0.76
210	Science and engineering professionals, nos	0.75
312	Mining, manufacturing and construction supervisors	0.75
215	Electrotechnology engineers	0.73
132	Manufacturing, mining, construction, and distribution managers	0.72
216	Architects, planners, surveyors and designers	0.71
112	Managing directors and chief executives	0.68
314	Life science technicians and related associate professionals	0.68
110	Chief executives, senior officials and legislators, nos	0.65
111	Legislators and senior officials	0.60
213	Life science professionals	0.59
311	Physical and engineering science technicians	0.58
142	Retail and wholesale trade managers	0.57
130	Production and specialized services managers, nos	0.54
242	Administration professionals	0.53
100	Managers, nos	0.53
143	Other services managers	0.53
741	Electrical equipment installers and repairers	0.51
740	Electrical and electronic trades workers, nos	0.50
310	Science and engineering associate professionals, nos	0.50
122	Sales, marketing and development managers	0.49
212	Mathematicians, actuaries and statisticians	0.49
313	Process control technicians	0.49
120	Administrative and commercial managers, nos	0.48
742	Electronics and telecommunications installers and repairers	0.48
754	Other craft and related workers	0.48

**Table 7** (continued)

ISCO	Job title	Predicted greenness
723	Machinery mechanics and repairers	0.46
140	Hospitality, retail and other services managers, nos	0.46
710	Building and related trades workers, excluding electricians, nos	0.45
711	Building frame and related trades workers	0.45
333	Business services agents	0.44
731	Handicraft workers	0.44
712	Building finishers and related trades workers	0.44
332	Sales and purchasing agents and brokers	0.43
133	Information and communications technology service managers	0.43
622	Fishery workers, hunters and trappers	0.43
240	Business and administration professionals, nos	0.43
612	Animal producers	0.43
121	Business services and administration managers	0.43
931	Mining and construction labourers	0.41
620	Market-oriented skilled forestry, fishery and hunting workers, nos	0.41
251	Software and applications developers and analysts	0.41
343	Artistic, cultural and culinary associate professionals	0.40
811	Mining and mineral processing plant operators	0.39
720	Metal, machinery and related trades workers, nos	0.39
610	Market-oriented skilled agricultural workers, nos	0.39
200	Professionals, nos	0.37
250	Information and communications technology professionals, nos	0.37
600	Skilled agricultural, forestry and fishery workers, nos	0.36
243	Sales, marketing and public relations professionals	0.36
813	Chemical and photographic products plant and machine operators	0.35
613	Mixed crop and animal producers	0.35
700	Craft and related trades workers, nos	0.35
252	Database and network professionals	0.35
621	Forestry and related workers	0.34
241	Finance professionals	0.34
721	Sheet and structural metal workers, moulders and welders, and related workers	0.34
315	Ship and aircraft controllers and technicians	0.33
611	Market gardeners and crop growers	0.33
634	Subsistence fishers, hunters, trappers and gatherers	0.33
713	Painters, building structure cleaners and related trades workers	0.32
300	Technicians and associate professionals, nos	0.32
835	Ships' deck crews and related workers	0.31
722	Blacksmiths, toolmakers and related trades workers	0.31
752	Wood treaters, cabinet-makers and related trades workers	0.31
352	Telecommunications and broadcasting technicians	0.30
134	Professional services managers	0.30
933	Transport and storage labourers	0.29
350	Information and communications technicians, nos	0.29
232	Vocational education teachers	0.28
141	Hotel and restaurant managers	0.28
330	Business and administration associate professionals, nos	0.28
225	Veterinarians	0.27
730	Handicraft and printing workers, nos	0.27
961	Refuse workers	0.27

**Table 7** (continued)

ISCO	Job title	Predicted greenness
821	Assemblers	0.27
351	Information and communications technology operations and user support technicians	0.27
834	Mobile plant operators	0.27
930	Labourers in mining, construction, manufacturing and transport, nos	0.27
261	Legal professionals	0.25
335	Regulatory government associate professionals	0.25
820	Assemblers, nos	0.24
331	Financial and mathematical associate professionals	0.24
750	Food processing, wood working, garment and other craft and related trades workers, nos	0.24
522	Shop salespersons	0.24
262	Librarians, archivists and curators	0.24
231	University and higher education teachers	0.23
632	Subsistence livestock farmers	0.23
830	Drivers and mobile plant operators, nos	0.23
411	General office clerks	0.23
630	Subsistence farmers, fishers, hunters and gatherers, nos	0.23
800	Plant and machine operators and assemblers, nos	0.23
221	Medical doctors	0.23
810	Stationary plant and machine operators, nos	0.22
921	Agricultural, forestry and fishery labourers	0.22
833	Heavy truck and bus drivers	0.22
751	Food processing and related trades workers	0.21
950	Street and related sales and service workers, nos	0.21
951	Street and related service workers	0.21
952	Street vendors (excluding food)	0.21
521	Street and market salespersons	0.21
960	Refuse workers and other elementary workers, nos	0.21
900	Elementary occupations, nos	0.21
340	Legal, social, cultural and related associate professionals, nos	0.20
520	Sales workers, nos	0.20
541	Protective services workers	0.20
814	Rubber, plastic and paper products machine operators	0.20
220	Health professionals, nos	0.20
223	Traditional and complementary medicine professionals	0.20
260	Legal, social and cultural professionals, nos	0.19
732	Printing trades workers	0.19
633	Subsistence mixed crop and livestock farmers	0.19
812	Metal processing and finishing plant operators	0.19
226	Other health professionals	0.18
816	Food and related products machine operators	0.18
832	Car, van and motorcycle drivers	0.18
524	Other sales workers	0.18
818	Other stationary plant and machine operators	0.18
513	Waiters and bartenders	0.18
430	Numerical and material recording clerks, nos	0.17
831	Locomotive engine drivers and related workers	0.17
514	Hairdressers, beauticians and related workers	0.17
512	Cooks	0.17



**Table 7** (continued)

ISCO	Job title	Predicted greenness
500	Service and sales workers, nos	0.17
432	Material-recording and transport clerks	0.16
941	Food preparation assistants	0.16
815	Textile, fur and leather products machine operators	0.16
631	Subsistence crop farmers	0.15
932	Manufacturing labourers	0.15
265	Creative and performing artists	0.15
753	Garment and related trades workers	0.15
817	Wood processing and papermaking plant operators	0.15
342	Sports and fitness workers	0.15
222	Nursing and midwifery professionals	0.15
431	Numerical clerks	0.15
912	Vehicle, window, laundry and other hand cleaning workers	0.14
510	Personal service workers, nos	0.14
910	Cleaners and helpers, nos	0.14
224	Paramedical practitioners	0.14
264	Authors, journalists and linguists	0.14
320	Health associate professionals, nos	0.13
324	Veterinary technicians and assistants	0.13
230	Teaching professionals, nos	0.13
321	Medical and pharmaceutical technicians	0.13
233	Secondary education teachers	0.12
235	Other teaching professionals	0.12
516	Other personal services workers	0.12
511	Travel attendants, conductors and guides	0.11
400	Clerical support workers, nos	0.11
323	Traditional and complementary medicine associate professionals	0.11
410	General and keyboard clerks, nos	0.10
911	Domestic, hotel and office cleaners and helpers	0.10
515	Building and housekeeping supervisors	0.10
325	Other health associate professionals	0.10
523	Cashiers and ticket clerks	0.09
441	Other clerical support workers	0.09
263	Social and religious professionals	0.09
234	Primary school and early childhood teachers	0.08
420	Customer services clerks, nos	0.08
412	Secretaries (general)	0.07
422	Client information workers	0.07
413	Keyboard operators	0.06
962	Other elementary workers	0.06
531	Child care workers and teachers' aides	0.04
421	Tellers, money collectors and related clerks	0.04
341	Legal, social and religious associate professionals	0.04
530	Personal care workers, nos	0.02
322	Nursing and midwifery associate professionals	0.02
334	Administrative and specialized secretaries	0.01
532	Personal care workers in health services	0.00

### Appendix 3: Industries used in the empirical analysis

Industry	Observations	$\tau_{2017}/\tau_{2008}$
D10–T12	1028	0.91
D13–T15	1550	1.07
D16–T18	972	0.92
D19–T20	873	0.99
D21	881	1.06
D22–T23	1140	0.77
D24–T25	1579	0.71
D26	1018	1.40
D27	749	1.30
D28	1221	1.16
D29–T30	1054	1.19
D31–T33	1548	0.96
D35	705	2.13
D36–T39	781	1.89
D41–T43	777	2.00
D45	1251	0.58
D46	985	0.77
D47	911	0.69
D49–T51	1903	0.60
D52	1721	0.60
D53	252	0.60
D55–T56	1563	0.23
D58–T60	1062	0.47
D61	390	0.22
D62–T63	1083	0.63
D64	1128	0.06
D65	1088	0.64
D68	350	1.03
D69–T70	1483	0.94
D71	738	0.94
D72	886	1.11
D73–T75	2065	0.40
D77–T82	2069	0.60
D85	2175	0.69
D87–T88	944	0.64
D90–T93	2033	2.13
D94–T96	1436	1.11

The first column shows the Noga nomenclature. The second column states the number of distinct ISCO occupations per year and industry. The third column shows the incremental change in the industry's implicit tax rate between 2017 and 2008. A value less than one means that the implicit tax rate has decreased, a value larger than one that it has increased

### Appendix 4: Robustness checks

See Tables 8, 9 and 10.

**Table 8** Association between Implicit Emission Tax and Employment: Varying considered occupations

	<i>Dependent variable</i>		
	$\log(\text{employment}_{i,j,t})$		
	(1)	(2)	(3)
	Excluded 1% max $\tau \eta$	Excluded 1% min $\tau \eta$	Full sample
Implicit emission tax $_{j,t} \times$	0.0677**	0.0645**	0.0655**
Green Potential $\hat{\eta}_i$	(0.0343)	(0.0271)	(0.0251)
Occupation fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Year dummies	✓	✓	✓
Year-industry fixed effects	✓	✓	✓
Year-occupation fixed effects	✓	✓	✓
Observations	22,301	22,281	22,642
Pseudo-R <sup>2</sup>	0.0404	0.0411	0.0422

The sample is an unbalanced panel covering 37 Swiss industries between 2008 and 2017. The dependent variable in all columns is the log of occupational employment. All model specifications include fixed effects for occupations, industries and years. In addition, yearly industry and occupation fixed effects are considered. Column (1) excludes the 1% of observations having the largest value of the variable of interest implicit emission tax interacted with the green potential and column (2) the 1% with the lowest value. Column (3) shows the full sample for comparison. Data are from the FSO and the SLFS. Standard errors in parentheses are clustered at the industry level. Significance levels for the coefficients are indicated as: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

**Table 9** Association between implicit emission tax and employment: varying time span and industries

	<i>Dependent variable</i>			
	<i>log(employment<sub>ijt</sub>)</i>			
	(1)	(2)	(3)	(4)
	2008– 2012	2013– 2017	15 industries Highest $\Delta \tau_{2008-2017}$	15 industries Lowest $\Delta \tau_{2008-2017}$
<b>Implicit emission tax<sub>ijt</sub> ×</b>	<b>0.0668***</b>	<b>0.0645**</b>	<b>0.0927***</b>	<b>0.0586</b>
<b>Green potential <math>\hat{\eta}_i</math></b>	<b>(0.0254)</b>	<b>(0.0259)</b>	<b>(0.0360)</b>	<b>(0.0544)</b>
Occupation fixed effects	✓	✓	✓	✓
Industry fixed effects	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Year-industry fixed effects	✓	✓	✓	✓
Year-occupation fixed effects	✓	✓	✓	✓
Observations	11,059	11,583	7616	7926
Pseudo-R <sup>2</sup>	0.0377	0.0378	0.0196	0.0044

The dependent variable in all columns is the log of occupational employment. All model specifications include fixed effects for occupations, industries and years. In addition, yearly industry and occupation fixed effects are considered. Column (1) shows an unbalanced panel covering 37 Swiss industries between 2008 and 2012 and column (2) between 2013 and 2017. Column (3) contains a subset of the 15 industries exhibiting the largest incremental increase in the implicit tax rate between 2008 and 2017 and column (4) a subset of the 15 industries with the lowest incremental increase between 2008 and 2017. Data are from the FSO and the SLFS. Standard errors in parentheses are clustered at the industry level. Significance levels for the coefficients are indicated as: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

**Table 10** Association between implicit emission tax and employment: alternative binary cases

	<i>Dependent variable</i>		
	<i>log(employment<sub>ijt</sub>)</i>		
	(1)	(2)	(3)
	$x = 0.5$	$x = 0.45$	$x = 0.55$
Implicit emission tax <sub>ijt</sub> × $I_{\eta \geq x}$	0.0381*** (0.0147)	0.0343*** (0.0140)	0.0419*** (0.0105)
Implicit emission tax <sub>ijt</sub> × $I_{\eta < x}$	0.0071 (0.0106)	0.0050 (0.0105)	0.0080 (0.0154)
Occupation fixed effects	✓	✓	✓
Industry fixed effects	✓	✓	✓
Year dummies	✓	✓	✓
Observations	22,642	22,642	22,642
Pseudo-R <sup>2</sup>	0.0693	0.0694	0.0692

The sample is an unbalanced panel covering 37 Swiss industries between 2008 and 2017. The dependent variable in all columns is the log of occupational employment. All model specifications include fixed effects for occupations, industries and years. The implicit emission tax is not included as otherwise one of the two green potential group dummies are fully absorbed. Data are from the FSO and the SLFS. Standard errors in parentheses are clustered at the industry level. Significance levels for the coefficients are indicated as: \* $p < 0.1$ ; \*\* $p < 0.05$ ; \*\*\* $p < 0.01$

#### Abbreviations

SLFS: Swiss labour force survey; SOC: Standard occupational classification system; ISCO: International standard classification of occupations; FTE: Full-time equivalents; EGSS: Environmental goods and services sector.

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#### Author contributions

ML carried out the descriptive analyses to describe the green potential in Switzerland. He was also responsible for the writing of the texts. CR performed the estimation of the green potential using data from O\*NET and conducted the regressions. All authors read and approved the final manuscript.

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#### Availability of data and materials

Data from O\*NET (U.S. Department of Labor, Employment and Training Administration) can be accessed via [https://www.onetcenter.org/db\\_releases.html](https://www.onetcenter.org/db_releases.html). Data from the SLFS was made available by the OFS after signing a data usage contract. The data can be requested from the OFS by stating the purpose of use.

## Declarations

### Competing interests

The authors declare that they have no competing interests.

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## References

- Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043–1171). Elsevier.
- BAFU. (2016). Bericht an den bundesrat, grüne wirtschaft: Massnahmen des bundes für eine ressourcenschonende, zukunftsfähige schweiz. Bern. Retrieved from <https://www.bafu.admin.ch/bafu/de/home/themen/wirtschaft-konsum/fachinformationen/massnahmen-des-bundes-fuer-ressourcenschonung.html>.
- BAFU. (2016). Bericht an den bundesrat, grüne wirtschaft: Massnahmen des bundes für eine ressourcenschonende, zukunftsfähige schweiz. Bern. Retrieved from <https://www.bafu.admin.ch/bafu/de/home/themen/wirtschaft-konsum/fachinformationen/massnahmen-des-bundes-fuer-ressourcenschonung.html>.
- Bowen, A., Kuralbayeva, K., & Tipoe, E. L. (2018). Characterising green employment: The impacts of 'greening' on workforce composition. *Energy Economics*, 72, 263–275.
- Bundesrat. (2016). Strategie nachhaltige entwicklung 2016–2019. Retrieved from <https://www.are.admin.ch/are/de/home/nachhaltige-entwicklung.html>.
- Bundesrat. (2018). Schlussbericht zur fachkräfteinitiative. Retrieved from <https://www.seco.admin.ch/seco/de/home/Arbeit/Fachkraefteinitiative.html>.
- Consoli, D., Marin, G., Marzocchi, A., & Vona, F. (2016). Do green jobs differ from non-green jobs in terms of skills and human capital? *Research Policy*, 45(5), 1046–1060.
- Degen, K., Ragni, T., Bieri, D., & Marti, S. (2016). Fachkräftemangel in der schweiz: Indikatorensystem zur beurteilung der fachkräftenachfrage. Bern: Staatssekretariat für Wirtschaft SECO. Retrieved from <https://www.seco.admin.ch/seco/de/home/wirtschaftslage---wirtschaftspolitik/wirtschaftspolitik-arbeitsmarkt/fachkraefteinitiative.html>
- Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D., & Lewis, P. (2009). Greening of the world of work: Implications for o\*net soc and new and emerging occupations. The National Center for O\*NET Development.
- Esposito, M., Halder, A., Samaan, D., & Semmler, W. (2017). Enhancing job creation through green transformation. In T. Altenburg & C. Assmann (Eds.), *Green industrial policy: Concept, policies, country experiences* (pp. 51–67). Geneva and Bonn: UN Environment and German Development Institute/Deutsches Institut für Entwicklungspolitik).
- Eurostat. (2016). Environmental goods and services sector accounts—Practical guide—2016 edition [Computer software manual]. Retrieved from <https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-GQ-16-011>. <https://doi.org/10.2785/688181>.
- ILO. (2018). Greening with jobs—World employment and social outlook 2018. International Labour Office. Retrieved from <https://www.ilo.org/global/research/global-reports/weso/greening-with-jobs/lang-en/index.htm>.
- Janser, M. (2018). The greening of jobs in germany: First evidence from a text mining based index and employment register data (Tech. Rep.). IAB-Discussion Paper.
- Marin, G., & Vona, F. (2019). Climate policies and skill-biased employment dynamics: Evidence from eu countries. *Journal of Environmental Economics and Management*, 98, 102253.
- Martinez-Fernandez, C., Hinojosa, C., & Miranda, G. (2010). Green jobs and skills: The local labour market implications of addressing climate change. Working document, CFE/LEED, OECD. Retrieved from [www.oecd.org/dataoecd/54/43/44683169.pdf?contentId=44683170](http://www.oecd.org/dataoecd/54/43/44683169.pdf?contentId=44683170).
- Niggli, M., & Rutzer, C. (2020). Environmental Policy and Heterogeneous Labor Market Effects: Evidence from Europe (Working paper No. 2020/09). Faculty of Business and Economics—University of Basel. Retrieved from <https://ideas.repec.org/p/bsl/wpaper/2020-09.html>.
- OECD. (2017). Getting skills right: Skills for jobs indicators. OECD Publishing, Paris. Retrieved from <https://doi.org/10.1787/9789264277878-en>.
- Rutzer, C., Niggli, M., & Weder, R. (2020). Estimating the Green Potential of Occupations: A New Approach Applied to the U.S. Labor Market (Working paper No. 2020/03). Faculty of Business and Economics—University of Basel. <https://ideas.repec.org/p/bsl/wpaper/2020-03.html>.
- Strietska-Iliina, O., Hofmann, C., Haro, M. D., & Jeon, S. (2011). Skills for green jobs: A global view. synthesis report based on 21 country studies. International Labour Office, Skills and Employability Department, Job Creation and Enterprise Development Department - Geneva: ILO.
- Vona, F., Marin, G., Consoli, D., & Popp, D. (2018). Environmental regulation and green skills: An empirical exploration. *Journal of the Association of Environmental and Resource Economists*, 5(4), 713–753.

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