INSTITUTE FOR EMPLOYMENT RESEARCH
The Research Institute of the Federal Employment Agency

IAB-DISCUSSION PAPER

Articles on labour market issues

12|2024 Disentangling the Greening of the Labour Market: The Role of Changing Occupations and Worker Flows

Ronald Bachmann, Markus Janser, Florian Lehmer, Christina Vonnahme

ISSN 2195-2663

Disentangling the Greening of the Labour Market: The Role of Changing Occupations and Worker Flows

Ronald Bachmann (RWI, Heinrich-Heine-Universität Düsseldorf, IZA)
Markus Janser (IAB)
Florian Lehmer (IAB)
Christina Vonnahme (RWI)

Content

Abstract

Using a text-mining approach applied to task descriptions of occupations together with worker-level administrative data, we explore the growth in the greenness of employment in Germany between 2012 and 2022. We first demonstrate that the greening of the labour market occurs both through an increase of green tasks and a decrease of brown tasks. Furthermore, the greening of occupations over time (“within-effect”) is at least as important for the overall greening of employment as shifting occupational employment shares (“between-effect”). Second, we show which occupations and which task types (brown or green) contribute most to the within-effect, and which worker flows are mainly responsible for the between-effect. Third, we investigate individual-level consequences of the greening of employment. We find that the employment prospects of foreign and of low-skilled workers are most at risk from the green transition, which may therefore increase existing labour-market inequalities.

Zusammenfassung

In diesem Papier untersuchen wir die Entwicklung der ökologischen Transformation auf dem deutschen Arbeitsmarkt zwischen 2012 und 2022. Wir zeigen zunächst, dass dieses sowohl durch eine Zunahme umwelt- bzw. klimaschutzbezogener beruflicher Tätigkeiten als auch durch einen Rückgang von umwelt-/klimaschädlichen Tätigkeiten erfolgt. Darüber hinaus ist diese Veränderung innerhalb von Berufen im Laufe der Zeit („Within-Effekt“) mindestens ebenso wichtig für die Gesamttransformation der Beschäftigung wie die Verschiebung von Beschäftigungsanteilen zwischen Berufen („Between-Effekt“). Zweitens zeigen wir, welche Berufe und welche Aufgabentypen ("brown" oder "green") am meisten zum Whithin-Effekt beitragen und welche Beschäftigtenflüsse hauptsächlich für den Between-Effekt verantwortlich sind. Drittens untersuchen wir die Folgen der ökologischen Transformation der Beschäftigung auf individueller Ebene. Wir stellen fest, dass die Beschäftigungsaussichten von Menschen mit ausländischer Staatsangehörigkeit und gering qualifizierten Beschäftigten am stärksten durch die ökologische Transformation gefährdet sind, was wiederum bestehende Ungleichheiten auf dem Arbeitsmarkt verstärken kann.

JEL classification

J23, J24, O33, Q55, R23

Keywords

Green transition; Job tasks; Occupational mobility; Worker flows

Acknowledgements

We thank Michael Böhm, Matías Cortés, Hans-Martin von Gaudecker, Myrielle Gonschor, Andrea Ichino, Michael Kvasnicka, Regina Riphahn, Bernhard Schmidpeter, Michel Serafinelli, Marcus Tamm, and participants at the annual conferences of the European Association of Labour Economists (EALE), of the European Association for Population Economics (ESPE), of the European Association of the European Association of Environmental and Resource Economists (EAERE), the German Economic Association, the Berlin Network of Labour Economists (BeNA) 20 Year Jubilee Conference, the envecon 2024 conference of the UK Network for Environmental Economists, the “Skills for the Future” conference at LISER, Luxemburg, workshops of the Horizon 2020 “Untangled” project and of the Horizon Europe “WeLaR” project at IBS, Warsaw, the IAB-IWH workshop in Nürnberg, the WiWi-Forum at Universität Duisburg-Essen and seminars at NTNU Trondheim, Otto-von-Guericke-Universität Magdeburg, and Universität Konstanz for helpful comments.

1 Introduction

The current climate crisis has raised the awareness that the emission of greenhouse gases must be strongly and rapidly reduced to avoid further damage[1]. Therefore, governments have increased the incentives to phase out fossil fuel technologies, for example through strengthening the European Union Emissions Trading System. Other aspects of environmental protection, including technology support measures and non-market based instruments such as emissions limit values, e.g. with respect to particulate matter, have also become more important in recent years (Frohm et al. 2023; Kruse et al. 2022). As a result, firms have an incentive to change their production process to cleaner technologies and to employ workers with the necessary skills (Borissov et al. 2019). “Brown” sectors and occupations which emit many greenhouse gases or are otherwise harmful to the environment are thus likely to shrink, and the skills required in these sectors and occupations may become obsolete or have to change considerably (Marin/Vona 2019). By contrast, “green” sectors and occupations which are more environment-neutral or even contribute to an improvement of the environment are likely to grow, making the skills in these sectors and occupations more valuable (Curtis/Marinescu 2022; Vona et al. 2018).

As these developments potentially imply important labour-market adjustments, they have ignited fears of job loss and rising unemployment (Vona 2019). Yet, crucial mechanisms underlying the greening of the labour-market are still unexplored. Especially, there are no analyses recognising that the greening of employment can occur along two broad margins. First, employment within occupations may become greener over time either through an increase of green tasks or a decrease of brown tasks and related skills (greening within occupations – “within-effect”). Second, occupations with a high share of green tasks and related skills may grow faster, and occupations with a high share of brown tasks may grow slower or may even shrink (greening between occupations – “between- effect”).

Differentiating the within- from the between-effect is crucial because these two adjustment margins differ in terms of costs and policy measures which may support these mechanisms: the within-effect involves adjustments on the worker side which can be supported by on-the-job training. The between-effect, by contrast, is strongly driven by workers switching occupations and is therefore likely to lead to losses of occupation-specific human capital. Correspondingly, this adjustment mechanism may require extensive policy measures addressing up- and reskilling.

In this paper, we therefore investigate the growth of the greenness of employment between 2012 and 2022, and its underlying mechanisms, using a task-based approach. We answer three research questions. First, to what extent has employment become “greener”, and which role do the within-effect and the between-effect play quantitatively? Second, which factors have contributed to the greening of occupations over time, i.e. the within-effect, and to differences in the employment growth between brown and green occupations, i.e. the between-effect? Third, which individual-level consequences does the greening of the labour market have, e.g. through an increasing risk of unemployment for workers in brown occupations?

[1] According to Bilal and Känzig (2024), the likely damage from climate change is considerably larger than previously thought, increasing the need for a fast reduction of carbon emissions.

To measure the greenness of employment, we use the Greenness-of-Jobs Index (GOJI) developed by Janser (2019, 2024). The GOJI is computed as the share of environment-friendly net of environment-harmful tasks in an occupation relative to all tasks performed in this occupation. This task-based approach together with detailed occupational data is particularly well suited for analysing the greening of the labour market because the approach allows a very fine-grained identification of green occupations and because tasks are closely related to the skills and competencies required in a specific occupation. This approach has therefore been extensively applied in the literature on the effects of technology on the labour market (Autor et al. 2003), and recently in the analysis of the greening of the labour market (Granata/Posadas 2024; Tyros et al. 2023; Vona 2021). Results from a task-based approach can therefore be interpreted with respect to the human capital required in an occupation, which allows drawing conclusions on how easy (or difficult) it is for workers to adapt to the ecological transformation.

We extract the frequency of different task types from very detailed textual descriptions of more than 4,400 single occupations applying text mining techniques to the expert-based database BERUFENET, the occupational information portal of the German Federal Employment Agency. Using such a database has the advantage that it provides an objective measure of the tasks performed and the skills required within occupations. In particular, it is much less subject to biases such as greenwashing (Darendeli et al. 2022) than using online job vacancies that are used in many analyses regarding the green transition.

BERUFENET is the German equivalent of the U.S. O*NET and features two major advantages over O*NET which has been extensively used in the analysis of the greenness of employment (see Section 3). First, the information contained in BERUFENET is updated at least once per year, which allows us to quantify the within-effect, i.e. occupations changing, over time. Second, we extract both green tasks and brown tasks from BERUFENET. By contrast, the U.S. O*NET has only identified green tasks twice – initially in 2010/11 and in 2022 with different approaches (Dierdorff 2009, 2011; Lewis 2022), and brown tasks have not been identified at all up to now using O*NET.

To examine worker-level outcomes, we use individual-level panel data from administrative records on the universe of the German workforce covered by social security legislation for the period 2012–2022. We can thus identify the employment shares of occupations, as well as worker transitions between different labour market states and occupations. We match the task-based GOJI to the administrative data at the “occupational type level” (5-digit level of the German classification of occupations, KldB 2010, about 1,300 occupational types per year). In the following, we will refer to occupational types as “occupations”.

We contribute to the literature, which is described in detail in Section 2, in several respects. First, we demonstrate the importance of within-occupation changes for the greening of the labour market. In contrast to existing evidence, we are able to do so because the occupational descriptions in BERUFENET are updated over time. Second, we provide evidence on which factors contribute to the greening within occupations over time. Third, we show which worker flows are driving the between-effect and therefore contribute to the international evidence in this context (Bluedorn et al. 2023; Curtis et al. 2024). Fourth, we identify worker groups which may be at risk of the ecological transition. Fifth, we provide evidence for Germany, a large European country, using a country-specific measure of the greenness of employment. This stands in contrast to existing evidence for Europe which has often relied on occupational measures of greenness from O*NET.

Our main results are as follows. Regarding the first research question, we document a considerable increase of the greening of employment over the observation period. Furthermore, we demonstrate that the within-effect and the between-effect each account for about half of the overall greening of employment. A decomposition exercise shows that changes in the worker composition over time only play a minor role for the greening of employment.

As for the second research question regarding the factors underlying the within- and the between-effects, we find that the within-effect is mostly driven by brown occupations becoming greener. This result is mainly caused by a reduction of brown tasks within brown occupations. However, we also observe an increase of green tasks in green occupations. The between-effect is mainly driven by a declining employment share of a subset of brown occupations with a moderate GOJI value, which we call light brown occupations. The effect is also, but to a smaller extent, driven by a growing employment share of light green occupations. Analysing worker flows, we show that flows to and from non-employment play a particularly important role for the change in employment stocks contributing to the greening of employment, i.e. the growth of green occupations and the decline of brown occupations. By contrast, there are relatively few direct transitions from brown to green occupations, indicating potentially high adjustment costs related to such transitions.

Answering the third research question on individual-level consequences of the greening of employment, we show that while employees in dark brown occupations have relatively bad employment prospects, the opposite is true for employees in dark green occupations. Furthermore, our individual-level analyses show that workers with specific characteristics, particularly low-skilled workers and foreign workers, are overrepresented in brown occupations, and that they have a relatively low probability of making transitions to greener occupations.

Our findings have important implications for the labour-market adjustment to the green transition. First, we demonstrate which occupations feature high proportions of green and brown tasks, and which occupations have been able to adjust their task content to the green transition. This provides important information to individuals choosing e.g. their field of study or their occupation. Second, we show which worker groups are most likely to suffer from the green transition, indicating a potential need for policy measures. Third, the importance of the within-effect implies that on-the-job training plays a crucial role for the adjustment process to the green transition. Therefore, social partners and policymakers should improve the opportunities to engage in such training measures, and workers should take advantage of such opportunities.

Our paper is structured as follows. Section 2 discusses the related literature. Section 3 describes the data and the calculation of the GOJI. Section 4 provides descriptive evidence on the overall greenness of employment, its evolution over time and disentangles how the within- vs. between-effect contribute to this evolution. In particular, it quantifies the importance of the within- and the between-effect. Sections 5 and 6 explore the factors underlying the within-effect and the between-effect, respectively. Section 7 analyses individual-level consequences of the greening of employment by GOJI group. Section 8 summarizes and concludes.

2 Theoretical background and existing empirical evidence

In this paper, we use the task approach to quantify the greenness of occupations. The task approach has been extensively used in the literature on the effects of technological change on the labour market (e.g. Autor et al. 2003) which provides several key insights. First, the labour market prospects of workers depend strongly on their skills which determine the tasks they are able to perform as technological change leads to the modification of existing tasks and the emergence of new tasks (Acemoglu and Restrepo 2018). For example, workers in occupations intensive in routine tasks are more susceptible to job loss than workers performing non-routine tasks (Bachmann et al. 2019; Cortes 2016). Second, job tasks are closely associated with the skills and competencies that workers possess, and are therefore an important determinant of successful labour-market careers (Gathmann/Schönberg 2010), in particular against the background of structural change (Acemoglu and Autor 2011).

The task approach is also particularly suitable for analysing the greening of the labour market for several reasons. First, the tasks performed in an occupation provide a very reliable and accurate estimate of green employment (Vona 2021; Curtis/Marinescu 2022). Second, similarly to technological change (Acemoglu and Restrepo 2018), the ecological transition leads to the modification of existing occupation-specific tasks and the emergence of new tasks (Vona/Consoli 2015; Vona 2021). These changes can be captured using the task approach. Third, job tasks are closely related to the skills and competencies required in a specific occupation. Therefore, using a task-based analysis allows to draw conclusions regarding effects of the greening of employment on changing skill requirements and necessary education measures, e.g. re- and upskilling.

For these reasons, the task approach has been used in the emerging literature on the labour-market effects of the green transition (e.g. Consoli et al. 2016; Vona et al. 2018; Saussay et al. 2022). These papers have established a number of stylised facts on several aspects of the green transition, mainly for the US labour market. The issue of heterogeneous effects and potential implications for transition costs has been taken up by a number of recent studies focusing on the socio-demographic and regional characteristics of green and brown employment in the U.S. Based on occupational descriptions from O*NET, Consoli et al. (2016) find that green jobs require a higher level of non-routine cognitive skills and on-the-job training, but not more years of schooling. Also based on O*NET, and additionally on Occupational Employment Statistics from the Bureau of Labor Statistics (BLS), Vona et al. (2018) find that skill gaps between green and brown occupations are small, and that green occupations require mostly additional technical skills. Finally, Vona et al. (2019) establish that green workers are relatively high-skilled, strongly geographically concentrated, and earn relatively high wages.

Saussay et al. (2022) use online job vacancies to establish further stylised facts. They find that low-carbon and high-carbon jobs have higher skill requirements than "generic" jobs, especially across technical and managerial skills; that the skill gap is narrower between low- and high-carbon vacancies than between low-carbon and generic jobs; and that the geographical overlap between low- and high-carbon jobs is limited.

The importance of task changes within occupations (i.e. the within-effect) has up to now not been analysed in the context of the ecological transition. However, the importance of changing task profiles within occupations has already been stressed in the literature on technological change. Freeman et al. (2020) find for the U.S. that the within-occupation change of task profiles, i.e. the change of the task profile of an occupation without worker transitions, accounts for most of the overall change in task profiles in the economy. For Germany, Bachmann et al. (2022) show that task changes within occupations play an important role for wage growth. They demonstrate that wage growth is higher in those routine occupations where the share of non-routine cognitive tasks increases over time than wage growth in other routine occupations where the share of non-routine cognitive tasks stays relatively constant over time. In the context of the green transition, Bowen et al. (2018) argue that non-green jobs differ from green jobs in only a few skill-specific aspects. Small differences in skill requirements could imply relatively low costs of adjustment to the ecological transition as similar skill requirements could facilitate both the adjustment of occupations (within-effect) and worker transitions between occupations (part of the between-effect).

Changing employment shares of occupations (i.e. the between-effect) are the net result of gross worker flows that occur between occupations and into and out of employment. Despite the importance of worker flows, there are only a few studies on this issue in the context of the ecological transition. Bluedorn et al. (2023) measure the greenness of occupations using job tasks taken from O*NET where some tasks are flagged as “green”, plus sectoral carbon emission intensities per worker. They match this measure to various micro data sets (European Labour Force Survey – EU-LFS, European Union Statistics on Income and Living Conditions – EU-SILC, ntegrated Public Use Microdata Series – IPUMS) to analyse worker-level outcomes for 31 countries for the period 2005–2019. They find that first, both green and brown jobs are concentrated among few socio-demographic subgroups of workers, and that the degrees of greenness or pollution intensity are relatively low on average across all workers and occupations. Second, when workers change their job, the new job often features a similar greenness as their old job. This implies difficulties for workers to move up the green ladder.

Difficulties in making successful job-to-job transitions are also documented by Haywood et al. (2024) for workers who are confronted with declining labour demand due to the green transition. Focusing on the coal phase-out in Germany, they find that occupational change is an important adjustment mechanism. Displaced workers often experience lower wages and less job security, rather than prolonged spells of unemployment, leading to important welfare losses which differ strongly between worker groups.

3 Data and methods

Our analysis is based on two data sets. First, BERUFENET, is an expert-based description of occupations including tasks, skills and technologies typically performed or used in a job. Applying text mining to this data set, we calculate the Greenness-of-Jobs Index (GOJI) (Janser 2019, 2024) which provides yearly measures of the greenness of all occupations in Germany.

Second, we use employment biographies from the universe of social security records (IAB Beschäftigtenhistorik, BeH), which allows us to perform worker-level analyses, and which also contains establishment-level information. We link the two data sets at the 5-digit occupation level of the German classification of occupations (KldB 2010). The resulting panel dataset contains workers' labour market biographies together with a measure of greenness of their occupations. We describe the two data sets and the calculation of the GOJI in the following.

3.1 The BERUFENET data

BERUFENET[2] is a textual database with descriptions of tasks carried out in different occupations and is thus comparable to the U.S. American occupational database O*NET[3]. BERUFENET is provided by the German Federal Employment Agency and describes more than 4,400 "single occupations" ("Einzelberufe"), i.e. all occupations that formally exist on the German labour market. The descriptions of occupations include the tasks typically performed in each occupation. The term "task" is used in a broad sense, it can also refer to required skills or technologies used in an occupation. In 2020 the descriptions cover 4,422 occupations and include 7,671 different tasks. On average, each occupation features 20 tasks.

The main purpose of the BERUFENET data is twofold: (i) the dataset is used by local employment agencies for career guidance and job placement of their clients (job seekers), and (ii) it serves the general public as a free online database for career orientation. Crucially for these main purposes – and for our analysis – is that the information included in BERUFENET is accurate and frequently updated (see also Dengler/Matthes 2018). The editorial maintenance of BERUFENET involves a structured process carried out by a joint team of experts with expertise and experience in the field of education and vocational training. The process works as follows:

1. Research and Data Collection: The editorial team gathers information from various sources, including vocational training regulations, study programs, professional associations, educational institutions, and governmental bodies. This information is continuously updated to reflect current trends and developments in various occupational fields.
2. Compilation and Analysis of Information: The collected data is systematically analysed and organised by experts.
3. Updating and Creation of Job Descriptions: Based on Step 2, the editorial team updates existing job descriptions and creates new ones. These descriptions provide detailed information about the tasks, requirements, training opportunities, working conditions, and career prospects associated with each occupation.
4. Professional Review: Before publication, the new or updated information undergoes a professional review by the Federal Employment Agency to verify its accuracy and completeness.
5. Publication: Once reviewed, the information is added to the BERUFENET database[4] and made available online[5].

[2] See https://web.arbeitsagentur.de/berufenet/.

[3] See https://www.onetonline.org/.

[4] Technically, this is the "Daten- und Steuerungspool Berufe", DPSB ("Data and control pool for occupations").

[5] See https://web.arbeitsagentur.de/berufenet/.

6. Continuous Review and Adjustment: The editorial team regularly reviews the information of every single occupation at least once a year (Dengler/Matthes 2018) to ensure it remains current and adjusts it as necessary based on feedback from users and ongoing monitoring of the occupational fields.

The described process ensures the provision of reliable and up-to-date occupational information for all user groups. The maintenance and updating of the database are dynamic and involve close collaboration between experts internal and external to the Federal Employment Agency. The steps of the collaborative process lead to a high degree of reliability, completeness and timeliness of the BERUFENET data. Importantly, according to information from experts involved in the editorial process, brown and green tasks and skill requirements were treated in the same way as all other tasks and skill requirements during the time period covered by our empirical analysis.

One particular advantage of using BERUFENET for analysing the labour-market effects of the ecological transformation is that it avoids bias from “greenwashing”. Such a bias is likely to arise in studies using online job vacancies as companies may try to make a positive impression on potential applications by mentioning more green tasks and less brown tasks compared to the tasks actually required (Darendeli et al. 2022). By contrast, the data generating process of BERUFENET is likely to be objective as the main goal of BERUFENET is to provide accurate information about occupations to job seekers.

3.2 Calculating the Greenness-of-Jobs Index (GOJI)

The detailed BERUFENET information on the tasks performed within occupations allows to compute a measure of the greenness of occupations, as done in early studies on this topic, e.g. by Peters (2014) and Consoli et al. (2016) who relied on U.S. O*NET data which includes a flag for green skills. Using yearly information from the BERUFENET data for 2012[6] through 2022, Janser (2019, 2024) extends this approach to measure the greenness of occupations in Germany. We use the resulting Greenness-of-Jobs Index (GOJI) as greenness measure in this paper.

The calculation of the GOJI with BERUFENET data relies on information on the job tasks typically performed and therefore the skills required in an occupation (see Janser (2024) for details). Analogous to the skills taxonomy used by the European Commission and the OECD (European Commission 2022; OECD 2023), the GOJI differentiates between “green tasks”, i.e. tasks that are beneficial to the environment, “white tasks” that are neutral towards the environment, and “brown tasks” that are harmful to the environment. This classification of tasks according to their environmental impact applies text mining to the occupational descriptions from BERUFENET in order to identify the frequency of words from keyword lists for green, brown and white skills. The keywords are taken from the literature and extended and adapted to the German context, and relate to the use of fossil fuels or greenhouse gas emissions in general, the efficiency of energy and material usage, the adoption of renewable sources of energy, water quality and noise emissions, and any other practices that affect the environment. Examples of keywords are

[6] Given a change in the occupational classification KldB in 2011, it is not possible to extend the GOJI to the period before 2012.

contained in Janser (2024)[7]. The resulting index, the GOJI, has been included in the BERUFENET of the German Federal Employment Agency since 2024. Since then, green tasks are flagged in the publicly available version of BERUFENET and their identification is complemented by a continuous editorial process of the BERUFENET team.[8]

The classification of tasks into green, white and brown tasks is a broader approach than that implemented in the O*NET data, where only environment-friendly tasks are flagged as green, but environment-harmful tasks are not identified. Crucially, as the BERUFENET data is updated at least annually, the change in the environmental impact of tasks can be studied annually by occupation, while the flagging of green tasks in O*NET was only implemented in 2010/2011 and – with a different methodology – in 2022.

We exploit the yearly updated BERUFENET data to calculate the share of green and the share of brown tasks over all tasks (i.e. green, brown and white tasks) for each 5-digit occupation occ and year t, and denote the resulting shares as $GOJI_{green}$ and $GOJI_{brown}$ following Janser (2024). Including the white tasks allows us to interpret the green and the brown component of the GOJI as the overall intensity of green and brown tasks in an occupation:

$$GOJI_{green,t}^{occ} = \frac{\sum green\ tasks_t^{occ}}{\sum all\ tasks_t^{occ}} \tag{1}$$

$$GOJI_{brown,t}^{occ} = \frac{\sum brown\ tasks_t^{occ}}{\sum all\ tasks_t^{occ}} \tag{2}$$

The initial calculation of these indices is performed at the 8-digit level of single occupations; this level of disaggregation is only used for information and counselling purposes at the Federal Employment Agency (BA 2020). As the worker-level data required for the analyses in this paper are only available for the 5-digit level of occupational types (henceforth “occupations”), the indices are averaged across all single occupations within each 5-digit occupation, assuming an equal distribution, as in Dengler/Matthes (2018).

To obtain one single measure of the greenness of an occupation, the GOJ_{Igreen} and the $GOJI_{brown}$ are combined at the 5-digit occupation level:

$$GOJI_t^{occ} = GOJI_{green,t}^{occ} - GOJI_{brown,t}^{occ} \tag{3}$$

The resulting net GOJI is available for the 1,277 5-digit occupations occ in each year t ϵ [2012; 2022]. Its distribution in our base year 2012 ranges from –0.45 to +0.79 (see Figure 10 in Appendix A).

For the following general descriptive analyses, we classify the 5-digit occupations into five groups by splitting brown occupations (with GOJI<0) and green occupations (with GOJI>0) into two sub-groups each. The five groups range from occupations with a relatively high share of environment-

[7] See also Appendix C where we show in Figure 14 a BERUFENET description of an example occupation in Figure 14and a list with the top 40 green and brown tasks for the year 2012 in Table 12. The green tasks fall into the broad categories indicated by Vona et al. (2018): engineering and technical, operation management, monitoring, and science.

[8] See Figure 14 in Appendix C.

harmful tasks (“dark brown occupations”, with GOJI<–0.1) over those with a moderate share of environment-harmful tasks (“light brown occupations”, with –0.1<=GOJI<0), “white” occupations (GOJI=0) and occupations with a moderate share of environment-friendly skills (“light green occupations”, with 0<GOJI<=0.1) to occupations with a relatively high share of environment-friendly tasks (“dark green occupations”, with GOJI>0.1). The threshold of 0.1 corresponds to the mean of the green GOJI for green occupations (rounded to one decimal place). The opposite (mean of -0.1) is true for brown occupations. Using this grouping for the year 2012, we find that the majority of occupations are in the white group (675 = 53 percent of all occupations), 83 = 7 percent of occupations in the dark brown, 237 = 19 percent in the light brown, 193 = 15 percent in the light green and 89 = 7 percent in the dark green group (see Figure 10 in Appendix A).

Examples of occupations for each of the five GOJI groups are displayed in Table 7 in Appendix A. It becomes apparent that the dark green group mainly consists of occupations that are related to areas with a direct impact on the environment: bus drivers contribute to the reduction of automobile traffic; workers in the occupation “renewable energy technology” substitute more harmful ways of producing energy. In addition, the dark green group also contains more general occupations such as “business organisation strategy”. The light green group includes similar occupations, but their environmental impact is often less direct. Examples include “occupations in technical railroad operation” or “building services engineering”. The opposite applies to the light brown and dark brown groups which include many occupations that are directly harmful to the environment, e.g. “airplane pilots in the transport sector”, or occupations involved in intensive energy use, e.g. “metallurgy”.

Given that we use the net value of the GOJI at the occupation level, it could be a concern that positive and negative values strongly cancel each other out. However, Figure 11 in Appendix A with mean values for the brown, the green and the net GOJI for each of the five GOJI groups shows that this is hardly the case: while each group contains occupations with both brown and green tasks, occupations in the dark and light brown groups contain relatively few green tasks, and vice-versa for occupations in the dark and light green groups

3.3 Administrative micro data for worker-level analyses

The IAB Employment History (IAB Beschäftigtenhistorik, BeH)[9] is a research dataset based on administrative data gathered by the Federal Employment Agency. It covers worker biographies from 1975 to the latest available date (here: 2022) of all employees’ subject to German social insurance contributions[10]. The main source of the BeH are mandatory annual notifications and (de-)registrations of firms to social security institutions. The BeH contains variables about personal characteristics (e.g., age, gender, education, place of residence), individual employment characteristics (e.g., gross daily wages, tenure, starting/ending date), and the current occupation at the 5-digit level of the German classification of occupations. The occupational information at this level of disaggregation includes very detailed information on the tasks and skills required in a very specific occupation (the first four digits of the classification) as well as the occupational

[9] The analyses in this paper are based on version V10.08.00-202212 of the BeH.

[10] Owing to this restriction, the BeH does not include data about civil servants, people doing military service, self-employed people etc. Detailed information about the BeH can be found in the description of the Sample of Integrated Labour Market Biographies (SIAB) by Antoni et al. (2016).

status such as “expert” or “helper” (in the fifth digit). Furthermore, it includes some basic employer information (e.g., location, sector, establishment identification number). We apply common imputation procedures suggested by Fitzenberger et al. (2006) to improve the BeH education variable. Our main analysis sample consists of the universe of employees between 16 and 65 years in regular employment. Where indicated, we also look at non-regular employees such as apprentices and workers in marginal employment (“Minijobs”). [11]Persons in part-time retirement schemes and workers in the military are excluded.

4 The Greenness of Employment in Germany

In this section, we analyse the worker and occupation characteristics of the GOJI groups, the evolution of the overall greenness of employment over time and to what extent the greening of employment is driven by the relative growth of the employment share of occupations with different GOJI levels on the one hand (“between-effect”), and the general greening of given occupations (“within-effect”). In order to quantify the between- and the within-effect, we conduct a shift-share analysis.

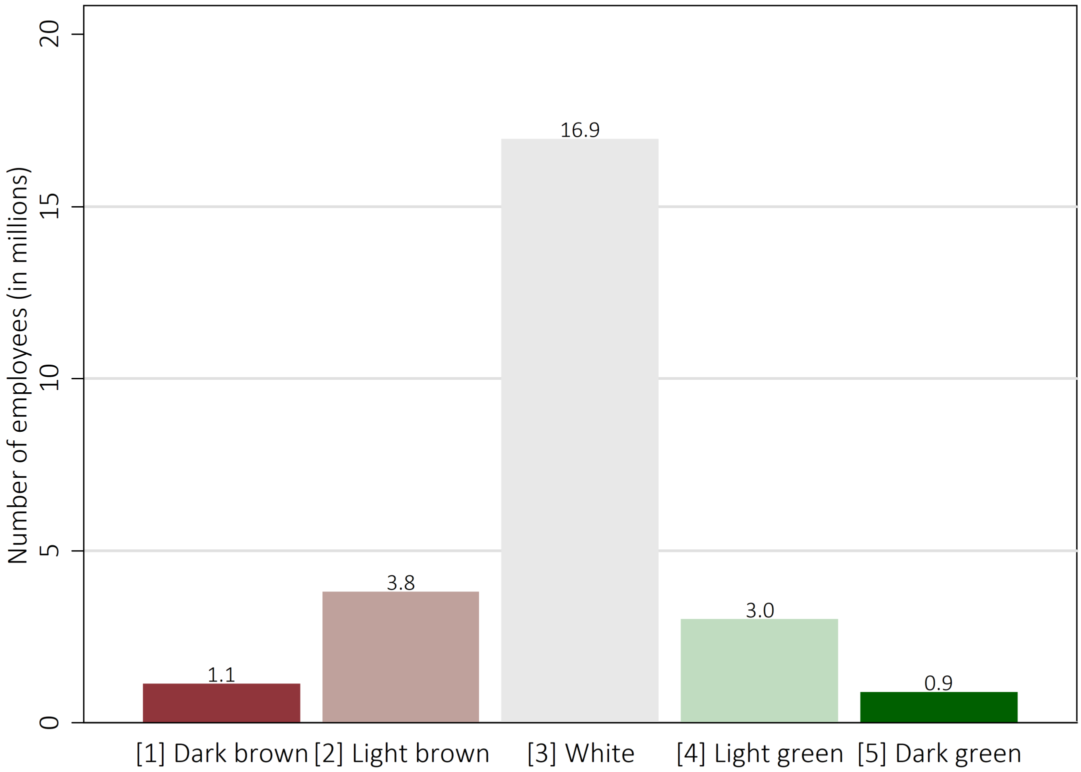
4.1 The worker and occupation characteristics of the GOJI groups

Using the worker-level data together with the definition of GOJI groups allows us to illustrate the distribution of employees across occupations with different environmental impacts.

In 2012, there were 1.1 million employees in dark brown occupations, 3.8 million employees in light brown occupations, 16.9 million in white occupations, 3.0 million in light green occupations and 0.9 million in dark green occupations (Figure 1).

[11] In case of multiple jobs, we focus on a person’s primary employment.

Figure 1: Number of employees per GOJI group (2012)



Notes: The numbers of employees refer to regular employment in 2012 across the indicated GOJI groups.
Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, own calculations.

We now provide evidence on the socio-demographic, regional and firm characteristics for the different GOJI groups, measured in 2012 (Table 1). It becomes apparent that the workforce in the five GOJI groups is very similar with respect to age. Compared to the female share in overall employment (42 percent), women are overrepresented in the white group (female share: 54 percent) and strongly underrepresented in dark brown (13 percent) and dark green occupations (11 percent). This is likely the case because women often work in environment-neutral service occupations, and because dark green occupations consist of occupations such as engineering where the female share is relatively low. The high female share in environment-neutral white occupations is in line with a relatively low full-time employment share in this GOJI group (70 percent) because women generally have a higher probability to work in part-time employment than men. With respect to the education level, dark brown occupations are characterised by the highest share of workers with low education (13 percent). The highest share of highly educated workers can be found in the white occupations (22 percent) and light green occupations (17 percent).

These figures are a first indication that men are likely to be more affected by the green transition than women, as men are overrepresented in both dark brown occupations and in dark green occupations. Furthermore, low-skilled workers and foreign workers are potential risk groups as they are overrepresented in the dark brown occupations, but underrepresented in the dark green occupations. This implies that they may face a higher risk of job loss in brown occupations, without corresponding job opportunities in green occupations.

Table 1: Worker and establishment characteristics by GOJI group (2012)

	All groups	[1] Dark brown	[2] Light brown	[3] White	[4] Light green	[5] Dark green
Worker characteristics						
Female	0.42	0.13	0.16	0.54	0.31	0.11
Age groups						
16-29	0.17	0.20	0.17	0.17	0.15	0.17
30-49	0.54	0.52	0.53	0.54	0.52	0.53
50-65	0.29	0.28	0.30	0.28	0.33	0.30
Education levels						
Low	0.08	0.13	0.08	0.07	0.11	0.08
Medium	0.74	0.79	0.84	0.70	0.72	0.84
High	0.18	0.07	0.07	0.22	0.17	0.08
Foreign	0.08	0.12	0.09	0.07	0.10	0.08
Full-time	0.82	0.88	0.89	0.78	0.83	0.87
Technological substitutability of occupation						
Low	0.36	0.37	0.28	0.38	0.33	0.34
Medium	0.47	0.37	0.26	0.54	0.49	0.39
High	0.17	0.26	0.45	0.08	0.19	0.26
Establishment characteristics						
Sector: Services (reference: Manufacturing/Construction)	0.66	0.42	0.40	0.76	0.63	0.46
Size						
1-49	0.42	0.47	0.42	0.41	0.43	0.45
50-449	0.38	0.37	0.38	0.39	0.37	0.34
>500	0.20	0.16	0.20	0.20	0.20	0.20
Region						
North	0.16	0.16	0.16	0.15	0.16	0.17
South	0.31	0.31	0.32	0.31	0.30	0.28
East	0.19	0.21	0.19	0.18	0.21	0.22
West	0.34	0.33	0.34	0.35	0.33	0.33
Region type						
Core cities	0.37	0.27	0.27	0.40	0.37	0.32
Urbanized districts	0.36	0.36	0.39	0.35	0.35	0.36
Rural districts with features of concentration	0.15	0.20	0.18	0.14	0.15	0.17
Rural districts-sparsely populated	0.13	0.18	0.15	0.11	0.13	0.15
Observations	25,739,741	1,126,691	3,792,921	16,939,077	3,006,839	874,213

Notes: All characteristics are measured at the employee level for employees in regular employment in 2012, overall and by GOJI group. Numbers of observations and full-time shares are not weighted, all other numbers are weighted with full-time equivalents.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, own calculations.

A trend interacting with the greening of the labour market is technological progress, in particular digitalisation and the deroutinisation of work. We therefore use an occupation-level measure of the technological substitutability of workers. This continuous “substitution potential” is also based on a task-based approach (Dengler/Matthes 2018) and can be divided into three categories (low, medium, high) which we use in our analysis. This substitution potential is very low among white occupations: only 8 percent of workers are affected by a high substitution potential in the year 2012. It is moderate for light green workers (19 percent), comparably high for dark brown and dark green workers (both 26 percent) and very high for employees in light brown occupations (45 percent). Therefore, workers in light brown occupations are at a relatively high

risk of being substituted by technology, and workers in dark brown occupations are at some risk of being substituted by technology – in addition to the employment risks through the greening of the labour market. But workers in dark green occupations also have an above-average risk of being substituted by technology.
As for regional characteristics, cities display the highest rate for white occupations, which is in line with environment-neutral occupations consisting of occupations in the service sector. Both dark brown and dark green occupations are overrepresented in rural areas and in East Germany. Dark green occupations are underrepresented in the southern federal states Bavaria and Baden-Wuerttemberg. With respect to establishment size, the differences are again small.

4.2 The greenness of employment over time

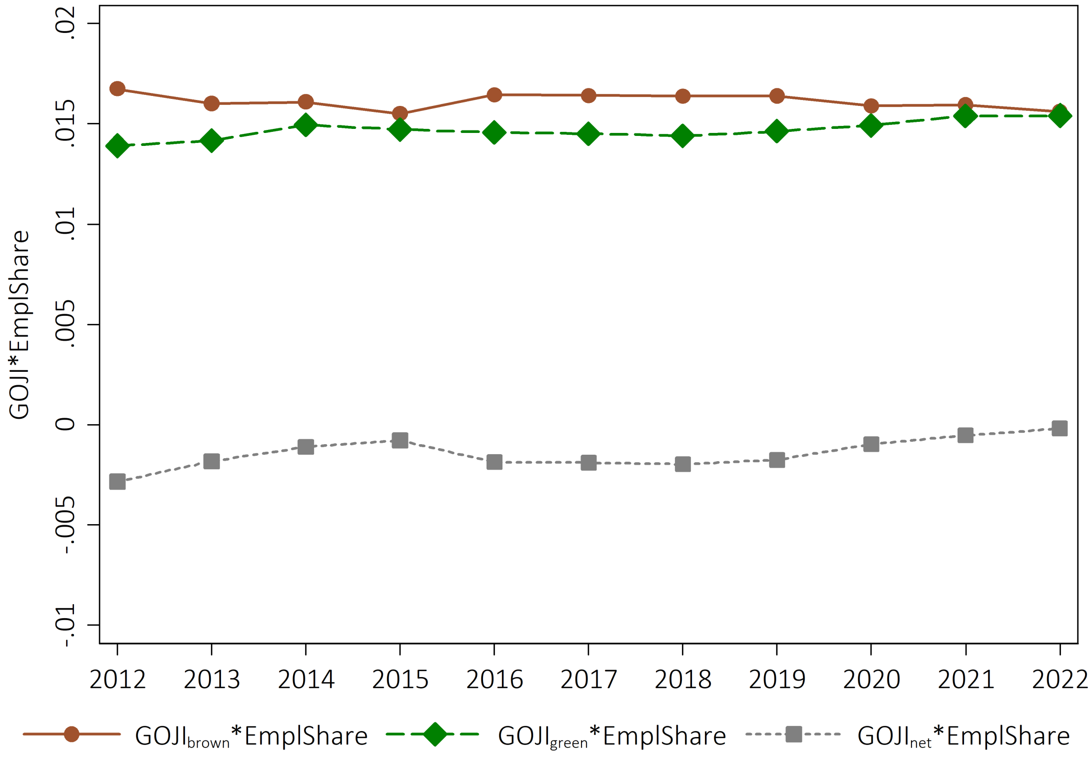
We now analyse the evolution of the greenness of employment over time. To do so, we first compute the greenness of total employment as the sum of employment-weighted occupation-specific GOJI values across all occupations occ ϵ [1;N] in each year t ϵ [2012; 2022]:

$$EmplGreenness_t = \sum_{occ=1}^{N} \frac{E_t^{occ}}{E_t} \, GOJI_t^{occ} \tag{4}$$

where E_t is employment in year *t*, E^{occ} and $GOJI^{occ}$ are occupation-specific employment and GOJI, respectively, and *N* is the number of occupations. In the following, we denote the employment share of each occupation, $\frac{E_t^{occ}}{E_t}$, as “Employment share”. As the measure for the overall greenness of employment only depends on the employment shares of each occupation, its change over time is not driven by general employment growth.

The result of the computation of the overall greenness of employment is displayed in Figure 2. The overall greenness of employment amounts to –0.0028 in 2012, the first year of our analysis, and increases by 0.0026 to a value of –0.0002 in 2022. This evolution is the result of an increase in $GOJI_{green}$ from 0.0139 to 0.0154, i.e. an increase of 11 percent, and of a decrease in $GOJI_{brown}$ from 0.0167 to 0.0156, i.e. a decrease of 7 percent.

Figure 2: Greenness of total employment and greenness components over time



Notes: The greenness of total employment and of greenness components is calculated according to Equation (4) as the sum of the $GOJI_{net}$ ($GOJI_{green}$, $GOJI_{brown}$) across all 5-digit occupations, weighted with the respective employment share of each occupation in total employment.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, own calculations.

The growth of the greenness of employment depicted in Figure 2 can in principle come from two sources: an increase in the GOJI of specific occupations, i.e. a change within occupations, or increasing employment shares of occupations with an initially high GOJI level relative to occupations with an initially low GOJI level, i.e. a change of employment shares between occupations. To decompose the change of the greenness of total employment over time into these two components (between-effect and within-effect), we follow Freeman et al. (2020) and conduct a shift-share decomposition:

$$\begin{aligned}\Delta EmplGreenness_t &= \sum_{occ=1}^{N} \frac{E_{2022}^{occ}}{E_{2022}} GOJI_{2022}^{occ} - \sum_{occ=1}^{N} \frac{E_{2012}^{occ}}{E_{2012}} GOJI_{2012}^{occ} \\ &= \underbrace{\sum\nolimits_{occ} \Delta \frac{E^{occ}}{E} \times GOJI_{2012}^{occ}}_{\text{"}between-effect\text{"}} + \underbrace{\sum\nolimits_{occ} \frac{E_{2012}^{occ}}{E_{2012}} \times \Delta GOJI^{occ}}_{\text{"}within-effect\text{"}} \\ &\quad + \underbrace{\sum\nolimits_{occ} \Delta \frac{E^{occ}}{E} \times \Delta\, GOJI^{occ}}_{\text{"}interaction\, effect\text{"}}\end{aligned} \tag{5}$$

The first term captures the between-effect which accounts for the change in the employment share of occupations in total employment between 2012 and 2022 ($\Delta \frac{E_{occ}}{E}$), holding the GOJI of occupations constant at the 2012 level. The second term captures the within-effect, i.e. the changes in the GOJI within occupations between 2012 and 2022 ($\Delta GOJI^{occ}$), holding the initial employment shares of occupations constant. The third term is an interaction effect which captures the residual change.

Table 2: Shift-share analysis of increase in greenness of employment

	Total change	Within-effect(%)	Between-effect(%)	Interaction effect (%)
KldB 2010 5-digit	0.0026	41.80	39.72	18.48
KldB 2010 3-digit	0.0026	56.12	35.69	8.19

Notes: “Total change” is calculated as the difference in the greenness of total regular employment between 2022 and 2012. Greenness of employment is calculated using the GOJI by 5-digit occupation weighted with the respective employment share of each occupation in total employment (see Figure 2and Equation (4)). The total change is decomposed into a within-effect, a between-effect and an interaction effect according to Equation (5).

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

The results of the shift-share analysis at the 5-digit ISCO level show that the within-effect accounts for 42 percent of the increase in the greenness of employment over time, whereas the between-effect accounts for 40 percent and the interaction effect for 18 percent (Table 2). Hence, the results show that the change of task profiles within occupations over time plays at least an equally important role for the greening of the labour market as the change of occupational employment shares. At a more aggregated occupation level (3-digit KldB 2010), the within-effect even accounts for 56 percent and the between-effect for 36 percent of the greening of employment. The increase of the within-effect occurs because employment transition between 5-digit occupations of the same 3-digit group now are part of the within-effect, but feed into the between-effect in the analysis using the 5-digit occupations.

Given that we observe some differences in the worker and establishment characteristics between the GOJI groups, a question that arises is to what extent the greening of employment over time documented in Figure 2 and Table 1 is driven by a changing composition of the workforce of the GOJI groups. For example, a high proportion of elderly workers in certain occupations may contribute to the shrinking employment shares of these occupations over time if many workers retire in a narrow time window. Conversely, many young workers choosing green occupations at the beginning of their labour-market career may contribute to the growth of these occupations.

4.3 The role of composition effects

To investigate composition effects, i.e. changing workforce characteristics of occupations, we conduct a Blinder-Oaxaca decomposition to disentangle the change in the greenness of employment between 2012 and 2022. This approach decomposes the overall change in the greenness of employment into a part that is “explained”, which comprises the “endowments effect” (i.e. how do characteristics change from 2012 to 2022), a part that is “unexplained”, which comprises the “coefficients effects”, and an interaction term (see Appendix B.2 for technical details). The coefficients effect is due to a difference in the estimated coefficients for the two years (2012 and 2022) and can be viewed as the payoff for or the penalty to the observable characteristics.

The results from this decomposition show that the greening of employment can be attributed to a negative endowments effect and a positive coefficients effect (see Table 10 in Appendix B.2). This means that the changing workforce composition of occupations is negatively correlated with greening, i.e. without a changing composition of the workforce, the greening of employment would have been larger than actually observed. This effect is mostly driven by the share of foreign workers, who are overrepresented in dark brown occupation (see Table 1). The negative composition effect is overcompensated by the other effects, i.e. the coefficients effect and the interaction effect. Performing this decomposition separately for $GOJI_{green}$ and $GOJI_{brown}$ (columns 2 and 3 of Table 10) shows that the overall endowments and coefficients effects are driven by the negative (brown) part of the net GOJI.

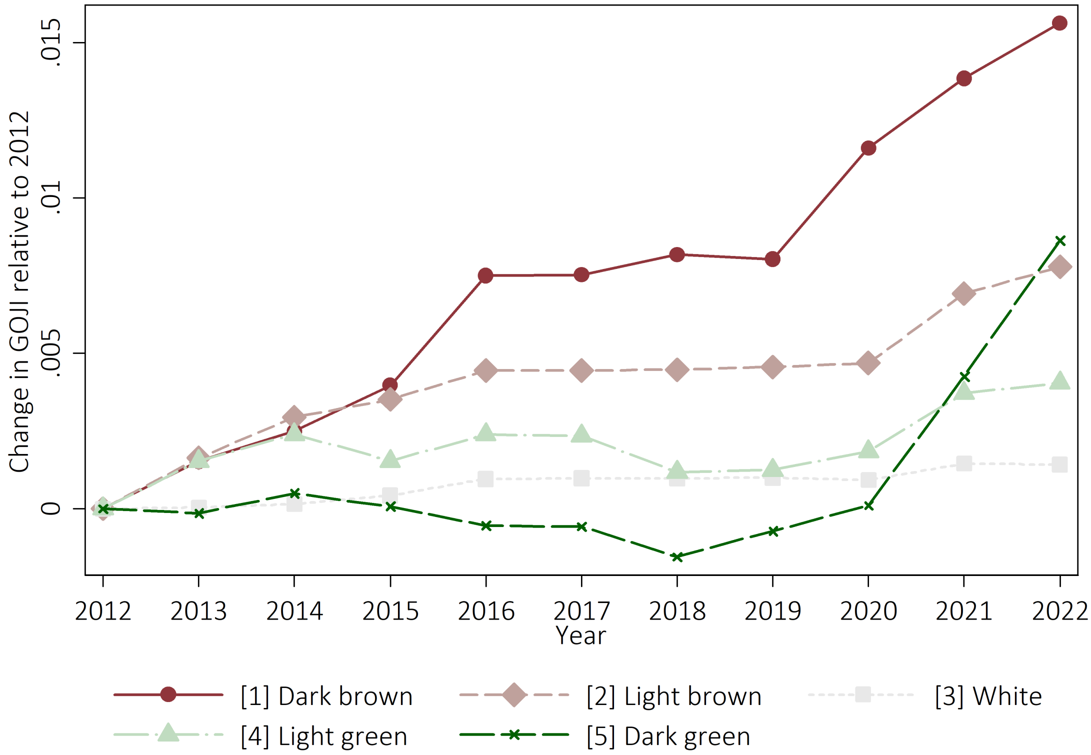
From the results of the Blinder-Oaxaca decomposition, we can conclude that changes in workforce characteristics are not a driver of the greening of employment in Germany. In the following two sections, we therefore analyse the within- and between-changes in more detail.

5 The within-effect: Which occupations become greener, and why

5.1 Descriptive evidence on the within-effect

As shown in the preceding section, the change of environment-related tasks within occupations is an important contributor to the greening of employment in Germany. In this section, we explore the within-effect in detail. Figure 3 depicts the evolution of the GOJI by our five GOJI groups over time. It becomes apparent that dark brown occupations display the strongest growth in the mean GOJI, followed by light brown and dark green occupations. These GOJI groups therefore drive the within-effect. White and light green occupations only play a minor role in this context.

Figure 3: GOJI intensity by GOJI group over time



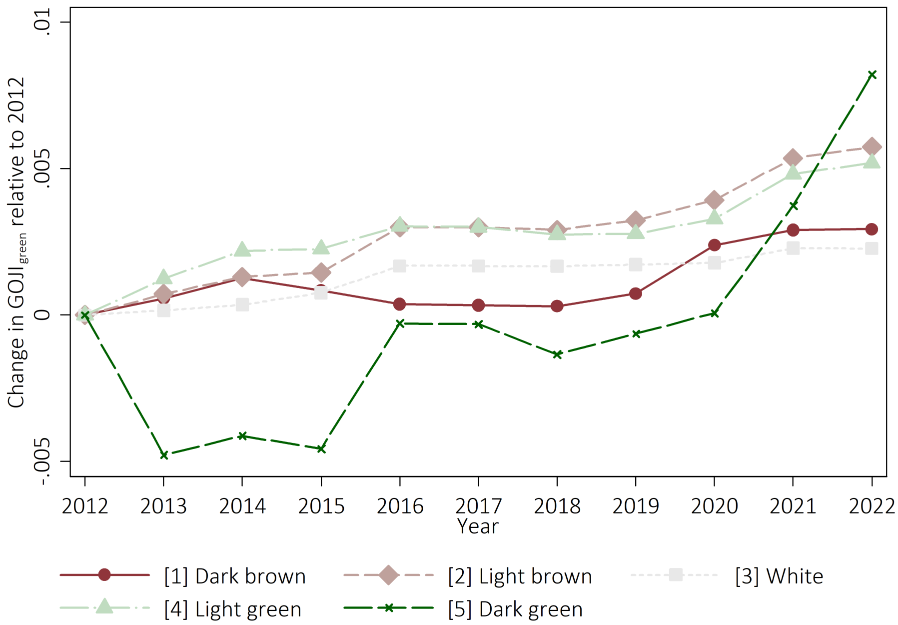
Notes: The mean GOJI is calculated as an unweighted average across all 5-digit occupations within each GOJI group. The depicted values show the absolute change in the mean GOJI relative to the base year (2012). Occupations are categorised into GOJI groups according to their 2012 GOJI value.
Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022

However, looking at the top 20 specific occupations with the largest within-effect, it becomes apparent that occupations from all GOJI groups are represented (Table 8): The largest contribution comes from technical occupations in the automotive industries (a dark brown occupation), the second-largest from occupations in public administration (white), the third-largest from occupations in postal and other delivery services (light green), and the fourth-largest from drivers of vehicles in road traffic (light brown). Bus and tram drivers, a dark green occupation, has the seventh-largest within-component. The fact that the average GOJI increases for all GOJI groups – although most strongly for brown occupations – raises the question which mechanism underlies the evolution of the within-effect.

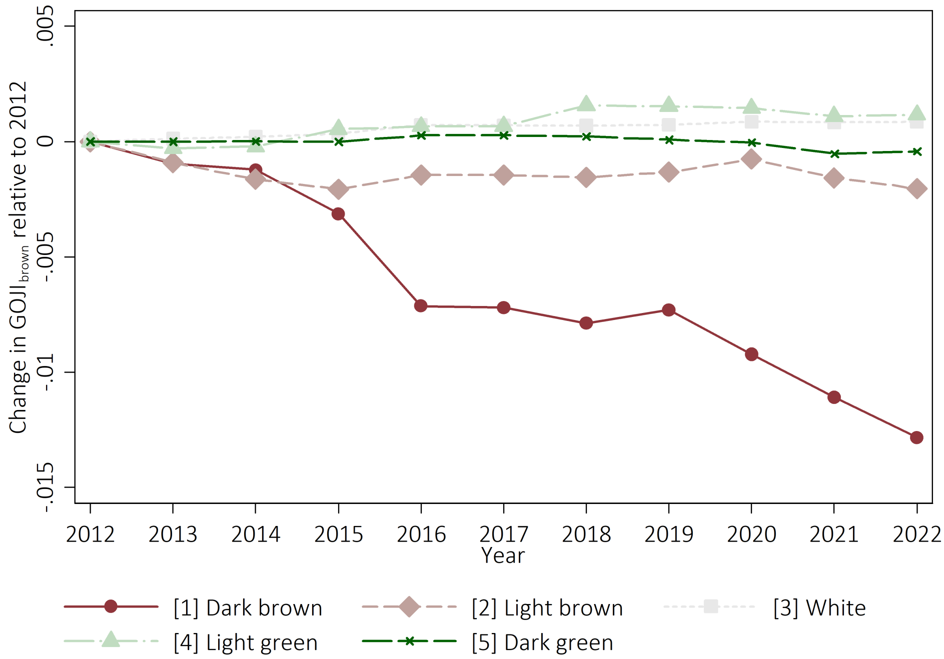
To better understand the evolution of the GOJI within occupations, we go back to its underlying components, i.e. $GOJI_{green}$ and $GOJI_{brown}$. As Figure 4 shows, the increase of green tasks ($GOJI_{green}$) plays some role for light green and light brown occupations, and especially for the increase of the net GOJI of dark green occupations since 2020. The reduction of brown tasks ($GOJI_{brown}$) only plays an important role for dark brown occupations.

Figure 4: Intensity of $GOJI_{green}$ and $GOJI_{brown}$ by GOJI group over time

A: Evolution of $GOJI_{green}$



B: Evolution of $GOJI_{brown}$



Notes: The mean $GOJI_{neg}$ (Panel A) and $GOJI_{neg}$ (Panel B) are calculated as unweighted average across all 5-digit occupations within each GOJI group. The depicted values show the absolute change in the mean GOJI relative to the base year (2012). Occupations are categorised into GOJI groups according to their 2012 GOJI value.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations

5.2 Determinants of the within-effect: Results from a regression analysis

The descriptive evidence suggests that occupations that are defined as dark brown at the beginning of our observation period contribute most to the greening within occupations. To examine whether this is driven by sectoral, regional or other structural differences between occupations, we conduct an econometric analysis of the change in the GOJI at the occupation level using the initial levels of occupational characteristics as explanatory variables. This allows us to draw conclusions on the importance of the initial conditions of occupations for their greening.

For the investigation of the role of the initial level of occupational characteristics, we estimate the following regression equation:

$$\Delta GOJI^{occ} = \alpha + \beta \ GOJI_{2012}^{occ} + X_{2012}^{occ}{}'\gamma \ + \epsilon^{occ} \tag{6}$$

The control variables are all at the occupation level, and they are measured in 2012, the first year of our period of analysis. They consist of the GOJI group and occupational characteristics X^{occ}. These include the share of different worker groups in total employment of the respective occupation, e.g. the female share and the share of young and old workers as well as the employment share of an occupation in a specific sector or region.

The results of this exercise corroborate that the observed greening of employment largely occurs within dark brown occupations (Table 3, column 1). Taking sectoral characteristics (column 2) and regional characteristics (column 3) of occupations into account strengthens this result even more. The initial level of worker and establishment characteristics (column 4) can explain the greening of occupations only to a small extent as most of the characteristics are not significant in the regression.[12] This also confirms the results from the Blinder-Oaxaca decomposition for the overall greening of employment where composition effects are not a driving factor either.

[12] This result also holds when we separately regress changes in $GOJI_{green}$ and $GOJI_{brown}$ on GOJI group indicators for the year 2012. The corresponding results – as the full results for Table 3 including control coefficients – are available from the authors upon request.

Table 3: Greening within occupations

	(1) Baseline Coeff./SE	(2) +Industries Coeff./SE	(3) +Regional characteristic Coeff./SE	(4) +Worker/est. characteristic Coeff./SE
GOJI group (reference: [3] White)				
[1] Dark brown	0.0181** (0.0088)	0.0205** (0.0086)	0.0248*** (0.0082)	0.0244*** (0.0075)
[2] Light brown	-0.0009 (0.0038)	0.0020 (0.0044)	0.0032 (0.0043)	0.0036 (0.0038)
[4] Light green	0.0009 (0.0037)	0.0014 (0.0040)	0.0009 (0.0039)	-0.0006 (0.0036)
[5] Dark green	-0.0114 (0.0147)	-0.0113 (0.0139)	-0.0124 (0.0133)	-0.0132 (0.0132)
Constant	0.0007 (0.0006)	-0.0088** (0.0035)	-0.0207 (0.0480)	-0.0202 (0.0459)
Worker and establishment characteristics				
Female				-0.0132* (0.0078)
Age group shares (reference: 30-49)				
16-29				-0.0036 (0.0281)
50-65				0.0011 (0.0302)
Education level shares				
Low				0.0297 (0.0294)
High				0.0010 (0.0047)
Foreign				-0.0459 (0.0391)
Full-time				-0.0120 (0.0182)
Technological substitutability of occupation shares				
Low				-0.0015 (0.0027)
High				-0.0075* (0.0039)
Missing				-0.0127** (0.0051)
Establishment size shares (reference: 50-499)				
1-49				0.00352 (0.0086)
>500				0.0069 (0.0115)
Industries	No	Yes	Yes	Yes
Regional characteristics	No	No	Yes	Yes
Adjusted R^2	0.05	0.13	0.18	0.20
N	1,278	1,278	1,278	1,278

Notes: The table reports results from ordinary least squares regression on the 5-digit occupation level with changes in the mean net GOJI between 2012 and 2022 as dependent and base year (2012) GOJI group indicators as independent variables. Control variables include base year sector shares (21 categories) in column 2 plus federal state shares (16 categories) and region type shares (4 categories) in column 3, plus worker and establishment characteristics as indicated in column 4. Robust standard errors in parentheses. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

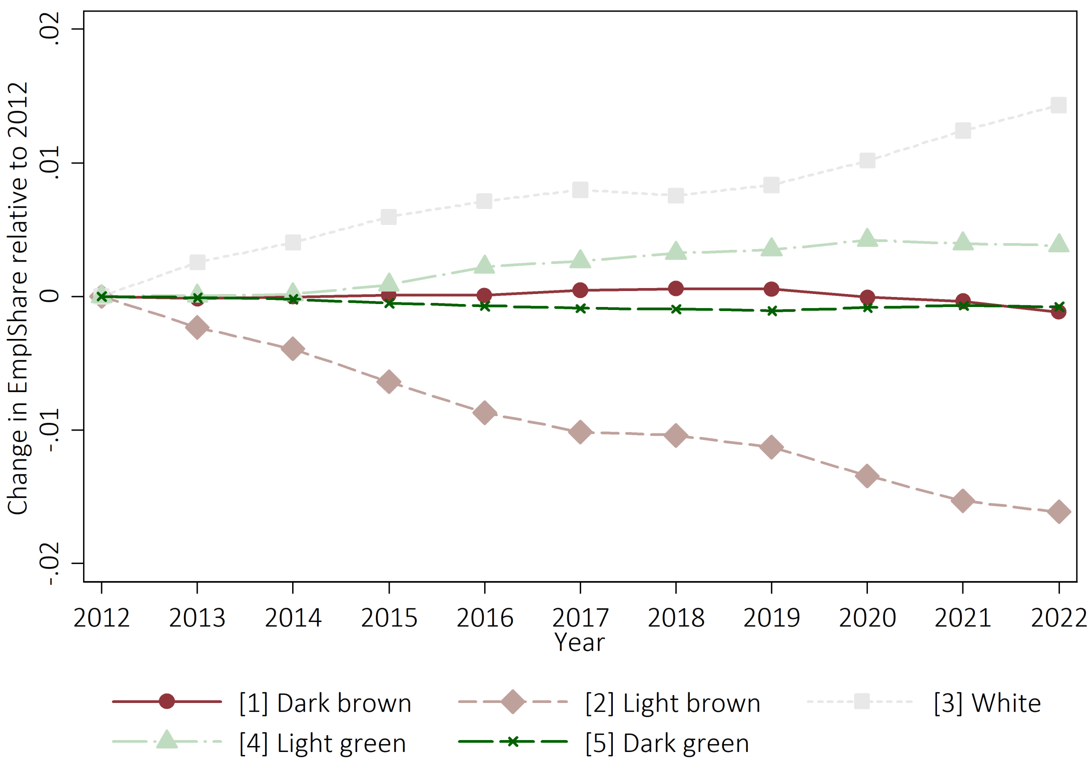
Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, own calculations.

6 The between-effect: The role of worker flows for the greening of employment

6.1 Descriptive evidence on the between-effect

We now turn to an analysis of the sources of the between-effect, i.e. changing occupational shares. To keep the analysis tractable, we focus on employment changes for the five broad GOJI groups. The evolution of the employment shares for these five groups over time is depicted in Figure 5. It becomes apparent that the employment share of white occupations has risen most (by 0.014 or 1.4 percentage points), followed by light green occupations (+0.4 percentage points). The employment shares of dark brown and dark green occupations have stayed relatively constant, whereas the employment share of light brown occupations has declined strongly (–1.6 percentage points). Therefore, the between-effect is driven by the growth of light green occupations and by the decline of light brown occupations, leading to a corresponding increase of white occupations.

Figure 5: Employment shares by GOJI group over time



Notes: The depicted values show the absolute change in the mean employment share across all 5-digit occupations within each GOJI group, relative to the base year (2012). Occupations are categorised into GOJI groups according to their 2012 GOJI value.
Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022

These net employment changes are the result of underlying gross dynamics, i.e. worker flows between labour market states and GOJI groups. In the next step of our analysis, we therefore examine the worker flows that generate the employment changes of the five GOJI groups. We first display the yearly worker outflows from these groups depending on the labour market / GOJI state in the preceding year, holding the classification of occupations into GOJI groups fixed at the classification in 2012. Afterwards, we analyse worker inflows into the GOJI groups.

The first source of employment change for the GOJI groups, employment outflows, is displayed in Table 4. The main findings are as follows. First, the rates of stayers in the different employment groups mirror these for employment inflows, i.e. they all range around 85 percent. Dark brown occupations have the lowest stayer rates (82.9 percent), followed by the light green, light brown, dark green and white GOJI groups

Table 4: Outflow rates from GOJI groups, yearly transitions 2012–2021

	Year t+1									
Year t	[1] Dark brown	[2] Light brown	[3] White	[4] Light green	[5] Dark green	[6] Not employed	[7] Apprentices	[8] Marginal employment	[9] Other	Sum
[1] Dark brown	82.9	2.1	3.1	1.1	0.5	8.8	0.3	0.9	0.3	100
[2] Light brown	0.6	86.2	3.1	0.9	0.4	7.3	0.2	0.8	0.4	100
[3] White	0.2	0.6	88.9	0.6	0.1	7.9	0.3	0.9	0.4	100
[4] Light green	0.3	1.0	3.8	84.4	0.3	8.1	0.2	1.4	0.4	100
[5] Dark green	0.5	1.7	2.1	1.1	87.0	6.4	0.1	0.7	0.3	100

Notes: The displayed numbers are the averages of the outflow rates from year t to year t+1 during the period t ϵ [2012; 2021]. Outflow rates consider transitions from regular employment in year t in the indicated GOJI groups. In total, we observe 27,969,897 transitions in the observation period. Occupations are categorised into GOJI groups according to their 2012 GOJI value. Labour market states in year t+1 include regular employment in the indicated GOJI groups plus further labour market states, where "Other" includes internships, student jobs, particular versions of part-time retirement, etc.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2020, own calculations.

Second, with respect to worker flows between GOJI groups, outflows to the white occupations are most important for all GOJI groups. For dark brown occupations, flows to light brown and light green occupations also play some role. For light brown occupations, outflows to light green occupations come second to outflows to white occupations. Furthermore, we observe sizeable transitions from dark green occupations to light green occupations (1.1 percent), but relatively little transitions in the reverse direction (0.3 percent). Transitions from light green and dark green occupations to light brown are also relatively important (1.0 percent and 1.7 percent, respectively). Third, outflows to non-employment are most important for dark brown occupations (8.8 percent).

As for worker inflows into GOJI groups and labour market states, several stylised facts emerge (Table 5). First, the share of workers staying in their GOJI group is relatively similar for all five groups, ranging between 81.9 percent (dark brown) and 87.3 percent (white). Second, the white GOJI group is the most important source state for the other GOJI groups, which reflects the relatively large size of the white GOJI group. The light green and the dark green GOJI groups obtain most direct inflows from employment from the white GOJI group (3.6 percent and 2.5 percent, respectively). For the dark green GOJI group, white (2.5 percent), light green (1.1

percent) and light brown (1.8 percent) occupations are also important sources of inflows from employment.

Third, non-employment is an important source of employment growth for all GOJI groups, and particularly for the dark brown group (8.9 percent). Fourth, inflows from an apprenticeship are most important for the dark green occupations (1.6 percent) and dark brown occupations (1.7 percent). The high inflow of apprentices into dark brown occupations seems surprising as these occupations are characterised by relatively unfavourable employment prospects, as we show at the end of this section.

Table 5: Inflow rates into GOJI groups, yearly transitions 2013–2022

	Year t				
Year t–1	**[1] Dark brown**	**[2] Light brown**	**[3] White**	**[4] Light green**	**[5] Dark green**
[1] Dark brown	81.9	0.7	0.2	0.4	0.6
[2] Light brown	1.8	86.0	0.6	1.1	1.8
[3] White	3.0	3.0	87.3	3.6	2.5
[4] Light green	0.9	0.9	0.7	82.9	1.1
[5] Dark green	0.4	0.4	0.1	0.3	85.9
[6] Not employed	8.9	6.5	7.7	8.2	5.6
[7] Apprentices	1.7	1.5	1.3	1.1	1.6
[8] Marginal employment	1.2	0.9	1.6	2.2	0.8
[9] Other	0.2	0.2	0.4	0.3	0.2
Sum	100	100	100	100	100

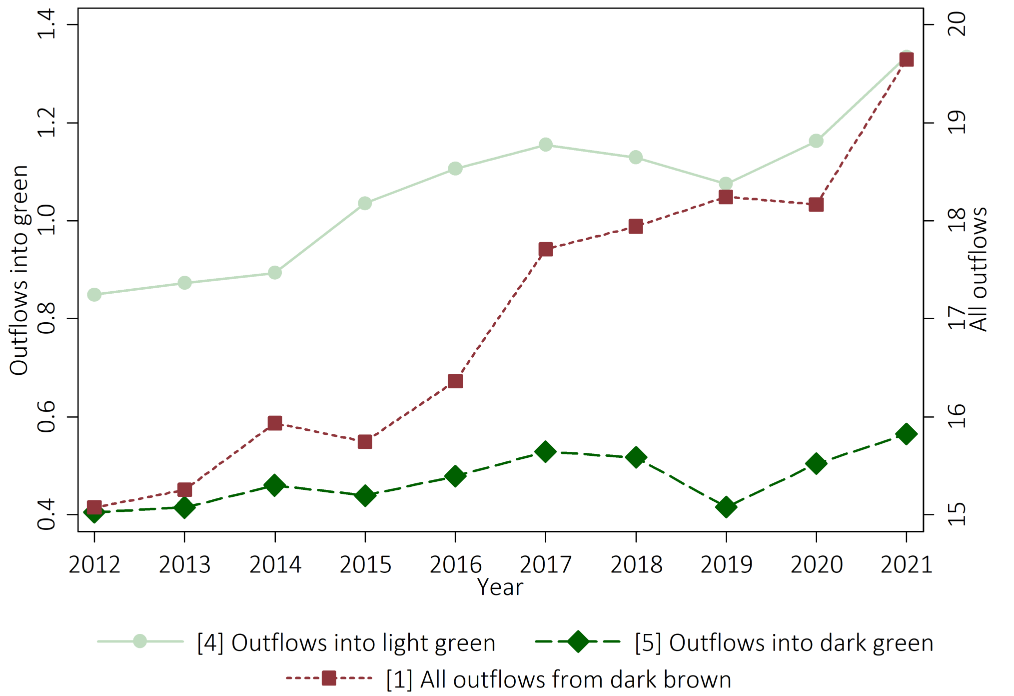
Notes: The displayed numbers are the averages of the inflow rates from year t–1 to year t during the period t ϵ [2013; 2022]. Inflow rates consider transitions into regular employment in year t in the indicated GOJI groups. In total, we observe 28,404,317 transitions in the observation period. Occupations are categorised into GOJI groups according to their 2012 GOJI value. Labour market states in year t–1 include regular employment in the indicated GOJI groups plus further labour market states, where “Other” includes internships, student jobs, particular versions of part-time retirement, etc.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations

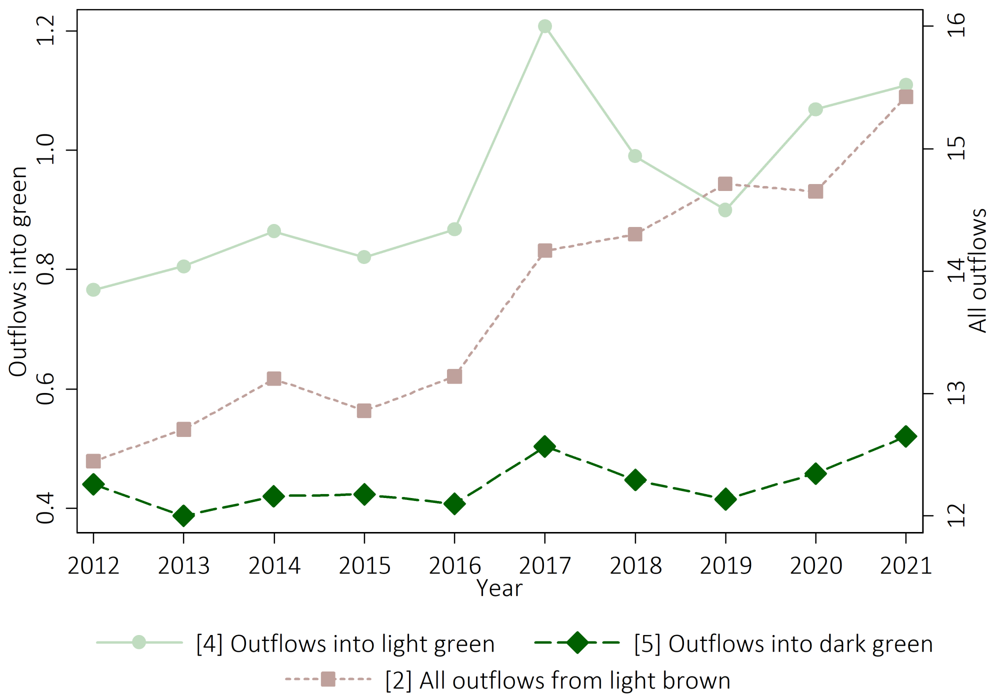
The preceding evidence presents average worker flows over the entire observation period. This may mask important changes in the evolution of these flows over time. We therefore now depict the evolution over time in more detail, focusing on worker outflows from brown occupations, and on worker inflows into green occupations. It becomes apparent that outflows from dark brown occupations strongly rise, from 15.1 percent in 2012 to 19.6 percent in 2021 (see right-hand axis in Figure 6, Panel A). The rise is particularly pronounced from 2016 onwards. This is partly due to a concurrent increase in worker flows from dark brown occupations to light green occupations (from 0.8 percent in 2012 to 1.3 percent in 2021, see left-hand axis in Figure 6, Panel A,

Figure 6: Outflow rates from brown occupations (in %)

A: Outflows from dark brown occupations



B: Outflows from light brown occupations



The depicted transition rates are calculated as the share of regular employees in the dark brown (Panel A) or light brown (Panel B) GOJI group in year t ϵ [2012; 2021] who transition to a different regular employment in year t+1 in the light green or dark green GOJI group or to any regular employment in other GOJI groups or other labour market states (for "all outflows"). See Table 4 for the full list of labour market states. Occupations are categorised into GOJI groups according to their 2012 GOJI value.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

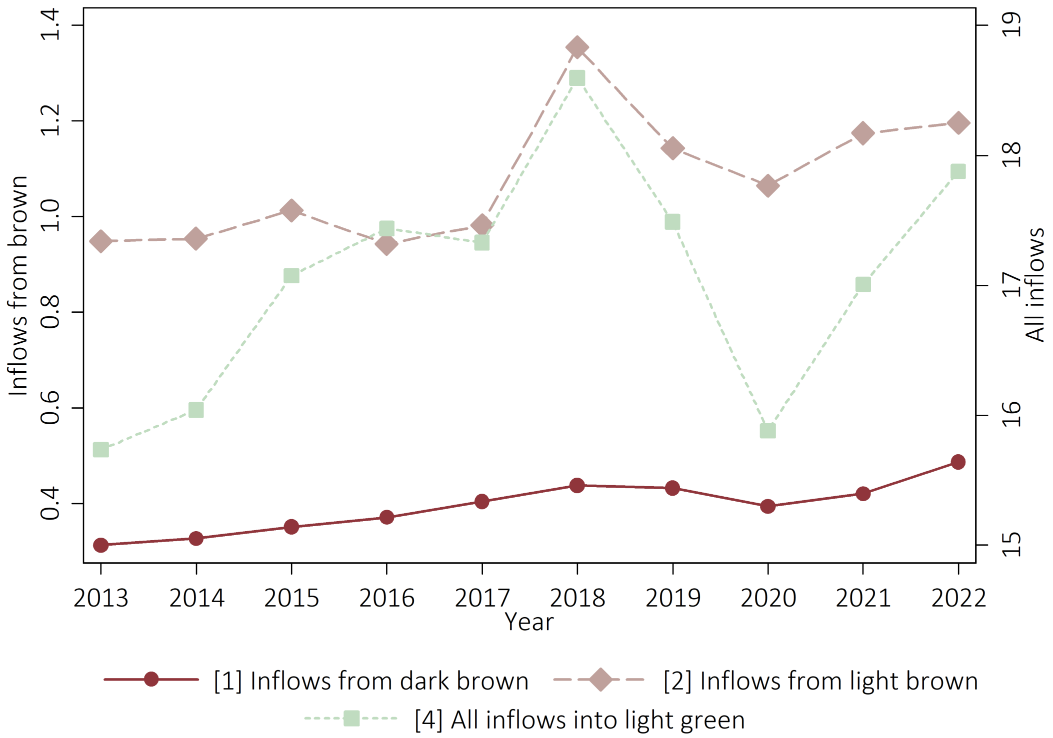
with an intermittent drop in 2018–2019), and partly to an increase in worker flows from dark brown occupations to dark green occupations (from 0.4 percent to 0.6 percent), which however remains at a relatively low level.

A similar picture emerges for outflows from light brown occupations (Figure 6, Panel B). These occupations also feature a sharp increase in outflows from 2016 onwards. This increase is again partly driven by rising outflows from light brown occupations to light green and dark green occupations, but less strongly than for outflows from dark brown occupations.

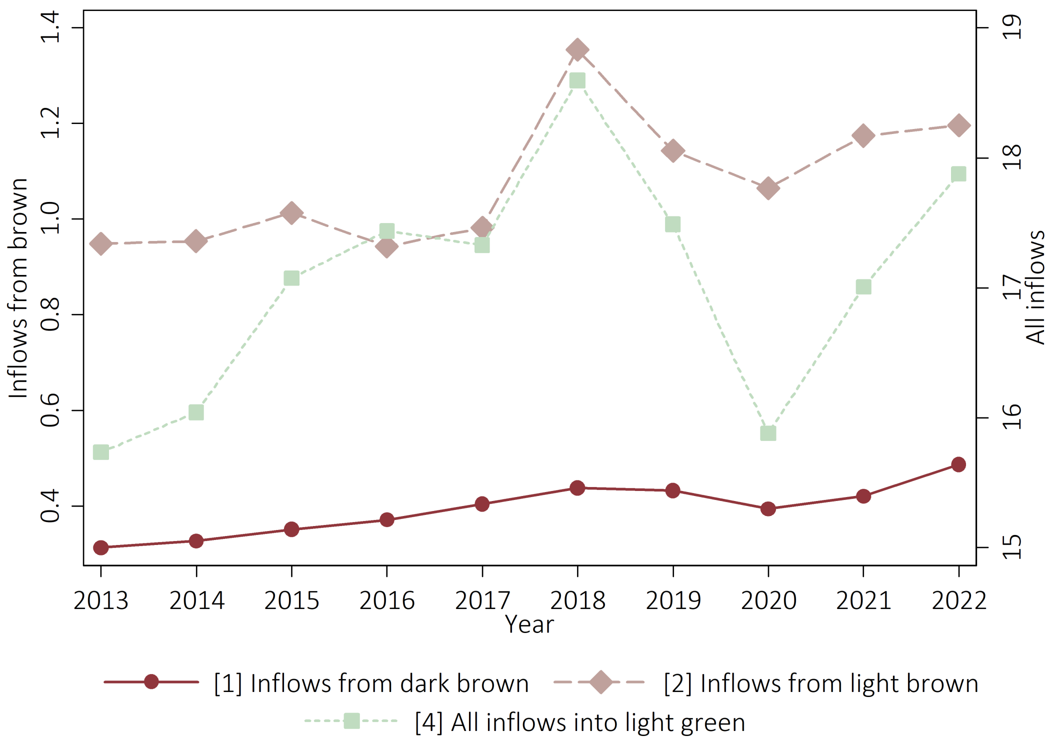
Turning to inflows into light green occupations, we again see an increase over time, with relatively strong fluctuations (Figure 7, Panel A). This increase in overall inflows can be attributed to a (relatively moderate) growth of the worker flows from dark brown and light brown occupations to light green occupations. As for inflows into dark green occupations, there is a strong – again fluctuating – increase in overall inflows into dark green occupations over time (Figure 7, Panel B). This goes together with a sustained increase in worker flows from light brown and dark brown occupations.

Figure 7: Inflow rates into green occupations (in %)

A: Inflows into light green occupations



B: Inflows into dark green occupations



The depicted transition rates are calculated as the share of regular employees in the light green (Panel A) or dark green (Panel B) GOJI group in year t ϵ [2013; 2022] who transition from a different regular employment from year t–1 to year t from the dark brown or light brown GOJI group or from any regular employment in other GOJI groups or from other labour market states (for "all outflows"). See Table 5 for the full list of labour market states. Occupations are categorised into GOJI groups according to their 2012 GOJI value.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

6.2 Counterfactual analysis

The transition matrices indicate that worker flows play an important role for changing employment stocks over time. However, the exact magnitude of the contribution of different worker flows to the evolution of occupational employment stocks remains unclear. We therefore use a counterfactual analysis in the spirit of Cortes et al. (2020) to quantify these respective contributions, again fixing the classification of occupations into GOJI groups at the classification for the year 2012. The counterfactual analysis is based on the stock-flow identity of the labour market:

$$E_{t+1}^{occ} = E_t^{occ} + \text{ Inflows into } occ_t \; - \text{Outflows from } occ_t \tag{7}$$

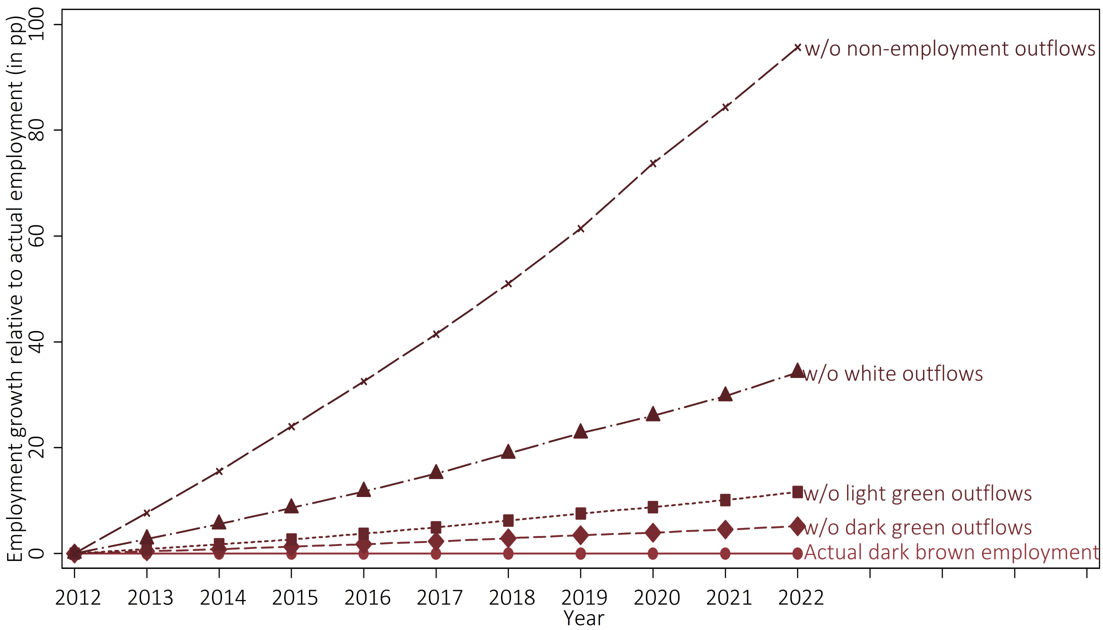
We use this identity to calculate counterfactual employment stocks, simulating a counterfactual scenario for a given employment stock where a specific worker flow is set to zero, and comparing the resulting counterfactual employment stock with its actual evolution. For brown occupations, we counterfactually set specific outflows to zero, for green occupations, we do so for specific inflows. If for example, we want to quantify the importance of worker outflows from dark brown to dark green occupations, we compute the counterfactual employment stock of dark brown occupations setting the worker flow from dark brown to dark green occupations to zero:

$$
\begin{aligned}
& \mathrm{E}_{\mathrm{t+1}}^{\mathrm{Dark\ brown}\ without\ outflows\ into\ dark\ green} = \mathrm{E}_{\mathrm{t}}^{\mathrm{Dark\ brown}} \\
& + (\text{All inflows into Dark brown})_{\mathrm{t} \rightarrow \mathrm{t+1}} \\
& - \binom{\text{All iutflows from Dark brown}}{w/o\ Outflow\ Dark\ brown \rightarrow Dark\ green}_{t \rightarrow \mathrm{t+1}}
\end{aligned}
\tag{8}
$$

To quantify the role of inflows for green occupations, we proceed in a similar way, setting specific inflows into green occupations to zero in order to compute counterfactual employment stocks of green occupations.

The results from this counterfactual analysis show for dark brown occupations that setting outflows from dark brown occupations to non-employment to zero has the largest impact on the counterfactual employment stock of dark brown occupations (Figure 8). Without outflows to non-employment, the employment stock of dark brown occupations would have been 96 percentage points higher in 2022 compared to actual employment stocks in 2022. This shows that the employment growth of these occupations over the time period 2012–2022 is most strongly limited by outflows to non-employment, i.e. without these outflows, the employment stock would have grown more strongly.

Figure 8: Growth of counterfactual employment stocks: Dark brown occupations



Notes: Each counterfactual employment growth curve is computed setting one specific outflow to zero (see Equation (8) and description in the text). The depicted values denote the difference between counterfactual employment growth and actual employment growth (normalised to zero) in percentage points (pp).

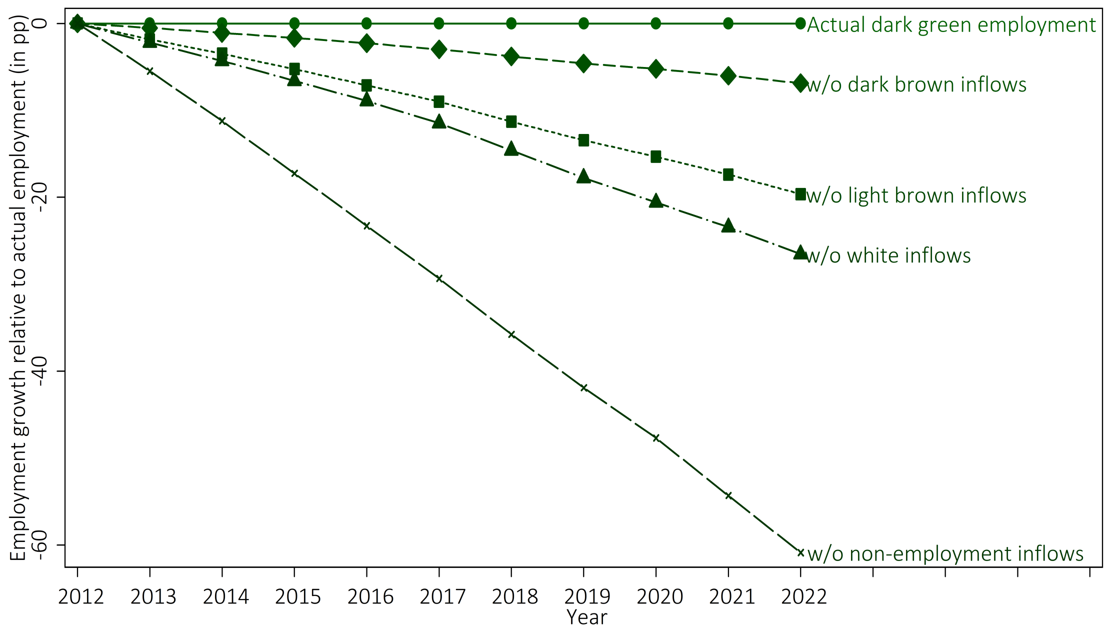
Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

Furthermore, outflows to white occupations play some role for the employment stock of dark brown occupations, outflows to light green and dark green occupations only play a minor role.

Performing the same analysis for light brown occupations yields a very similar picture (Figure 12 in Appendix B.3).

The counterfactual analysis for dark green occupations yields comparable results for inflows into dark green occupations (Figure 9). It becomes apparent that the growth of dark green occupations is most strongly driven by inflows from non-employment. Inflows from white occupations also play some role. The role of inflows from dark brown and light brown occupations for the evolution of the stock of dark green occupations is negligible. Analysing the role of inflows for light green occupations yields a very similar picture (Figure 13).

Figure 9: Growth of counterfactual employment stocks: Dark green occupations



Notes: Each counterfactual employment growth curve is computed setting one specific outflow to zero (see Equation (8) and description in the text). The depicted values denote the difference between counterfactual employment growth and actual employment growth (normalised to zero) in percentage points (pp).

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

7 Individual-level consequences of the greening of employment

In a final step, we analyse the individual-level consequences of the greening of the labour market. To do so, we analyse the employment probabilities and the labour-market transitions of workers belonging to different GOJI groups. To analyse employment probabilities, we run a logit model for the individual employment probability of a worker over different yearly time horizons to see whether employment prospects change over time.

The results of this regression analysis show that workers in dark brown occupations have the lowest employment probabilities, and their employment prospects worsen over time (Table 6).

Workers in light green occupations feature employment probabilities very similar to workers in white occupations. Workers in light brown occupations have relatively favourable employment prospects compared to the reference group. Finally, workers in dark green occupations have the best employment prospects, and their employment probabilities even become better over time. These results may be an indication that dark green occupations are relatively attractive for workers, which could help ease the greening of the labour market.

As a robustness test, we re-estimate Table 6 for workers who are aged 16–50 in 2012, i.e. who could reach retirement during our observation period. This yields very similar results to those for the entire sample (see Table 11 in Appendix B.2). The probability of remaining in employment in the reference group is naturally generally higher for employees under 50 (by 10 percentage points in the last year), but employees in dark brown occupations still have the lowest probability of employment, and those in dark green occupations the highest. Therefore, labour-market exits due to retirement do not seem to play an important role for the reported employment probabilities and the differences between GOJI groups.

Table 6: Worker-level employment probabilities by GOJI group

Emty cell	t+1	t+3	t+5	t+7	t+9
[1] Dark brown	−0.008***	−0.010***	−0.015***	−0.015***	−0.023***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[2] Light brown	0.004***	0.003**	0.003	0.005***	0.003
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[3] White			Reference category		
[4] Light green	−0.001	−0.004**	−0.007**	−0.003	−0.004*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[5] Dark green	0.006***	0.011***	0.011***	0.012***	0.015***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)
Mean of reference group	0.923	0.869	0.832	0.790	0.738
Observations	393,042	393,042	393,042	393,042	393,042

Notes: Marginal effects from a logit regression with dependent variable being employed in 1 through 9 years after year t=2012 and base year (2012) GOJI group indicators as independent variables. Controls include dummies for females, foreign citizenship, 3 formal education levels, full-time employment, linear and squared terms of age and tenure, the substitution potential (3 categories), log establishment size and its square, as well as regional controls (federal states and region types) and a manufacturing dummy. Standard errors in parentheses. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), 10% sample, BERUFENET, 2012–2022, own calculations.

Worker transitions are also an important determinant of workers' welfare. In the final step of our analysis, we therefore investigate the importance of individual- and occupation-level characteristics for worker transitions, e.g. from dark brown to dark green occupations. This allows us to identify worker groups and factors which are strongly correlated with specific labour-market transitions. To do so, we use a multinomial regression model for worker outflows from each of the five GOJI groups to employment in the other four GOJI groups and to other labour market states. The results (see Appendix B.4 and descriptions in the following paragraphs) show how the staying rates in the respective group and the transition rates to other GOJI groups and labour market states differ by individual and establishment characteristics and years in the sample.

For dark brown occupations (Table 7 in Appendix B.4), it becomes apparent that women are less likely than men to stay in this GOJI group or to make a transition to light brown, light green, or dark green occupations. In contrast, they are more likely to transition to white occupations, non-employment or marginal employment. Foreign workers are more likely than German citizens to stay in dark brown occupations or to make a transition to any other than dark green occupations. Foreigners are also more likely to transition to non-employment or marginal employment. These relatively high probabilities of transitioning to unfavourable labour-market states, together with the overrepresentation of foreign workers in dark brown occupations (see Section 4.1), indicate that foreign workers are at a relatively high risk of being negatively affected by the greening of the labour market.

Regarding age groups, the results are mixed. Compared to medium-aged workers (30–49 years), young workers exhibit higher staying rates in dark brown occupations, but also higher transition rates into all other groups or labour market states except for transitions into dark green occupations. Workers in the older (50–65) age group are less likely than medium-aged workers to stay in dark brown occupations or to transition into light brown or dark green occupations or other labour market states. Differences by full-time vs. part-time employment are relatively small.

The substitutability through technology, defined by the importance of routine task intensity for a specific occupation, also plays a role in this context. Our results show that staying rates for dark brown occupations are higher for occupations with low and lower for occupations with high substitutability. This indicates that technological substitutability is a push factor out of dark brown occupations. Therefore, workers in dark brown occupations with high substitutability are a particularly vulnerable risk group as their jobs are threatened by both the green and the digital transition. However, their risk is mitigated as they mainly have a higher probability of making transitions to light brown and to white occupations, rather than to non-employment. The results for transitions from light brown occupations (Table 8) are relatively similar to the results for transitions from dark brown occupations.

Finally, we turn to the econometric analysis of inflows into the light green and dark green GOJI groups. For light green occupations (see Table 9 in Appendix B.4), it becomes apparent that women only have a higher probability than men of making a transition to these occupations if they come from white occupations. Furthermore, inflows into light green occupations are highest for young workers, independently of their previous occupation or labour-market state. Looking at regional differences, it becomes apparent that inflows from dark brown, white and dark green occupations into light green occupations are highest in the east, but also more positive in the north and south, all compared to the west. The results for inflows into dark green occupations (see Table 10) are very similar to the results for light green occupations. This concerns the results for women (they only have a higher probability of making a transition to dark green occupations if they come from white occupations) and age groups (younger workers have the highest inflow rates, independently of their previous occupation or labour-market state).

8 Conclusion

The ecological transition has important labour-market implications as occupations that are harmful to the environment, and particularly those that emit many greenhouse gases, are shrinking, and the skills required in these occupations become obsolete to an extent. By contrast, occupations which are more environment-friendly are growing, making the skills in these sectors and occupations more valuable. The required adjustments on the labour market can occur through a change occurring within occupations ("within-effect") or through changes in employment shares between occupations with different levels of greenness ("between-effect"). In this paper, we have therefore investigated the relative importance of the within-effect and of the between-effect, and potential mechanisms underlying these two effects. In our analysis, we have used a task-based measure of the greenness of occupations and have combined this occupation-level measure with detailed administrative data on worker-level outcomes.

Our results are as follows. First, the greenness of employment in Germany has risen considerably in the period 2012–2022, with green tasks rising by 11 percent and brown tasks falling by 7 percent. Second, the within-effect, which has up to now been neglected in the literature, plays an equally important role as the between-effect for the greening of employment in Germany. By contrast, composition effects with respect to worker and establishment characteristics do not play a role for the greening of the labour market, on the contrary: without composition effects, the greening of the labour market would have been larger than the greening actually observed. Third, the within-effect can mainly be attributed to brown occupations becoming less environment-harmful, which in turn is due to a reduction of brown occupational requirements; the increase of green occupational requirements in dark green occupations also plays some role for the within-effect. Fourth, the between-effect is mainly driven by flows to and from non-employment. Direct worker transitions to greener occupations are relatively rare. Fifth, workers in relatively brown occupations have worse employment prospects than workers in relatively green occupations. This is in line with relatively high transition rates to non-employment among workers in relatively brown occupations. Sixth, foreign workers and workers with low education are at a higher risk of being negatively affected by the green transition than other worker groups, hence raising existing inequalities in the labour market.

Our results have important policy implications. First, the important role of the within-effect for the greening of the labour market implies that workers do not necessarily have to change their occupation to adapt to changing skill requirements caused by the greening of employment. However, adapting to changing occupations likely requires efforts from both workers and employers in engaging in and providing on-the-job training, respectively. At the same time, the between-effect also plays an important role. As this effect is strongly driven by workers switching occupations and is therefore likely to lead to losses of occupation-specific human capital, this adjustment mechanism probably requires more extensive policy measures of up- and reskilling.

Second, our result that the within-effect is mainly driven by a decrease in brown skill requirements of brown occupations implies that brown requirements become obsolete to an extent. This finding, and in addition the importance of worker transitions to non-employment, and the worse employment prospects of workers in initially brown occupations, shows that there is a danger of sizeable welfare losses for the affected workers. This is especially true for workers with low education levels and for foreign workers. Therefore, appropriate up- and reskilling measures play a crucial role in the ecological transition of the labour market.

References

Acemoglu, D.; Autor, D. (2011), Skills, Tasks and Technologies: Implications for Employment and Earnings. In: Handbook of Labor Economics: Elsevier, p. 1043–1171.

Acemoglu, D.; Restrepo, P. (2018), The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment. In: American Economic Review 108 (6), p. 1488–1542.

Antoni, M., Ganzer, A.; vom Berge, P. (2016), Sample of Integrated Labour Market Biographies (SIAB) 1975–2014. FDZ-Datenreport: 74.

Autor, D. H.; Levy, F.; Murnane, R. J. (2003), The Skill Content of Recent Technological Change: An Empirical Exploration. In: The Quarterly Journal of Economics 118 (4), p. 1279–1333.

Bachmann, R.; Cimc, M.; Green, C. (2019), Long-Run Patterns of Labour Market Polarization: Evidence from German Micro Data. In: British Journal of Industrial Relations 57 (2), p. 350–376.

Bachmann, R.; Demir, G.; Green C.; Uhlendorff; A. (2022), The Role of Within-Occupation Task Changes in Wage Development. Ruhr Economic Paper No. 975.

Bilal, A.; Känzig D. R.(2024), The Macroeconomic Impact of Climate Change: Global vs. Local Temperature. In: NBER Working Paper (No. 32450).

Bluedorn, J.; Hansen, N.-J.; Noureldin, D.; Shibata, I.; Tavares, M. M. (2023), Transitioning to a greener labor market: Cross-country evidence from microdata. In: Energy Economics 126, p. 106836.

Borissov, K.; Brausmann, A.; Bretschger, L. (2019), Carbon pricing, technology transition, and skill-based development. In: European Economic Review 118, p. 252–269.

Bowen, A.; Kuralbayeva, K.; Tipoe, E. L. (2018), Characterising green employment: The impacts of 'greening' on workforce composition. In: Energy Economics 72, p. 263–275.

Consoli, D.; Marin, G.; Marzucchi, A.; Vona, F. (2016), Do green jobs differ from non-green jobs in terms of skills and human capital? In: Research Policy 45 (5), p.1046–1060.

Cortes, G. M. (2016), Where Have the Middle-Wage Workers Gone? A Study of Polarization Using Panel Data. In: Journal of Labor Economics 34 (1), p.63–105.

Cortes, G. M.; Jaimovich, N.; Nekarda, C. J.; Siu, H. E. (2020), The Dynamics of Disappearing Routine Jobs: A Flows Approach. In: Labour Economics 65, p. 101823.

Curtis, E. M.; Marinescu, I. (2022), Green Energy Jobs in the US: What Are They, and Where Are They? In: NBER Working Paper Series (No. 30332).

Curtis, E. M.; O'Kane, L.; Park, R. J. (2024), Workers and the Green-Energy Transition: Evidence from 300 Million Job Transitions. In: Environmental and Energy Policy and the Economy 5, p. 127–161.

Darendeli, A.; Law, K. K. F.; Shen, M. (2022), Green new hiring. In: Review of Accounting Studies 27, p. 986–1037.

Dengler, K.; Matthes, B. (2018), The impacts of digital transformation on the labour market: Substitution potentials of occupations in Germany. In: Technological Forecasting and Social Change 137, p. 304–316.

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. Technical Report. Raleigh.

Dierdorff, E. C.; Norton, J. J.; Gregory, C. M.; Rivkin, D.; Lewis, P. (2011), Greening of the World of Work: Revisiting Occupational Consequences. Technical Report. Raleigh.

European Commission (2022), Green Skills and Knowledge Concepts: Labelling the ESCO Classification. Technical Report. Brussels.

Fitzenberger, B.; Osikominu, A.; Völter, R. (2006), Imputation Rules to Improve the Education Variable in the IAB Employment Subsample. In: Schmollers Jahrbuch (Journal of the Applied Social Sciences) 126 (3), p. 405–436.

Freeman, R. B.; Ganguli, I.; Handel, M. J. (2020), Within-Occupation Changes Dominate Changes in What Workers Do: A Shift-Share Decomposition, 2005–2015. In: AEA Papers and Proceedings 110, p. 394–399.

Frohm, E.; D’Arcangelo, F. M.; Kruse, T.; Pisu, M.; Sila, U. (2023), Environmental policy stringency and CO2 emissions: Evidence from cross-country sector-level data. OECD Economics Department Working Papers No. 1773.

Gathmann, C.; Schönberg, U. (2010), How General Is Human Capital? A Task-Based Approach. In: Journal of Labor Economics 28 (1), p. 1–49.

Granata, J.; Posadas, J. (2024), Why Look at Tasks When Designing Skills Policy for the Green Transition? – A Methodological Note on How to Identify Green Occupations and the Skills They Require. World Bank Policy Research Working Paper No. 10753.

Haywood, L.; Janser, M.; Koch, N. (2024), The welfare costs of job loss and decarbonization – evidence from Germany’s coal phase out. In: Journal of the Association of Environmental and Resource Economists 11 (3), p. 577–611.

Janser, M. (2019), The greening of jobs: Empirical studies on the relationship between environmental sustainability and the labor market (Doctoral dissertation, Otto-Friedrich-Universität Bamberg). 213.

Janser, M. (2024), Green and brown jobs in transition. Measuring ecological transition and decarbonization using the Greenness-of-Jobs Index (GOJI). Mimeo.

Kruse, T.; Dechezleprêtre, A.; Saffar, R.; Robert, L. (2022), Measuring environmental policy stringency in OECD countries: An update of the OECD composite EPS indicator. OECD Economics Department Working Papers No. 1703.

Lewis, P.; Morris, J.; Gregory, C. (2022), Green Topics: Identifying Linkages to Occupations and Education Programs Using a Linguistic Approach. O*NET Working Paper.

Marin, G.; Vona, F. (2019), Climate policies and skill-biased employment dynamics: Evidence from EU countries. In: Journal of Environmental Economics and Management 98, p102253.

OECD (2023), Assessing; Anticipating Skills for the Green Transition: Unlocking Talent for a Sustainable Future, Getting Skills Right. Paris.

Peters, D. J. (2014), Understanding Green Occupations from a Task-Based Approach. In: Applied Economic Perspectives and Policy 36 (2), p. 238–264.

Saussay, A.; Sato, M.; Vona, F.; O'Kane, F. (2022), Who's fit for the low-carbon transition? Emerging skills and wage gaps in job ad data. FEEM Working Paper No. 31.

Tyros, S.; Andrews, D.; d. Serres, A. (2023), Doing green things: skills, reallocation, and the green transition. OECD Economics Department Working Papers No. 1763.

Vona, F. (2019), Job Losses and the Political Acceptability of Climate Policies: why the "job-killing" argument is so persistent and how to overturn it. Climate Policy 19 (4): 524–532.

Vona, F. (2021), Labour Markets and the Green Transition: A Practitioner's Guide to the Task-based Approach. JRC 126681. Publications Office of the European Union, Luxembourg.

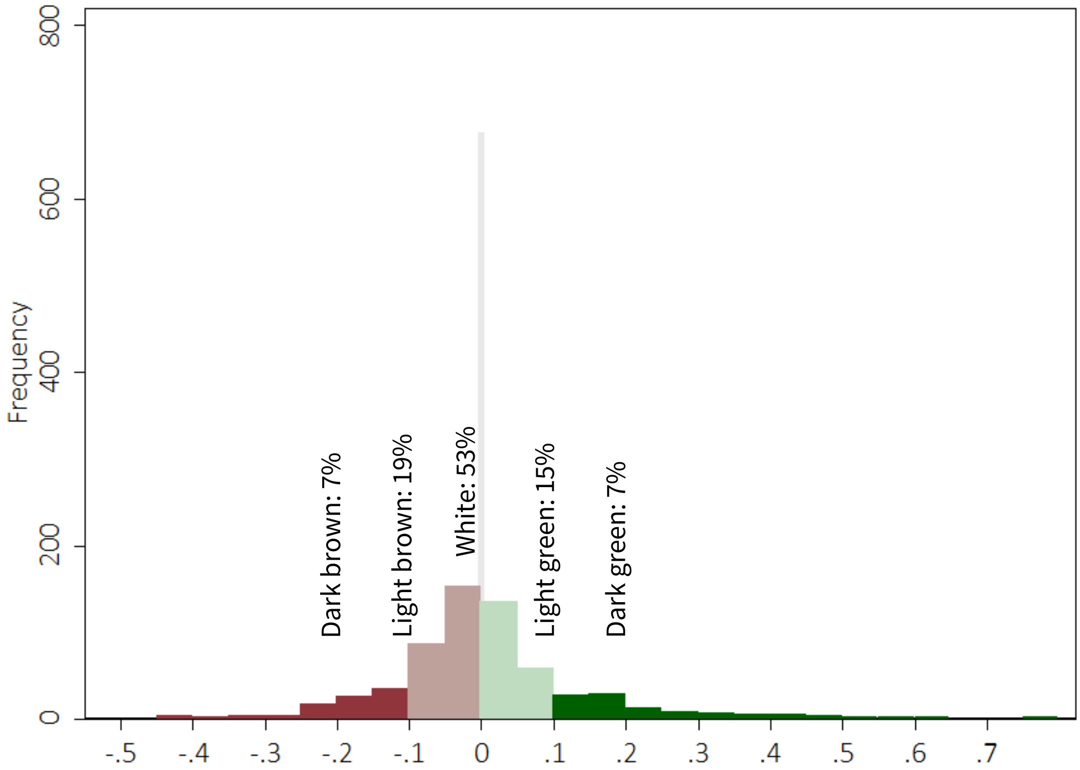
Vona, F.; Consoli, D. (2015), Innovation and Skill Dynamics: A Life-cycle Approach. In: Industrial and Corporate Change 24 (6), p. 1393–1415.

Vona, F.; Marin, G.; Consoli, D. (2019), Measures, drivers and effects of green employment: evidence from US local labor markets, 2006–2014. In: Journal of Economic Geography 19 (5), p. 1021–1048.

Vona, F.; Marin, G.; Consoli, D.; Popp, D. (2018), Environmental Regulation and Green Skills: An Empirical Exploration. In: Journal of the Association of Environmental and Resource Economists 5 (4), p. 713–753.

Appendix A: The Greenness-of-Jobs Index (GOJI)

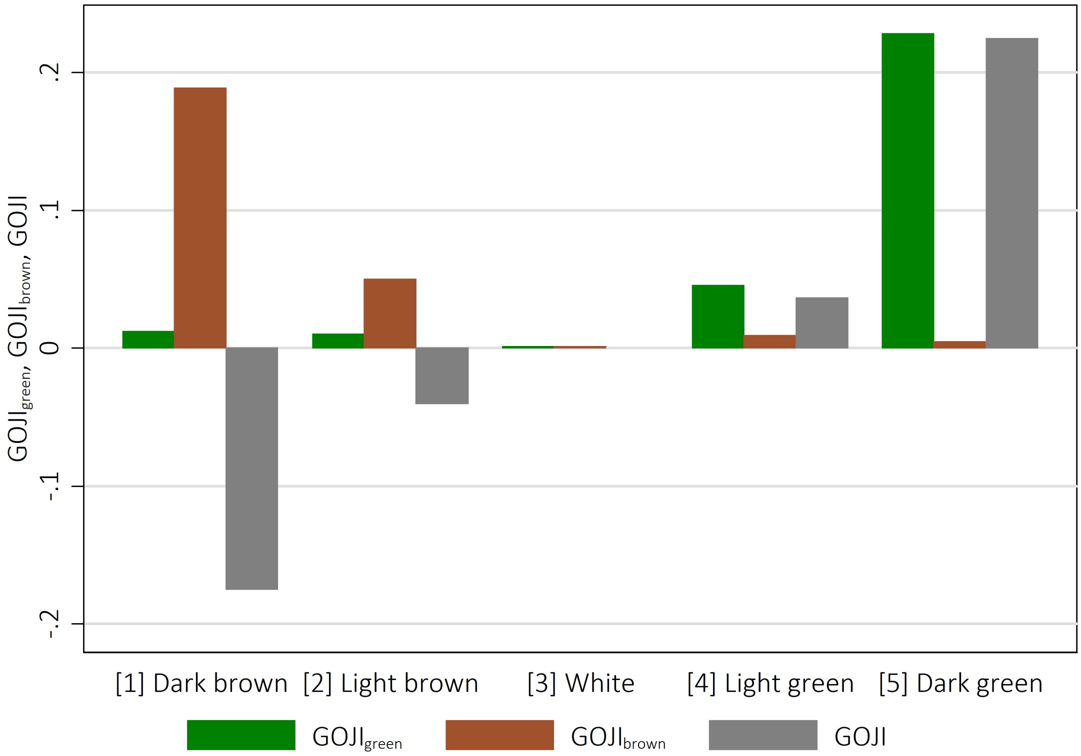
Figure 10: Distribution of the GOJI at the occupational level, 2012



Source: BERUFENET, own calculations. The histogram shows the absolute frequency (y-axis) and relative distribution of 1,277 5-digit occupations in the 5 GOJI groups (see Chapter 3.2 for the classification).

One potential concern in taking a net value of the GOJI index, i.e. subtracting $GOJI_{green}$ from $GOJI_{brown}$ as in Equation (3), is that this subtraction may mask strong differences in the levels of $GOJI_{green}$ from $GOJI_{brown}$ between occupations. We therefore plot these two components (green and brown bar), along with the net GOJI (gray bar) in Figure 11 for each of the five GOJI groups. It becomes apparent that within each GOJI group, the net GOJI is mostly driven by either green or brown tasks: The dark and light brown occupations contain only few green tasks, and the dark and light green occupations contain only few brown tasks. Overall, our classification into five groups is therefore strongly driven by environment-harmful tasks for the dark brown and the light brown group, and by environment-friendly tasks for the light green and the dark green group.

Figure 11: GOJI components by GOJI group (2012)



Notes: The columns show the unweighted mean absolute values of $GOJI_{pos}$ and $GOJI_{neg}$ (see Equations (1) and (2)) and the net GOJI (see Equation (3)) across all 5-digit occupations in each GOJI group.

Source: BERUFENET 2012, own calculations.

Table 7: Example occupations by GOJI group (2012)

GOJI group	Number	and title of occupation (KldB 2010, 5-digit level)	GOJI	Employees
Dark green	52132	Bus, streetcar drivers – skilled tasks	0.257	100,055
	11712	Forestry – skilled tasks	0.240	9,776
	26242	Renewable energy technology – skilled tasks	0.188	2,093
	71384	Business org.,strategy – highly complex tasks	0.143	1,491
	34212	Plumbing, heating, air-conditioning – skilled tasks	0.118	138,731
Light green	51113	Technical railroad operation – complex tasks	0.050	1,980
	34102	Building services engineering – skilled tasks	0.044	186,013
	34213	Plumbing, Heating, Air Conditioning – complex tasks	0.025	4,884
	25183	Mechanical Engineering, Operat. Tec – complex tasks	0.014	3,534
	41284	Biology – highly complex tasks	0.007	2,484
White	83314	Theology – highly complex tasks	0.000	11,452
	62102	Sales – skilled tasks	0.000	693,967
	81102	Medical assistant – skilled tasks	0.000	288,098
	73202	Public administration – skilled tasks	0.000	312,254
	63301	Catering service – unskilled/semiskilled tasks	0.000	67,706
Light brown	21113	Mining and surface mining – complex tasks	-0.041	1,710
	23113	Paper manufacturing – complex tasks	-0.043	269
	11101	Agriculture – unskilled/semiskilled tasks	-0.050	60,416
	25213	Automotive Technology – complex tasks	-0.055	7,873
	24112	Metallurgy – skilled tasks	-0.087	13,908
Dark brown	25222	Agricultural, constr. machinery technology – skilled tasks	-0.101	27,357
	32113	Concrete and reinforced concrete construct. – complex tasks	-0.129	971
	52112	Professional driver (pers./car) – skilled tasks	-0.161	62,361
	29232	Meat processing – skilled tasks	-0.180	53,413
	52314	Pilots, commercial airline pilots – highly complex tasks	-0.414	2,881

Notes: The 5-digit occupations of the KldB 2010 indicate different skill specifications of occupations in the first 4 digits. The 5th digit of the KldB 2010 distinguishes between four complexity levels of the tasks typically performed in an occupation: (1) unskilled/semiskilled tasks, (2) skilled tasks, (3) complex tasks, and (4) highly complex tasks.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012, own calculations.

Table 8: The top 20 occupations with the largest within-component

Number	and title of occupation (KldB 2010, 5-digit level)	Within-component	Employees 2012	Delta GOJI (2022 vs. 2012)	GOJI 2012
51222	Occupations in the inspection and maintenance of railway infrastructure – skilled tasks	0.331	7,025	0.000090	-0.019
34302	Occupations in building services and waste disposal (without specialisation) – skilled tasks	0.188	9,784	0.000071	0.000
51321	Occupations in postal and other delivery services – unskilled/semiskilled tasks	0.124	66,002	0.000317	0.028
52202	Drivers of train engines and other railway vehicles – skilled tasks	0.098	24,637	0.000093	0.154
52182	Drivers of vehicles in road traffic (with specialisation, not elsewhere classified) – skilled tasks	0.080	85,065	0.000263	-0.076
32102	Occupations in building construction (without specialisation) – skilled tasks	0.072	45,991	0.000128	-0.231
32142	Occupations in roofing – skilled tasks	0.058	46,851	0.000105	0.105
25212	Technical occupations in the automotive industries – skilled tasks	0.052	242,051	0.000484	-0.118
31104	Occupations in construction scheduling and supervision (without specialisation) – highly complex tasks	0.050	41,727	0.000081	-0.163
26304	Occupations in electrical engineering (without specialisation) – highly complex tasks	0.044	42,557	0.000072	0.031
12142	Occupations in horticulture, landscape gardening, and sports field maintenance – skilled tasks	0.043	41,737	0.000070	0.181
73203	Occupations in public administration (without specialisation) – complex tasks	0.042	58,950	0.000097	0.000
25104	Occupations in machine-building and -operating (without specialisation) – highly complex tasks	0.041	42,260	0.000067	-0.009
25132	Technical service staff in maintenance and repair – skilled tasks	0.039	138,395	0.000209	-0.011
52132	Bus and tram drivers – skilled tasks	0.036	100,055	0.000140	0.257
73202	Occupations in public administration (without specialisation) – skilled tasks	0.030	312,254	0.000359	0.000
25112	Machine and equipment assemblers – skilled tasks	0.029	159,284	0.000180	-0.059
62412	Sales occupations (retail) selling drugstore products and pharmaceuticals – skilled tasks	0.017	82,857	0.000055	0.010
33212	Painters and varnishers – skilled tasks	0.015	104,326	0.000063	0.027
34102	Occupations in building services engineering (without specialisation) – skilled tasks	0.011	186,013	0.000077	0.044

Notes: Occupations are categorised into GOJI groups according to their 2012 GOJI value. This is visualized by the colours in column 1. The 5-digit occupations of the KldB 2010 indicate different skill specifications of occupations in the first 4 digits. The 5th digit of the KldB 2010 contains information on job requirement categories that are sorted by increasing complexity. It distinguishes (1) unskilled tasks, (2) skilled tasks, (3) complex tasks, and (4) highly complex tasks. The entries are sorted in descending order of the within-component (column 3).

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

Table 9: The top 20 occupations with the largest between-component

Number	and title of occupation (KldB 2010, 5-digit level)	Between-component	Employees 2012	Delta EmplShare	GOJI 2012
22102	Occupations in plastic- and rubber-making (without specialisation) – skilled tasks	0.000231	104,103	-0.000926	-0.249
52122	Professional drivers (cargo trucks) – skilled tasks	0.000192	518,274	-0.002730	-0.070
24412	Occupations in metal constructing – skilled tasks	0.000174	214,570	-0.002790	-0.062
25212	Technical occupations in the automotive industries – skilled tasks	0.000124	242,051	-0.001053	-0.118
54101	Occupations in cleaning services (without specialisation) – unskilled/semiskilled tasks	0.000073	514,109	0.001469	0.050
51422	Service occupations in air traffic – skilled tasks	0.000064	35,560	-0.000390	-0.165
21112	Occupations in underground and surface mining – skilled tasks	0.000063	23,677	-0.000644	-0.098
51322	Occupations in postal and other delivery services – skilled tasks	0.000050	91,693	0.000871	0.058
52132	Bus and tram drivers – skilled tasks	0.000049	100,055	0.000192	0.257
51122	Technical occupations in aircraft operation – skilled tasks	0.000049	9,174	-0.000118	-0.417
52112	Professional drivers (passengers transport) – skilled tasks	0.000047	62,361	-0.000293	-0.161
62212	Sales occupations (retail trade) selling clothing, sporting goods, leather goods and shoes – skilled tasks	0.000042	123,838	-0.001270	-0.033
32122	Occupations in the bricklayer's trade – skilled tasks	0.000039	89,350	-0.000905	-0.043
42314	Occupations in environmental protection administration and environmental protection consulting – highly complex tasks	0.000038	3,260	0.000067	0.564
34301	Occupations in building services and waste disposal (without specialisation) – unskilled/semiskilled tasks	0.000034	36,626	0.000095	0.364
12101	Occupations in gardening (without specialisation) – unskilled/semiskilled tasks	0.000033	61,461	0.000581	0.058
52202	Drivers of train engines and other railway vehicles – skilled tasks	0.000033	24,637	0.000218	0.154
25101	Occupations in machine-building and -operating (without specialisation) – unskilled/semiskilled tasks	0.000033	134,396	-0.000659	-0.050
34102	Occupations in building services engineering (without specialisation) – skilled tasks	0.000032	186,013	0.000718	0.044
24522	Occupations in tool making – skilled tasks	0.000030	76,562	-0.000882	-0.034

Notes: Occupations are categorised into GOJI groups according to their 2012 GOJI value. The 5-digit occupations of the KldB 2010 indicate different skill specifications of occupations in the first 4 digits. The 5th digit of the KldB 2010 contains information on job requirement categories that are sorted by increasing complexity. It distinguishes (1) unskilled tasks, (2) skilled tasks, (3) complex tasks, and (4) highly complex tasks. The entries are sorted in descending order of the between-component (column (3)).

Sources:IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

Appendix B: Further results

B.1 Oaxaca-Blinder decomposition

In this section, we provide details on the Blinder-Oaxaca decomposition of the change in the greenness of employment over time discussed in Section 4.1. We decompose the difference in the greenness of occupations between 2012 and 2022 into an “explained” part, the endowments effect, and an “unexplained” part, the coefficients effects, complemented by an “interaction effect”. Formally, this is

$$\begin{aligned} \Delta GOJI^{occ} &\coloneqq \underbrace{X \cdot \Delta\beta}_{\text{coefficients effect}} + \underbrace{\Delta\bar{X} \cdot B}_{\substack{\text{endowments}\\ \text{effect}}} + \underbrace{\Delta X \cdot \Delta\beta}_{\substack{\text{interaction}\\ \text{effect}}} + \epsilon^{occ} \\ &= X_{2012} * (\beta_{2022} - \beta_{2012}) + (X_{2022} - X_{2012}) * \beta_{2012} + \\ &(X_{2022} - X_{2012}) * (\beta_{2022} - \beta_{2012}) \end{aligned} \tag{9}$$

As the dependent variable, the greenness of occupations, is measured at the occupation level, the explanatory variables are also measured at the occupation level. To construct the explanatory variables, we therefore compute shares by occupation, e.g. the share of a specific age group in an occupation.

Table 10: Blinder-Oaxaca decomposition

	(1) Net GOJI Coeff.	SE	(2) $GOJI_{green}$ Coeff.	SE	(3) $GOJI_{brown}$ Coeff.	SE
Overall						
Group 1	-0.0002	(0.0017)	0.0154***	(0.0012)	0.0156***	(0.0012)
Group 2	-0.0028*	(0.0017)	0.0139***	(0.0012)	0.0167***	(0.0013)
Difference	0.0026	(0.0024)	0.0015	(0.0017)	-0.0011	(0.0018)
Endowments	-0.0171***	(0.0048)	-0.0038	(0.0029)	0.0133***	(0.0036)
Coefficients	0.0103***	(0.0038)	0.0013	(0.0024)	-0.0090***	(0.0026)
Interaction	0.0094*	(0.0056)	0.0040	(0.0034)	-0.0054	(0.0040)
Endowments						
Age group shares	-0.0015	(0.0030)	0.0001	(0.0018)	0.0016	(0.0022)
Education group shares	0.0022	(0.0030)	0.0002	(0.0017)	-0.0020	(0.0021)
Female share	-0.0000	(0.0003)	-0.0000	(0.0004)	-0.0000	(0.0001)
Foreign share	-0.0217***	(0.0052)	-0.0065**	(0.0030)	0.0151***	(0.0037)
Full-time share	0.0032***	(0.0011)	0.0017***	(0.0006)	-0.0014**	(0.0007)
Substitution potentials	-0.0002	(0.0002)	0.0000	(0.0002)	0.0003	(0.0003)
Regional characteristics	0.0005	(0.0011)	-0.0004	(0.0006)	-0.0008	(0.0010)
Establishment size	0.0002	(0.0002)	0.0003	(0.0003)	0.0001	(0.0002)
Sectors	0.0003	(0.0013)	0.0008	(0.0012)	0.0005	(0.0008)
Coefficients						
Age group shares	0.0037	(0.0301)	0.0085	(0.0187)	0.0047	(0.0214)
Education group shares	-0.0043	(0.0073)	-0.0078*	(0.0045)	-0.0035	(0.0052)
Female share	-0.0133*	(0.0075)	-0.0108**	(0.0047)	0.0024	(0.0053)
Foreign share	0.0120*	(0.0066)	0.0079**	(0.0040)	-0.0041	(0.0047)
Full-time share	-0.0148	(0.0200)	-0.0209*	(0.0124)	-0.0061	(0.0142)
Substitution potentials	-0.0011	(0.0026)	-0.0007	(0.0016)	0.0004	(0.0018)
Regional characteristics	0.0236	(0.1352)	0.0747	(0.0839)	0.0510	(0.0960)
Establishment size	-0.0041	(0.0134)	-0.0106	(0.0083)	-0.0065	(0.0095)
Sectors	0.0036	(0.0131)	-0.0091	(0.0082)	-0.0127	(0.0093)
Constant	0.0052	(0.1464)	-0.0298	(0.0910)	-0.0347	(0.1039)
Interaction						
Age group shares	-0.0005	(0.0037)	0.0002	(0.0023)	0.0007	(0.0026)
Education group shares	-0.0023	(0.0039)	-0.0045*	(0.0024)	-0.0021	(0.0028)
Female share	-0.0000	(0.0004)	-0.0000	(0.0003)	0.0000	(0.0001)
Foreign share	0.0109*	(0.0061)	0.0072**	(0.0037)	-0.0037	(0.0043)
Full-time share	0.0009	(0.0012)	0.0013	(0.0008)	0.0004	(0.0009)
Substitution potentials	0.0002	(0.0003)	0.0000	(0.0002)	-0.0002	(0.0002)
Regional characteristics	-0.0008	(0.0013)	-0.0002	(0.0008)	0.0006	(0.0010)
Establishment size	0.0001	(0.0002)	-0.0002	(0.0002)	-0.0003	(0.0002)
Sectors	0.0009	(0.0009)	0.0001	(0.0005)	-0.0008	(0.0006)
N	2,554		2,554		2,554	

Notes: Results from a Oaxaca-Blinder decomposition as explained in Chapter 4.1 and Equation (9). “Group 1” is the greenness of occupations in 2022, “Group 2” is the greenness of occupations in 2012. “Endowments” indicates the importance of composition effects for the greening of occupations over time, “Coefficients” the importance of the importance of specific occupational characteristics for the greening of occupations over time, holding the composition of characteristics constant. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, own calculations.

B.2 Individual-level analyses

Table 11: Worker-level employment probabilities by GOJI group for age group 16–50

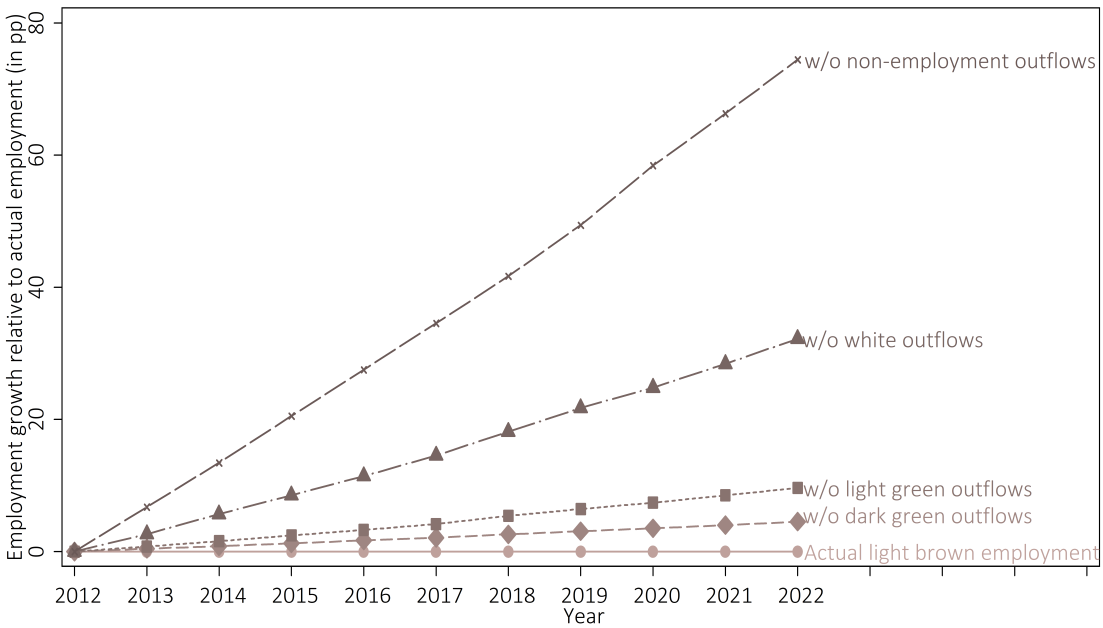
	t+1	t+3	t+5	t+7	t+9
[1] Dark brown	−0.010***	−0.013***	−0.016***	−0.019***	−0.024***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[2] Light brown	0.004***	0.003*	0.003*	0.005**	0.004**
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[3] White			Reference category		
[4] Light green	−0.001	−0.004**	−0.006***	−0.003*	−0.004*
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[5] Dark green	0.005***	0.008***	0.009***	0.005**	0.007***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Mean of reference group	0.921	0.882	0.867	0.885	0.838
Observations	274,203	274,203	274,203	274,203	274,203

Notes: Marginal effects from a logit regression with dependent variable being employed in 1 through 9 years after year t=2012 and base year (2012) GOJI group indicators as independent variables. Controls include dummies for females, foreign citizenship, 3 formal education levels, full-time employment, linear and squared terms of age and tenure, the substitution potential (3 categories), log establishment size and its square, as well as regional controls (federal states and region types) and a manufacturing dummy. Standard errors in parentheses. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), 10% sample, BERUFENET, 2012–2022, own calculations.

B.3 Counterfactual analyses

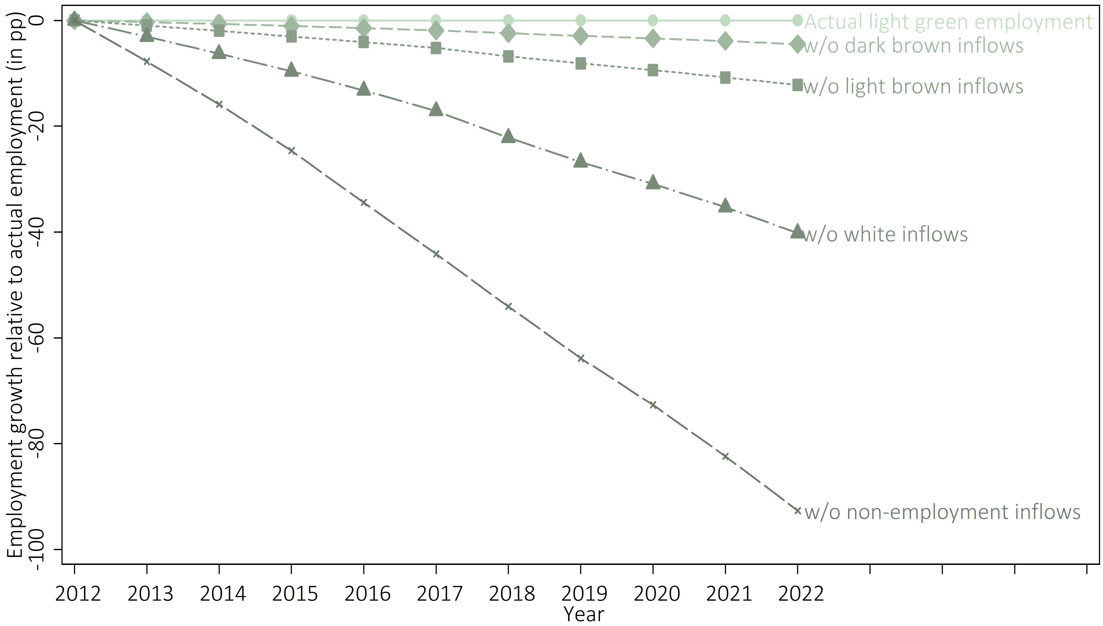
Figure 12: Growth of counterfactual employment stocks: Light brown occupations



Notes: Each counterfactual employment growth curve is computed setting one specific outflow to zero (see Equation (8) and description in the text). The depicted values denote the difference between counterfactual employment growth and actual employment growth (normalised to zero) in percentage points (pp).

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations.

Figure 13: Growth of counterfactual employment stocks: Light green occupations



Notes: Each counterfactual employment growth curve is computed setting one specific outflow to zero (see Equation (8) and description in the text). The depicted values denote the difference between counterfactual employment growth and actual employment growth (normalised to zero) in percentage points (pp).

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), BERUFENET, 2012–2022, own calculations

B.4 Multinomial logit regression result

Table 12: Multinomial logit model for transitions from dark brown occupations

	[1] Dark brown	[2] Light brown	[3] White	[4] Light green	[5] Dark green	[6] Not employed	[7] Apprentices	[8] Marginal	[9] Other
Worker characteristics									
Female	-0.00186***	-0.00889***	0.01544***	-0.00145***	-0.01588***	0.00738***	0.00177***	0.00329***	0.00019
Foreign	0.00358***	0.00656***	0.01130***	0.00400***	-0.07448***	0.05603***	-0.00930***	0.00291***	-0.00060***
Full-time	-0.00071**	0.00180**	0.00010	-0.00259***	0.03771***	-0.02930***	0.00540***	-0.01116***	-0.00124***
Age groups (reference: 30-49)									
18-29	0.00600***	0.01228***	0.01793***	0.00713***	-0.17238***	0.03971***	0.07182***	0.01019***	0.00732***
50-65	-0.00322***	-0.00869***	-0.01348***	-0.00459***	0.04219***	-0.00974***	-0.00099***	-0.00137***	-0.00013**
Education levels (reference: medium)									
Low	0.00037	-0.00659***	0.00072	-0.00107***	-0.04085***	0.03570***	0.00641***	0.00415***	0.00116***
High	-0.00227***	-0.00816***	0.01510***	0.00302***	-0.01411***	0.01131***	-0.01139***	0.00115***	0.00534***
Establishment characteristics									
Sector: Services (reference: Manufacturing/Construction)	0.00124***	0.00142***	0.01073***	0.00448***	-0.04287***	0.02334***	-0.00367***	0.00451***	0.00082***
Size (reference: 50-499 employees)									
1-49	0.00207***	0.00252***	-0.00356***	0.00329***	-0.02121***	0.01028***	0.00260***	0.00347***	0.00055***
>500	-0.00158***	0.00024	-0.00617***	-0.00050*	0.03148***	-0.01877***	-0.00130***	-0.00316***	-0.00023**
Substitution potential (reference: Medium)									
Low	0.00277***	-0.00270***	0.00066*	-0.00555***	0.00133	0.00391***	-0.00232***	0.00200***	-0.00011
High	0.00663***	0.01602***	0.02951***	-0.00061	-0.04612***	-0.00015	-0.00592***	0.00082***	-0.00017
Region (reference: West)									
North	-0.00023	0.00167***	0.00034	0.00201***	-0.00532***	0.00124	0.00110***	-0.00064**	-0.00018
South	-0.00071***	0.00288***	0.00046	-0.00071**	0.00465***	-0.00569***	0.00052	-0.00141***	-0.00001
East	0.00042	0.00408***	0.00224***	0.00129***	-0.01162***	0.00787***	-0.00214***	-0.00280***	0.00066***
Region types (reference: Urbanized districts)									
Core cities	-0.00049**	0.00020	0.00149***	0.00158***	-0.00466***	0.00194***	0.00003	-0.00065***	0.00055***
Rural districts with features of concentration	0.00124***	-0.00011	0.00091*	-0.00001	-0.00024	-0.00057	-0.00093**	-0.00029	-0.00002
Rural districts-sparsely populated	0.00169***	0.00147***	-0.00021	0.00054	-0.00395***	0.00153*	-0.00067	-0.00027	-0.00014
Year dummies (reference: 2013)									
2014	0.00048	-0.00174***	-0.00096	0.00009	0.00061	0.00115	-0.00005	0.00016	0.00026
2015	0.00048	-0.00084	0.00014	-0.00038	-0.00351**	0.00207*	0.00075	0.00124***	0.00005
2016	0.00067*	-0.00018	0.00002	0.00013	-0.00084	0.00025	-0.00016	-0.00025	0.00035*
2017	0.00159***	-0.00035	0.00181***	0.00046	-0.00376**	-0.00121	0.00129**	-0.00027	0.00044**
2018	0.00227***	0.00349***	0.00665***	0.00305***	-0.01585***	0.00081	0.00050	-0.00119***	0.00026
2019	0.00231***	0.00186***	0.00671***	0.00163***	-0.00841***	-0.00378***	0.00024	-0.00117***	0.00060***
2020	0.00062*	0.00006	0.00381***	0.00077*	0.00347**	-0.00754***	0.00000	-0.00172***	0.00053***
2021	0.00217***	0.00137**	0.00367***	0.00190***	-0.00766***	-0.00200*	0.00237***	-0.00239***	0.00056***
Observations	845,128	845,128	845,128	845,128	845,128	845,128	845,128	845,128	845,128

Notes: Marginal effects (row sum=1) from a multinomial logit model for inflows from dark brown occupations in year t–1 to regular employment in the indicated GOJI groups plus further labour market states in year t, where "Other" includes internships, student jobs, particular versions of part-time retirement, etc. Reference group: male, medium-aged German citizens with medium education, working part-time in Manufacturing/Construction in a medium-sized establishment with medium substitution potential in the West of Germany in an urbanized district in the year 2013. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), 10% sample, BERUFENET, 2012–2022, own calculations.

Table 13: Multinomial logit model for transitions from light brown occupations

	[1] Dark brown	[2] Light brown	[3] White	[4] Light green	[5] Dark green	[6] Not employed	[7] Apprentices	[8] Marginal	[9] Other
Worker characteristics									
Female	-0.00377***	-0.00823***	0.00584***	0.01773***	-0.00279***	-0.01561***	0.00255***	0.00487***	-0.00058***
Foreign	0.00297***	0.00348***	0.00957***	-0.07241***	-0.00028**	0.06379***	-0.00944***	0.00401***	-0.00168***
Full-time	0.00079***	0.00367***	0.00167***	0.04432***	0.00160***	-0.02811***	0.00542***	-0.02811***	-0.00123***
Age groups (reference: 30-49)									
18-29	0.00278***	0.00666***	0.02518***	-0.20724***	0.00211***	0.08311***	0.05394***	0.02162***	0.01185***
50-65	-0.00220***	-0.00511***	-0.01916***	0.06299***	-0.00149***	-0.02555***	-0.00055***	-0.00863***	-0.00030***
Education levels (reference: medium)									
Low	-0.00065***	-0.00472***	-0.00961***	-0.03413***	-0.00169***	0.04030***	0.00292***	0.00639***	0.00120***
High	-0.00209***	-0.00591***	0.01749***	-0.01864***	-0.00182***	0.01760***	-0.00827***	-0.00466***	0.00630***
Establishment characteristics									
Sector: Services (reference: Manufacturing/Construction)	-0.00090***	-0.00137***	0.00816***	-0.03482***	0.00054***	0.02145***	-0.00181***	0.00773***	0.00103***
Size (reference: 50-499 employees)									
1-49	0.00158***	0.00116***	0.00196***	-0.03154***	0.00103***	0.01864***	0.00128***	0.00566***	0.00024***
>500	-0.00081***	0.00000	-0.00141***	0.02529***	-0.00001	-0.01629***	-0.00078***	-0.00555***	-0.00045***
Substitution potential (reference: Medium)									
Low	0.00074***	-0.00238***	0.00059**	-0.01004***	-0.00069***	0.01080***	-0.00565***	0.00696***	-0.00031***
High	-0.00225***	-0.00435***	-0.00859***	0.04060***	-0.00162***	-0.01826***	0.00502***	-0.00954***	-0.00101***
Region (reference: West)									
North	-0.00004	0.00073***	0.00313***	-0.00657***	0.00028***	0.00376***	0.00000	-0.00108***	-0.00022**
South	-0.00014	-0.00018	0.00270***	0.00541***	-0.00031***	-0.00382***	-0.00052***	-0.00273***	-0.00043***
East	0.00077***	0.00166***	0.00197***	-0.01480***	0.00021**	0.01648***	-0.00146***	-0.00491***	0.00007
Region types (reference: Urbanized districts)									
Core cities	-0.00014	-0.00147***	0.00233***	-0.00110**	-0.00024***	0.00226***	0.00036**	-0.00244***	0.00045***
Rural districts with features of concentration	0.00077***	0.00094***	0.00010	-0.00206***	0.00008	-0.00011	-0.00002	0.00050*	-0.00020**
Rural districts-sparsely populated	0.00071***	0.00098***	-0.00107***	-0.00110	0.00010	0.00088	0.00005	-0.00018	-0.00037***
Year dummies (reference: 2013)									
2014	0.00014	0.00014	0.00144***	-0.00231**	-0.00007	0.00063	0.00012	-0.00003	-0.00006
2015	0.00038***	0.00081***	0.00122***	-0.00978***	0.00023*	0.00294***	0.00106***	0.00306***	0.00010
2016	0.00054***	0.00018	0.00295***	-0.01085***	0.00012	0.00682***	0.00043*	-0.00041	0.00022*
2017	0.00086***	0.00062***	0.00451***	-0.00825***	0.00006	0.00250***	0.00075***	-0.00155***	0.00050***
2018	0.00119***	0.00442***	0.01377***	-0.02010***	0.00071***	0.00118*	0.00089***	-0.00274***	0.00067***
2019	0.00114***	0.00243***	0.00944***	-0.00842***	0.00047***	-0.00273***	0.00051**	-0.00375***	0.00092***
2020	0.00076***	0.00171***	0.00562***	0.00749***	0.00023*	-0.01100***	0.00033	-0.00567***	0.00052***
2021	0.00100***	0.00283***	0.00759***	-0.00249***	0.00055***	-0.00556***	0.00291***	-0.00753***	0.00071***
Observations	3,025,129	3,025,129	3,025,129	3,025,129	3,025,129	3,025,129	3,025,129	3,025,129	3,025,129

Notes: Marginal effects (row sum=1) from a multinomial logit model for flows from light brown occupations in year t–1 to regular employment in the indicated GOJI groups plus further labour market states in year t, where “Other” includes internships, student jobs, particular versions of part-time retirement, etc. Reference group: male, medium-aged German citizens with medium education, working part-time in Manufacturing/Construction in a medium-sized establishment with medium substitution potential in the West of Germany in an urbanized district in the year 2013. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), 10% sample, BERUFENET, 2012–2022, own calculations.

Table 14: Multinomial logit model for transitions into light green occupations

	[1] Dark brown	[2] Light brown	[3] White	[4] Light green	[5] Dark green	[6] Not employed	[7] Apprentices	[8] Marginal	[9] Other
Worker characteristics									
Female	-0.00412***	-0.01190***	0.01018***	-0.00396***	-0.00336***	0.01267***	0.00043***	0.00094***	-0.00088***
Foreign	0.00312***	-0.05287***	0.00324***	0.00241***	0.00107***	0.04594***	-0.00196***	0.00038**	-0.00133***
Full-time	-0.00063***	0.03062***	-0.00532***	-0.00220***	0.00116***	-0.01395***	-0.00168***	-0.00592***	-0.00209***
Age groups (reference: 30-49)									
18-29	0.00474***	-0.09409***	0.02839***	0.00705***	0.00400***	0.03415***	0.00626***	0.00706***	0.00243***
50-65	-0.00298***	-0.07427***	-0.01826***	-0.00505***	-0.00246***	0.06636***	-0.00023***	0.01637***	0.02052***
Education levels (reference: medium)									
Low	0.00047***	-0.05302***	-0.00075**	0.00045***	-0.00086***	0.04229***	0.00527***	0.00349***	0.00266***
High	-0.00176***	-0.02030***	0.02088***	0.00320***	-0.00200***	0.00231***	-0.00015***	-0.00301***	0.00084***
Establishment characteristics									
Sector: Services (reference: Manufacturing/Construction)	0.00093***	-0.03248***	0.01645***	0.00268***	0.00108***	0.00923***	0.00041***	0.00200***	-0.00030***
Size (reference: 50-499 employees)									
1-49	0.00244***	-0.02954***	0.00397***	0.00396***	0.00087***	0.01483***	-0.00006	0.00408***	-0.00056***
>500	-0.00145***	0.02073***	-0.00515***	-0.00119***	-0.00010	-0.01588***	-0.00068***	-0.00231***	0.00604***
Substitution potential (reference: Medium)									
Low	0.00091***	0.00235***	-0.00485***	0.00019	-0.00011	0.00123***	-0.00037***	0.00131***	-0.00066***
High	0.00059***	-0.00538***	0.00206***	0.00207***	0.00093***	-0.00041	0.00003	0.00010	0.00001
Region (reference: West)									
North	0.00061***	-0.00155***	-0.00028	0.00138***	0.00053***	-0.00134***	-0.00003	-0.00030*	0.00098***
South	-0.00009	0.00125***	0.00344***	0.00025**	0.00033***	-0.00636***	0.00030***	-0.00033***	0.00121***
East	0.00176***	-0.01045***	0.00296***	0.00292***	0.00139***	0.00392***	-0.00028***	-0.00209***	-0.00011
Region types (reference: Urbanized districts)									
Core cities	0.00039***	-0.01239***	0.00577***	0.00113***	0.00026***	0.00449***	-0.00040***	-0.00000	0.00075***
Rural districts with features of concentration	0.00079***	0.00297***	-0.00192***	-0.00038**	0.00007	-0.00082**	-0.00018***	-0.00014	-0.00039***
Rural districts-sparsely populated	0.00106***	0.00158***	-0.00282***	-0.00022	-0.00007	0.00187***	-0.00026***	-0.00011	-0.00104***
Year dummies (reference: 2013)									
2014	0.00043**	-0.00287***	-0.00179***	0.00063***	0.00037***	0.00207***	0.00007	0.00108***	0.00001
2015	-0.00025	0.00187**	-0.00148***	0.00016	0.00042***	-0.00076	0.00009	-0.00027	0.00021
2016	0.00045***	0.00045	0.00038	0.00065***	0.00029**	-0.00172***	0.00004	-0.00077***	0.00022
2017	0.00097***	-0.00767***	0.00487***	0.00404***	0.00128***	-0.00327***	0.00019**	-0.00119***	0.00079***
2018	0.00094***	-0.00710***	0.00428***	0.00187***	0.00073***	-0.00038	0.00040***	-0.00115***	0.00041***
2019	0.00009	-0.00945***	-0.00056	0.00101***	0.00046***	0.00942***	0.00050***	-0.00208***	0.00061***
2020	0.00088***	-0.00824***	0.00536***	0.00277***	0.00096***	-0.00047	0.00028***	-0.00282***	0.00128***
2021	0.00112***	-0.01410***	0.00789***	0.00317***	0.00161***	0.00117**	0.00030***	-0.00256***	0.00139***
Observations	3,506,560	3,506,560	3,506,560	3,506,560	3,506,560	3,506,560	3,506,560	3,506,560	3,506,560

Notes: Marginal effects (row sum=1) from a multinomial logit model for flows into light green occupations in year t from regular employment in the indicated GOJI groups plus further labour market states in year t–1, where "Other" includes internships, student jobs, particular versions of part-time retirement, etc. Reference group: male, medium-aged German citizens with medium education, working part-time in Manufacturing/Construction in a medium-sized establishment with medium substitution potential in the West of Germany in an urbanized district in the year 2013. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1.

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), 10% sample, BERUFENET, 2012–2022, own calculations.

Table 15: Multinomial logit model for transitions into dark green occupations

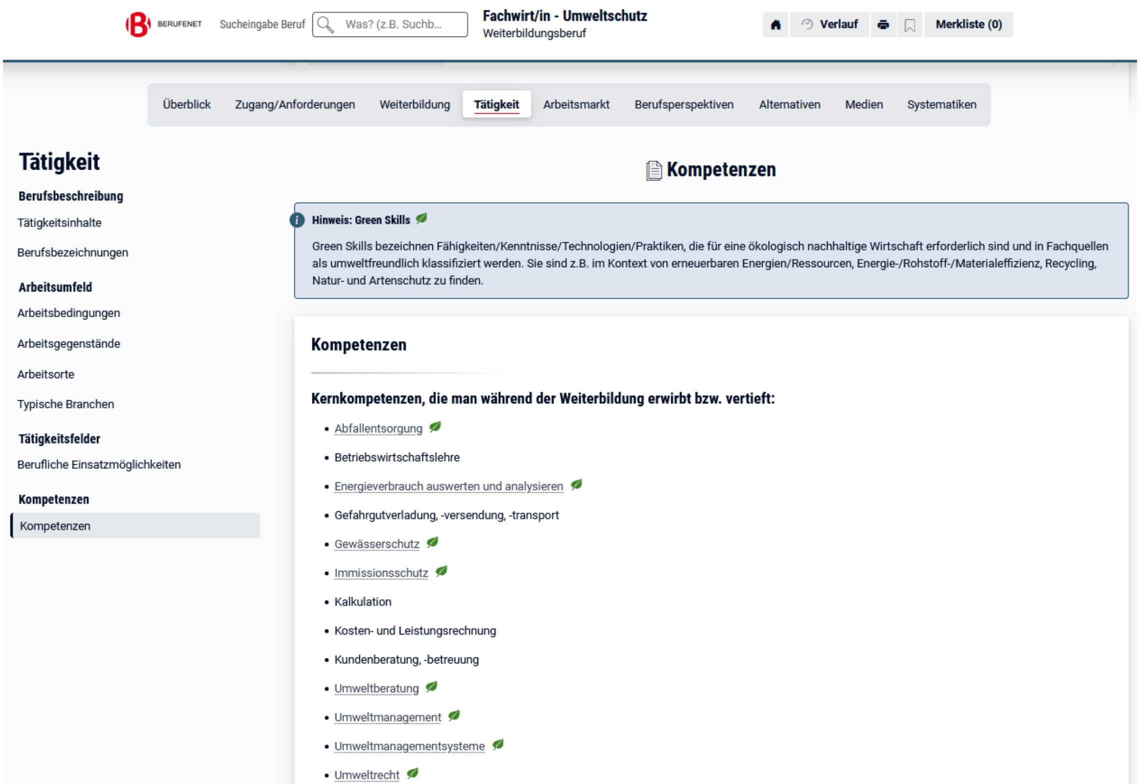
	[1] Dark brown	[2] Light brown	[3] White	[4] Light green	[5] Dark green	[6] Not employed	[7] Apprentices	[8] Marginal	[9] Other
Worker characteristics									
Female	-0.02237***	-0.00888***	0.01339***	0.00016	-0.00230***	0.01854***	0.00011	0.00172***	-0.00036**
Foreign	-0.07184***	0.00583***	0.01106***	0.00383***	-0.00024	0.05625***	-0.00411***	0.00096***	-0.00174***
Full-time	0.03968***	0.00130***	-0.00330***	-0.00169***	0.00054**	-0.02704***	-0.00066***	-0.00704***	-0.00179***
Age groups (reference: 30-49)									
18-29	-0.10267***	0.01438***	0.02368***	0.00629***	0.00459***	0.03626***	0.00963***	0.00572***	0.00211***
50-65	-0.06356***	-0.01052***	-0.01742***	-0.00632***	-0.00265***	0.06743***	-0.00030***	0.01547***	0.01786***
Education levels (reference: medium)									
Low	-0.04830***	-0.00717***	0.00220***	-0.00047*	-0.00150***	0.04618***	0.00606***	0.00170***	0.00131***
High	0.01714***	-0.01240***	0.01190***	0.00083**	-0.00212***	-0.01291***	-0.00037***	-0.00345***	0.00139***
Establishment characteristics									
Sector: Services (reference: Manufacturing/Construction)	-0.02189***	0.00638***	0.01294***	0.00141***	0.00158***	-0.00216***	-0.00015	0.00256***	-0.00065***
Size (reference: 50-499 employees)									
1-49	-0.03074***	0.00549***	-0.00073*	0.00492***	0.00119***	0.01507***	0.00028**	0.00510***	-0.00058***
>500	0.03723***	-0.00799***	-0.00684***	-0.00376***	-0.00098***	-0.01794***	-0.00149***	-0.00326***	0.00503***
Substitution potential (reference: Medium)									
Low	-0.03577***	0.00369***	-0.00204***	0.00470***	0.00381***	0.02160***	0.00192***	0.00345***	-0.00136***
High	-0.04002***	0.00501***	0.01754***	0.00212***	0.00414***	0.00805***	0.00300***	0.00238***	-0.00222***
Region (reference: West)									
North	-0.00705***	0.00021	0.00366***	0.00066**	0.00018	0.00103	0.00032**	-0.00009	0.00107***
South	0.00204**	0.00212***	0.00356***	0.00084***	-0.00005	-0.00966***	0.00044***	-0.00071***	0.00141***
East	-0.00883***	0.00227***	0.00424***	0.00173***	0.00039*	0.00387***	-0.00093***	-0.00285***	0.00011
Region types (reference: Urbanized districts)									
Core cities	-0.00900***	-0.00100***	0.00372***	0.00158***	-0.00016	0.00500***	-0.00092***	-0.00013	0.00090***
Rural districts with features of concentration	0.00436***	0.00125***	-0.00127***	-0.00058**	-0.00002	-0.00286***	-0.00035**	-0.00041	-0.00014
Rural districts-sparsely populated	0.00041	0.00178***	-0.00044	-0.00023	0.00012	-0.00008	-0.00013	-0.00030	-0.00111***
Year dummies (reference: 2013)									
2014	-0.00410***	0.00002	0.00127*	0.00016	0.00047*	0.00155	0.00020	0.00061	-0.00020
2015	0.00147	-0.00036	0.00103	0.00157***	0.00032	-0.00292**	0.00009	-0.00130***	0.00011
2016	-0.00225	0.00130**	0.00249***	0.00221***	0.00075***	-0.00300**	0.00016	-0.00180***	0.00015
2017	-0.01217***	0.00689***	0.00555***	0.00260***	0.00126***	-0.00263**	0.00014	-0.00207***	0.00043*
2018	-0.01146***	0.00449***	0.00486***	0.00233***	0.00121***	-0.00013	0.00051**	-0.00220***	0.00039*
2019	-0.01228***	-0.00031	-0.00017	0.00178***	0.00025	0.01211***	0.00054**	-0.00258***	0.00066***
2020	-0.01209***	0.00523***	0.00514***	0.00268***	0.00125***	-0.00043	0.00034	-0.00315***	0.00103***
2021	-0.02425***	0.00577***	0.01131***	0.00439***	0.00193***	0.00268**	0.00037*	-0.00363***	0.00143***
Observations	1,114,753	1,114,753	1,114,753	1,114,753	1,114,753	1,114,753	1,114,753	1,114,753	1,114,753

Notes: Marginal effects (row sum=1) from a multinomial logit model for flows into dark green occupations in year t to regular employment in the indicated GOJI groups plus further labour market states in year t–1, where "Other" includes internships, student jobs, particular versions of part-time retirement, etc. Reference group: male, medium-aged German citizens with medium education, working part-time in Manufacturing/Construction in a medium-sized establishment with medium substitution potential in the West of Germany in an urbanized district in the year 2013. Asterisks indicate p-values according to: *** p<0.01; **p<0.05; *p<0.1

Sources: IAB Employment History (Beschäftigtenhistorik—BeH), 10% sample, BERUFENET, 2012–2022, own calculations.

Appendix C: Further background information

Figure 14: Example occupation in BERUFENET database



Notes: Screenshot of BERUFENET description of the 5-digit occupation entitled “Environmental protection specialist” (Long title: Environmental protection management and environmental protection consulting) with a list of tasks typically performed in this occupation. Although the German term “Kompetenzen” refers to competencies, the listed keywords correspond to tasks as used in the task approach and related literature. Green tasks (waste disposal, energy consumption evaluation, water protection, immission control, environmental consulting, environmental management, environmental management systems, environmental law) are flagged with a leaf, other tasks (business administration, loading, shipping and transportation of dangerous goods, calculation, cost and performance accounting, customer advice/support) are not flagged.

Sources: BERUFENET, 2024, online available at: https://web.arbeitsagentur.de/berufenet/beruf/6059#taetigkeit_kompetenzen_kompetenzen.

Table 16: Top 40 green and brown tasks

Green tasks	Number	Brown tasks	Numbe r
Environmental technology	138	Plastics processing	125
Nature conservation	80	Vehicle maintenance, vehicle repair	60
Environmental law	75	Animal feed analyses, extraction	50
Animal welfare	68	Concrete technology	41
Energy-efficient building insulation	59	Concreting	41
Electrical drive technology	53	Iron weaving, reinforcement production	34
Water protection	44	Forging	33
Landscape conservation	43	Precast concrete construction	33
Waste disposal	42	Dairy farming and production	29
Immission control	40	Road construction	26
Insulation production	39	Commercial vehicle technology	25
Organic farming	39	Plastic welding	25
Environmental analysis	37	Firing (ceramics, enamel)	24
Irrigation systems	35	Engine technology	21
Photovoltaic systems	33	Machining and processing precious metals	21
Ecology	33	Glass melting	21
Composting	27	Textile printing	19
Recycling	26	Concrete construction	19
Solar thermal systems	24	Leather working, leather processing	19
Rail transport	23	Cattle breeding and husbandry	19
Sewage plants	22	Plastics technology	18
Tree care, pruning	20	Pig breeding and husbandry	18
Environmental counselling	20	Meat production	18
Regional and spatial planning	20	Plaster mould casting	17
Analysing water samples	19	Paint and varnish technology	17
Propagating and cultivating woody plants	19	Concrete mixing	17
Water treatment	18	Air navigation	16
Forest protection	17	Air freight forwarding	16
Energy-saving technology	17	Reinforced concrete construction	15
Noise protection	16	Caoutchouc, rubber processing	15
Environmental auditing	16	Poultry breeding, poultry farming	15
(Transport) timetable planning	15	Fish processing, fish product manufacturing	15
Energy management	15	Flight preparation	15
Transport planning	15	Meat processing, meat technology	15
Environmental management	15	Steel construction (planning, monitoring)	14
Electrochemistry	14	Polymer, plastics chemistry	13
Energy consulting	14	Production of precast concrete parts	13
Water law	14	Flight planning	13
Water management	12	Baths and swimming pool technology	13
Groundwater protection	11	Flight tourism	12

Notes: The numbers refer to how often a task appears in the task descriptions of all 5-digit occupations. Each list is sorted in descending order of this number

Sources: BERUFENET 2012, Janser 2024.

Imprint

IAB-Discussion Paper 12|2024

Date of publication

27. September 2024

Publisher

Institute for Employment Research
of the Federal Employment Agency
Regensburger Str. 104
90478 Nürnberg Germany

Download of this IAB-Discussion Paper

https://doku.iab.de/discussionpapers/2024/dp1224.pdf

All publications in the series "IAB-Discussion Paper" can be downloaded from

https://iab.de/en/publications/iab-publications/iab-discussion-paper-en/

Website

https://iab.de/en/

ISSN

2195-2663

DOI

10.48720/IAB.DP.2412

Corresponding authors

Markus Janser
Phone: +49 911 179-5816
Email: markus.janser@iab.de
Florian Lehmer
Phone: +49 911 179-5664
Email: florian.lehmer@iab.de