The greening of jobs in Germany

First evidence from a text mining based index and employment register data

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Abstract

The transition towards a greener, less carbon-intensive economy is supposed to lead to a greening of jobs, i.e. to an increasing share of environmentally friendly requirements within occupations (greening of occupations) and to a rising labor demand for employees in these occupations (greening of employment). This paper measures, describes and analyzes the greening of jobs and its associations with employment and wage growth. The cornerstone of this paper is the new task-based 'greenness-of-jobs index' (*goji*), which allows for the first time to measure the greening of jobs over time. The *goji* is derived by performing text mining algorithms on yearly data from 2011 to 2016 of BERUFENET, an occupa-tional data base provided by the German Federal Employment Agency. The descriptive results of the paper show that there is a notable greening of jobs which varies strongly between sectors and regions. The econometric analysis is based on employment register data from 2011 to 2016. The estimation results reveal that the overall level of greenness of occupations is positively correlated with employment growth. Furthermore, the increase of greenness is related to a slight increase in wage growth.

JEL-Classification: J23, J24, O33, Q55, R23

Keywords: Human capital; Occupational tasks; Structural change; Labor market outcomes; Green jobs; Text mining

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1 Introduction

Global environmental challenges such as climate change have led to manifold initiatives aimed at improving the ecological sustainability of economic activity. These initiatives take place at international (e.g. OECD 2011, UNEP 2011), supranational (e.g. EU 2015), national (e.g. BMBF 2016) and local level (e.g. Stappen/Schels 2002). Moreover, climate protection targets, environmental regulations and changes in consumer behavior have intensified the transitions towards a greener, less carbon-intensive economy. These structural changes of the economy are supposed to impact the labor market as well. Both organizations and employees have to adapt their practices and integrate new skills. Besides the formation of new occupations, the share of environmentally friendly requirements within occupations is supposed to increase ('greening of occupations'). The growing demand for green requirements may also lead to a rising labor demand for occupations containing these requirements ('greening of employment'). Together, these two trends form the 'greening of jobs', which is analyzed in this paper.

Most previous studies base their analysis on an output-oriented identification of green jobs (e.g. Antoni et al. 2015; Becker/Shadbegian 2009; Eurostat 2016; Hillebrand et al. 2006; Horbach/Janser 2016; Lehr et al. 2012; OECD/Cedefop 2014; Rennings/Zwick 2002; UN et al. 2017, 2014; US DOL/BLS 2013a/b; US DOC 2010). These approaches have the drawback that they do not cover the activities in terms of integrated environmental protection or application of clean techonologies (e.g. energy management within firms). Only a few studies have already started to apply a task-based approach to the greenness of occupations (as a static parameter at tasks-level) and its associations with employment (Peters 2014, Vona et al. 2015, Consoli et al. 2016). In terms of the geographical coverage, some studies have already measured the greenness of occupations and its associations with employment in countries such as the USA (Deschenes 2013, Peters 2014, Vona et al. 2015, Consoli et al. 2016) and Australia (Annandale et al. 2004), but no method has yet been established to measure the greenness of occupations and its relations with labor demand in Germany. Furthermore, little is known about the extent to which the greening of occupations (as a dynamic parameter) really takes place, how it is distributed and how the greening of occupations is associated with employment growth. To fill these research gaps, the paper has three research objectives: (1) to develop an indicator to measure the greening of occupations in Germany, (2) to describe the occupational, sectoral and regional distribution of the greening of jobs and (3) to examine the relationship between the greening of occupations and labor market outcomes such as employment and wages.

The underlying question of the first research objective is *'What indicator can best be used to analyze the greenness and greening of occupations – given the available data structure in Germany?'* To answer this question, the paper introduces the task-based 'greenness-of-jobs index' (*goji*). For each individual occupation, this index describes the share of the total number of all requirements that are relevant for protecting the environment ('green tasks'). For the first time, the *goji* facilitates a task-based measurement of the greenness and greening of jobs for the entire range of occupations in Germany. The *goji* is derived by performing text mining procedures on the German occupations database BERUFENET provided by the Federal Employment Agency. These data are available for the years 2006 and 2011 to 2016. I also use employment statistics data to develop employment-weighted occupational, sectoral and regional *goji* aggregates. To calculate the *goji*, I apply and extend approaches by Dengler et al. (2014) and Consoli et al. (2016). The development of the *goji* is the cornerstone of this paper, because it is necessary for any further analyses on the greening of jobs in this and possibly also in future research. For the first time, the *goji* facilitates a task-based estimation of the greenness and greening of jobs for the entire range of occupations in Germany. The central questions related to the second research objective are *'How green are occupations in Germany?'* and *'Is there a greening of jobs in Germany?'* To answer these questions, I analyze the distribution of the *goji* and present summary statistics of different aggregation levels of occupations, sectors and regions. In respect to the third objective, the *goji* is applied in an econometric analysis of employment and wage growth to answer the question *'Do occupations with larger greenness/greening show larger employment and wage growth?'* The results of this empirical example also help to clarify whether the new indicator *goji* has potential for further econometric analysis. To answer these questions, the paper examines the relationship between the *goji* and growth in employment and wages for the period from 2012 to 2016. The *goji* is applied both in terms of levels (*'greenness'*) and trends (*'greening'*). In order to examine the correlations with employment and wage growth, cross-sectional and panel data regressions are applied. For the econometric analysis, I also use a novel data source by linking the *goji* with a project-specific occupational panel based on individual administrative employment data of the Federal Employment Agency from 2011 to 2016.

According to the results of this paper, there is a greening of jobs which varies strongly between sectors and regions. The estimation results show that the total level of greenness of occupations is positively correlated with employment growth. Furthermore, the change of greenness is related to a slight increase in wage growth. The results also reveal pronounced differences between the requirements types of core and additional requirements. The econometric application demonstrates the potential of the new index for further empirical analyses.

This paper is valuable both for the scientific community and for policy purposes: the *goji* facilitates scientific studies of the greening of jobs in Germany in detail. From a methodological point of view, the application of text mining methods in order to exploit occupational data might be useful for related research questions (e.g. Genz et al. 2018). The descriptive and analytical results may help to disentangle some relationships between the greenness/greening of jobs and labor market outcomes, which may also be useful for future policy evaluations. Vona et al. (2015: 2) emphasize this potential for policy advice: *"... understanding the extent to which greening the economy can induce significant changes in the demand for certain skills and, most cogently, which skills these might be, is crucial to inform policy."* The authors also stress that these insights – and thus also the results of the paper in hand – may help to design training policies that meet the changing demands of the labor market and thus enable the labor force to mitigate negative employment impacts that are conventionally associated with environmental regulation (e.g. Becker/Henderson 2000; Greenstone 2002).

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The paper is organized as follows: Section 2 contains an overview of related literature. The different data sources used in this paper and the sample description are presented in section 3. Section 4 introduces the greenness-of-jobs index (goji). Section 5 covers the econometric analysis of the associations between the greenness / greening of jobs and labor market outcomes. Section 6 concludes with a summary and reflections on practical or political implications.

2 Literature review and conceptional framework

2.1 Descriptive findings on the greenness and greening of jobs

The following overview of descriptive evidence in literature reflects the predominant use of output-oriented approaches to measure green jobs. Most of the relevant articles still work with a definition of green jobs as employment in the environmental goods and services sector. Therefore, I start with a review of the main papers within this field.

There are two main sources that have been used for previous analysis of green jobs in the German labor market: the IAB Establishment Panel survey conducted by the Institute for Employment Research and the statistical data of the Federal Statistical Office. Both deal with an output-oriented approach to green jobs ('employment in the environmental goods and services sector').

Three survey waves of the IAB Establishment Panel—1999, 2005 and 2012—include questions about environmental goods and services. There are several studies based on these data including relevant descriptive information for the present paper. Horbach/Janser (2016) show that environmental establishments have slightly higher employment growth (+0.6 percentage points from 2009 to 2012) than other establishments. Furthermore, they identify marked differences between sub-groups of the environmental establishments: the subgroup of 'environmental remediation, soil conservation' has the highest employment growth from 2009 to 2012 (+16.8 percent), while 'waste management, recycling' has the lowest value (+0.6 percent). 'Climate protection, renewable energies, energy saving' increased by 6.2 percent, outperforming the average for the entire environmental sector (+4.7 percent). This study of the period from 2009 to 2012 documents a far more positive situation in the environmental sector than Horbach et al. (2009), who examined employment trends from 1999 to 2005. They report a drastic decline in employment in environmental firms dominated by end-of-pipe technologies. However, firms that produce or trade in clean technologies usually have positive employment trends. Looking at the shares of employees with a university education, environmental establishments employ a larger share (13.4 percent) compared to the total sample of establishments (9.9 percent) (Horbach/Janser 2016). Corresponding to this result, the share of innovative establishments is also higher in the group of environmental establishments (53.4 percent) in comparison with the total sample (40.4 percent). The environmental sector seems also to be affected by labor shortages to a disproportionately large degree (Horbach 2014a).

The current way of estimating the gross employment effects of environmental protection in Germany is based on the method presented by Blazejczak/Edler (2015). The authors estimate environmental employment from the production of environmental goods using a demand-driven approach using input-output methods. They calculate environmental employment from the provision of services using a supply-driven approach based on multiple data sources. One of these data sources is also the IAB Establishment Panel mentioned above. According to this method, 2.2 million people were working for environmental protection in Germany in 2012 (Edler/Blazejczak 2016).

Deschenes (2013), who works with US labor statistics data, finds that—so far—green jobs only account for a small share of total employment in the USA. Over the last ten years, this share has seen relatively weak growth. Elliott/Lindley (2017) describe the distribution of green jobs in the USA in 2010. Not surprisingly, the distribution of green jobs varies widely between the states: measured as a share of total employment North Carolina has the largest share of green jobs, at 5.1 percent, whereas Florida has the smallest share, at 1.6 percent. The spatial distribution of the quantitative development of green jobs is also very heterogeneous, showing both positive and negative values of change in the percentage of green employment (largest increase: Maryland with +0.538 and largest decrease in Minnesota with -0.184). These findings correspond to the studies of Weinstein et al. (2010), Weinstein/Partridge (2010) and Vona et al. (2017), who also describe large heterogeneity between and within US states.

Considering the sectoral distribution, the manufacturing industry has the largest absolute number of green jobs in the private economy of the USA (507,168 green jobs) and the financial activities sector is the smallest sector, with 475 green jobs (Elliot/Lindley 2017). According to Elliott/Lindley (2017), measured as a percentage of total employment, the utilities sector is the largest provider of green jobs (12 percent), whereas the financial activities sector remains the smallest provider of such jobs (0.002 percent). Using a more detailed (3-digit) industry level, their results reveal that there is also high heterogeneity within sector aggregates, e.g. in manufacturing. In this perspective, 'construction' is largest provider of green employment in absolute figures and 'transit/ground passenger transport' the largest percentage of green employment (55 percent). As an overall result of their descriptive analysis they conclude that those US states and sectors that were relatively green in 2010 became greener in 2011. Elliott/Lindley (2017) use data from the US American Green Goods and Services Survey (GGS), which was conducted from 2010 to 2012 before being discontinued due to public spending cuts in 2013[1]. The challenge of discontinuous green employment data also exists in Germany in the case of the IAB Establishment Panel survey, which is used in Horbach/Janser (2016).[2]

Meanwhile, many further studies have been conducted on single countries or groups of countries. Most of them are based on different output-definitions of green jobs, which makes it difficult to compare their results. Literature reviews about these studies are provided by GHK (2009) and Bowen/Kuralbayeva (2015). Horbach et al. (2015) present a comprehensive overview of relevant studies with a focus on employment in a circular economy.[3]

After summarizing the descriptive evidence from output-oriented green jobs approaches, I continue with the few articles available working with the task-based approach, usually presented on occupational level. Consoli et al. (2016) work with US-American O*NET data[4] and compare differences between green and non-green occupations in terms of skill contents and human capital. They find that occupations with green tasks require more high-level cognitive skills and interpersonal skills as well as higher levels of formal education, work experience and on-the-job training. Vona et al. (2017) also work with O*NET data and discover

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[1] For information about the survey, see also Sommers (2013). In 2013, the Bureau of Labor Statistics (BLS) had to cut its budget as a result of the national spending cuts due to the Balanced Budget and Emergency Deficit Control Act. The BLS decided to withdraw all "measuring green jobs" products, including data on employment by industry and occupation for businesses that produce green goods and services; data on the occupations and wages of jobs related to green technologies and practices; and green career information publications (Sources: www.bls.gov/ggs/ and www.bls.gov/bls/sequester_info.htm).

[2] The questions changed between 2005 and 2012. It is therefore not possible to directly compare the EGSS data of these two years. It is not yet clear whether the EGSS question will be included in the questionnaire again.

[3] The concept of the circular economy is part of the sustainability strategy of the European Union (EU 2015) and can be regarded as an essential element of the green economy. The Ellen MacArthur Foundation (2015, p. 5) defines a circular economy as an economy *'… that is restorative and regenerative by design and aims to keep products, components, and materials at their highest utility and value at all times, distinguishing between technical and biological cycles.'* (see also Ghisellini et al. 2016 and Lieder/Rashid 2016 for extensive literature reviews)

[4] see also Dierdorff et al. (2009) and National Center for O*NET Development (2010).

that the proportion of green employment is between two and three percent and that the green wage premium is about four percent. In terms of geographical characteristics, they report that green jobs are more spatially concentrated than comparable non-green jobs and that the greenest regions are mostly high-tech regions. Vona et al. (2015) illustrate that green skills (i.e. green tasks in the sense of this paper) are high-level analytical and technical know-how related to the design, production, management and monitoring of technology.

Peters (2014), who analyzes about one thousand O*NET occupations using text mining methods, counts 176 occupations with at least one green task. Among these 176 green occupations there are 70 occupations that involve green tasks to a considerable extent. The latter ‘green-intense’ occupations generally have good working conditions: they are mainly full-time jobs, paying above-average salaries and covered by health insurance. The author reports positive employment prospects for all green jobs, though the new employment growth is lagging behind other sectors. He also finds that green jobs are accessible to disadvantaged workers with limited training and experience. According to the author, most of the green occupations are male-dominated but ethnically diverse.

One contribution to the literature of my paper is to add first task-based evidence about the greening of jobs in Germany. Similar to the studies mentioned above, I examine the demographic, occupational, sectoral and regional distribution of the greening of jobs.

2.2 Theoretical framework and previous analytical findings

To prepare for the econometric part of the paper, this subsection provides the theoretical framework for the econometric model and presents analytical findings from previous literature. From a theoretical perspective, the labor market impacts of the trend towards a green(er) economy may be explained by the interplay between the drivers of a greening economy (e.g. environmental regulation, change towards sustainable consumption patterns), innovation processes (e.g. eco-innovations, technological and structural change, social transitions) and economic outcomes (e.g. economic competitiveness, labor demand and wages). In terms of the interplay between environmental regulation, innovation and economic competitiveness, Porter/Van der Linde (1995) point out that environmental regulations may promote innovation and thus improve competitiveness—as long as the regulations are designed well. Acemoglu et al. (2012, 2016) also stress the high importance of directed technical change. According to them, a combination of both environmental regulation (e.g. by carbon taxes) and temporary research subsidies may lead to climate protection and sustainable long-run growth.

This is in contrast to scientific papers that present a more static model of the economy where regulations inherently lead to a loss of competitiveness or which at least do not find these positive impacts (e.g. Jaffe/Palmer 1997). Another reason for possible low employment effects—at least for technology-related green jobs—is presented by Peters (2014). He notes that the numbers of jobs created on account of green energy should be rather small because energy technologies are generally capital-intensive. According to Deschenes (2013), it is difficult to draw a definitive conclusion on the employment potential of green policies. He calls for more careful and detailed empirical studies to learn more about the labor market impacts of green jobs. By means of the index and measurement approach presented in the following, the present paper contributes to this research strand.

Another important theoretical thread is the task-based approach and the literature on employment polarization and technological change (see Autor et al. 2003, Autor 2013, Autor/Dorn al 2013, Goos et al 2014, Autor 2015), i.e. the rising employment shares in the highest and lowest paid occupations due to the shift in labor demand towards non-routine tasks. Especially computerization seems to cause substitution of repetitive, routine tasks which are mainly performed by medium-skilled occupations, whereas non-routine cognitive tasks predominantly used in high-skill occupations are complemented by computerization (Acemoglu/Autor 2011, Autor et al. 2003; Autor, 2013; Autor/Dorn 2013). Consequently, occupations with a large share of routine task show a higher risk of being replaced by computer algorithms and/or robots (Acemoglu/Restrepo 2017, Blien/Ludewig 2017, Dauth et al. 2018 and Dengler/Matthes 2018). This important trend also may interact with the greening trends. Therefore the model of this paper also takes into account the task contents of occupations.

Now I turn to the last setion of the literature review, presenting previous relevant analytical findings about labor market impacts of green jobs. Pollack (2012) works with US data and reports that, in terms of employment, green sectors grew faster between 2000 and 2010 than the economy as a whole. For every percentage-point increase in a sector's green intensity (i.e. the share of employment in green jobs), annual employment growth was 0.034 percentage points stronger. Furthermore, green sectors had a larger proportion of workers without a college degree. For every percentage-point increase in green intensity in a particular industry, there was a corresponding 0.28 percentage-point increase in the proportion of jobs held by workers without a four-year college degree in that sector. The author also reports that manufacturing plays an important role in the green economy. Although it accounts for only 10.8 percent of total private employment, the manufacturing industry provides 20.4 percent of green jobs.

However, Elliot/Lindley (2017) relativize these findings and show that Pollack's results are largely driven by a limited sample of small industries. Elliot/ Lindley (2017) work with a larger sample and put green goods and services into a Cobb-Douglas production function. In their empirical analysis, they find that there is a negative correlation between productivity growth and green employment intensity. Furthermore, they show that industries that have increased their technology investment significantly over the past few years and that have generally grown relatively faster overall have at the same time grown more slowly in terms of the production of environmental protection goods and services. Their results largely support those obtained by Becker/Shadbegian (2009) who find no differences between environmental product manufacturers and other manufacturers in terms of wages, employment, production and exports. According to Becker/Shadbegian (2009), the only larger difference between these two groups of firms is that environmental product manufacturers employ fewer workers in production.

Elliott/Lindley (2017) and Weinstein et al. (2010) present evidence of a wide spread spatial distribution of green jobs in the USA in 2010. Analyzing the distribution of green jobs in Ohio, Weinstein/Partridge (2010) demonstrate that even within US states there is a strong heterogeneity. Vona et al. (2017) investigate employment effects of green jobs on US local labor markets and reveal that local subsidies under the American Recovery and Reinvestment Act (ARRA), the endowment of green knowledge and resilience to the great recession have the strongest impact on the creation of green jobs, whereas direct changes in environmental regulation are a secondary force. For Germany, no such in-depth spatial analyses of green jobs have been conducted yet. Closely connected to green jobs in general, Horbach (2014b) also documents a broad regional distribution of eco-innovations in Germany. Interestingly, he reveals higher probabilities of eco-innovations in regions with high poverty rates. This is in line with another finding in the same paper that eco-innovations are less dependent on urbanization advantages.

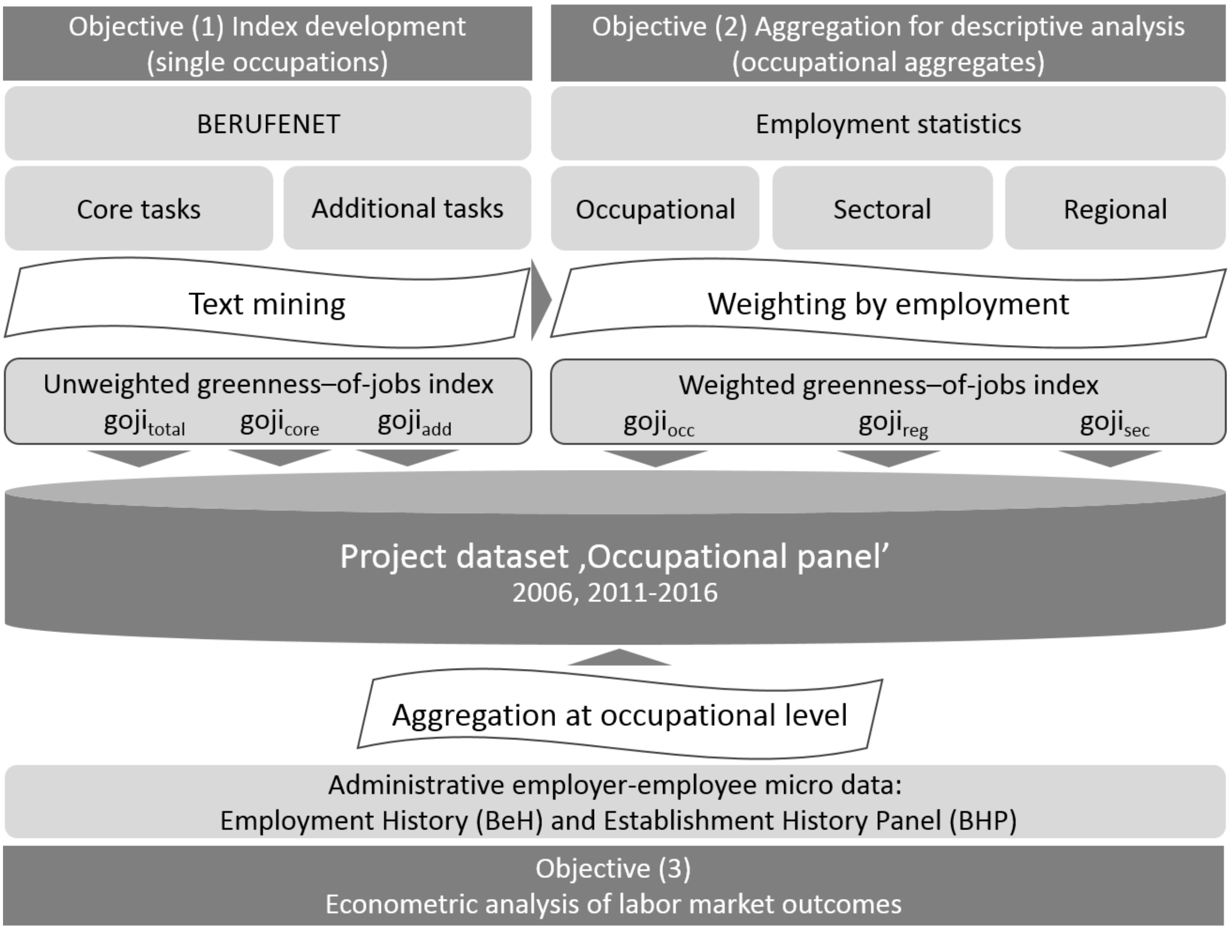
In general, eco-innovation seems to be closely linked with the creation of green jobs. For example, Cecere/Mazzanti (2017) investigate the relationship between green jobs and eco-innovations in European small and medium-sized enterprises and reveal that green innovation is highly relevant for the formation of green jobs. They report that the decision to hire for green jobs is especially driven by the interaction term between an eco-management system and product/service innovations. Observing the time period between 2001 and 2008, Gagliardi et al. (2016) also find that the emergence of eco-innovation has contributed considerably to long-run job creation. This positive influence of eco-innovation is shown both for product innovation (Horbach 2010) and process innovation (Horbach/Rennings 2013). Horbach (2010) finds that the positive effect of eco-product innovation is even greater compared to other non-eco-innovation fields. Licht and Peters (2014) confirm that both environmental and non-environmental product innovations are correlated to employment growth, but that non-eco product innovations are more likely to increase employment.

Based on cross sectional data analysis, the paper in hand contributes to the analytical literature by examining the interrelationships between the greenness of jobs and labor market outcomes in Germany. Using panel data analysis, it also contributes first insights how the growth of greenness, i.e. the greening of jobs, is associated with employment and wage growth.

3 Data

To address the objectives of this paper, I develop a new occupational index and link employment data sources into one comprehensive panel dataset at occupational level. First, I use BERUFENET data and text mining results to create the greenness-of-jobs index *goji*. Second, I weight the *goji* by occupational, sectoral and regional employment statistics data. The project dataset includes both weighted and unweighted versions. Third, the empirical analysis of the relation between greenness of jobs and employment growth, I add administrative employer-employee data. The occupational aggregates of these micro data are linked with the weighted greenness-of-jobs index and form the basis for the econometric analyses. Figure 1 provides an overview of the research objectives and the associated data sources. All of these data sources are described in the remainder of this section.

Figure 1: Research objectives and the associated project dataset



Source: Own illustration.

3.1 Occupational BERUFENET data for basic index development

BERUFENET is an online database provided by the Federal Employment Agency in Germany. It covers all items of the classification of occupations (Klassifikation der Berufe 2010—KldB2010, see also Paulus/Matthes 2013). The purpose of this database is two-fold: it is used by vocational counselors and job placement officers at local employment agencies for career guidance and job placement, but it also serves the general public as a free database for career orientation[5]. BERUFENET is continuously updated by an editorial team who receives

[5] https://berufenet.arbeitsagentur.de/, for a sample page of occupational requirements see Online-Appendix 1 (TM)

and implements change requests from the Federal Employment Agency resulting from the operational advisory processes. The updates are based on both official sources such as training regulations and requests for change from the counseling processes of the federal employment agencies. Both the application in public services and the central content management lead to a high degree of completeness and currency. BERUFENET has already been used for research projects, e.g. to derive occupational tasks (Dengler et al. 2014) as well as to develop an index for the degree of substitutability of occupations due to digitalization and automation (Dengler/Matthes 2015). The data extract of BERUFENET used for this project contains information about the requirements of occupations for the years 2006 and 2011 to 2016. Both occupations and requirements together form an n:n occupations-requirements matrix. The data only include occupations that are actively used in the job placement system of the Federal Employment Agency. Furthermore, occupations of civil servants and military services are not present in the data.

The requirements of BERUFENET are divided into three dimensions: core requirements, additional requirements and requirements groups (Dengler et al. 2014). Core requirements are compulsory parts of every vocational training, further training or course of study. If occupations do not have a formal syllabus these requirements contain competencies that are usually carried out in practice. In turn, additional requirements comprise those competencies that may be relevant for the pursuit of the occupation, but are non-compulsory elements of official curricula of occupations. For example, core requirements for roofers are ‘tile a roof’ and ‘roof drainage’, whereas additional requirements are ‘scaffolding’, ‘energy consulting’ and ‘photovoltaics’ (among others). The latter requirement of ‘photovoltaics’ illustrates the matrix format of the BERUFENET: in the case of a roofer it is an additional requirement, in the case of an engineer for renewable energies, it is listed as a core requirement. A third dimension is called ‘requirement groups’. Requirement groups collect knowledge areas or tools that might also be relevant for practicing the occupation (e.g. competence group ‘CAD software’, competence group ‘roof types’). Unlike core and additional requirements, requirement groups are applied very differently in BERUFENET. Hence, and in line with Dengler et al. 2014, these requirement groups are not used in the following.

BERUFENET contains comprehensive lists of occupational requirements for every single occupation, but it does not include actual job descriptions of job offers. Therefore, this study is based on the overall requirements of every occupation as a set of common requirements rather than an analysis of current job offers. As BERUFENET is continuously being edited and developed on the basis of feedback from employers, employees and public institutions (e.g. to include new regulations of vocational training courses), it is still a dynamic, but more stable source of occupational requirements. Based on the information about requirements, it is not always possible to identify the firms’ final products and services. The approach of this paper is therefore unable to identify jobs that have no environment-related requirements but are involved in the production of green goods and services (e.g. an office clerk who sells solar panels). As there are already several studies dealing with the issues of green employment in the green goods and services sector (e.g. Horbach et al. 2009, Becker/Shadbegian 2009, Deschenes 2013, Horbach/Janser 2016, Elliott/Lindley 2017), my contribution is to extend this knowledge with a focus on tasks and occupations.

The general approach of this paper for calculating the greenness of jobs is largely based on Consoli et al. (2016), who work with data from the US American occupational database O*NET[6]. The basic blocks of their research are green tasks, which are flagged in O*NET. These green tasks flags are a result of the 'Green Task Development Project (GTDP)' (National Center for O*NET Development 2010). In Germany, neither BERUFENET nor any other data source provides information similar to the green flag of O*NET.[7] Therefore, one of the steps in the groundwork for this paper is identifying 'green tasks' in Germany, to calculate the greening-of-jobs index (goji) at individual occupations level., and to weight the goji by employment to aggregate at higher occupational, sectoral and regional levels. To achieve this goal, I use text mining, index building and weighting approaches which are presented in section 4 as well as in the online appendix.

3.2 Statistical data to aggregate the *goji* at occupational, sectoral and regional level

Aggregating the greenness-of-jobs index at occupational, sectoral and regional level requires statistical macro data of the Federal Employment Agency. All employment statistics I use for the *goji* aggregations cover data on every employee liable for social security contributions in Germany. In the descriptives based on statistical data, I exclude marginally employed workers and trainees. At the end of the weighting process, there are *goji* values at 16 aggregate levels for each year (2006 and 2011 to 2016). **Fehler! Verweisquelle konnte nicht gefunden werden.** illustrates the *goji* aggregation levels resulting from this procedure. Some of them are presented in the remainder of this paper.[8]

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[6] https://www.onetonline.org/

[7] The only environmental-related information in BERUFENET is the occupational field *‚occupations in environmental protection and nature conservation‘*, which covers currently (January 2018) 38 occupations. (https://berufenet.arbeitsagentur.de/ > Berufsfelder >Landwirtschaft, Natur, Umwelt > Berufe im Umwelt- und Naturschutz). Compared to the broader definition of green tasks of this paper, the definition of the occupational field is much narrower and is based on an output-oriented approach (environmental goods and services).

[8] Further *goji* aggregates are shown in the online appendix ('Text Mining and Descriptives'). A selection of csv files with aggregated *goji* values is available on request from the author.

3.3 Administrative micro data for econometric analyses

The IAB Employment History (Beschäftigten-Historik—BeH) is a research dataset based on administrative data gathered by the Federal Employment Agency. It covers employee biographies from 1975 to the latest available data (here: 2016) of every employee subject to German social insurance contributions[9]. The main source of the BeH are mandatory annual notifications and (de-)registrations of firms to the health insurance institutions. The BeH contains variables about personal characteristics (e.g. age, gender, education, place of residence), individual employment characteristics (e.g. gross wages, tenure, staring/ending date), occupation characteristics (current occupation, occupational status), and some basic employer information (e.g. location, sector, establishment identification number). The present paper uses the full sample of all BeH employees aggregated at the 5-digit level of the KldB2010 ('occupational panel'). Because the earliest BERUFENET data are from 2006, I set up a BeH panel dataset starting from 2006 to 2016 (the most recent data available). Furthermore, I apply common imputation procedures suggested by Fitzenberger et al. (2006) to improve the BeH education variable and by Gartner (2005) to impute wages above the social security contribution assessment threshold.

The Establishment History Panel (Betriebs-Historik-Panel—BHP) provides a full sample of every German establishment that employs at least one worker liable for social security contributions or at least one marginal part-time worker. It is based on cross-sectional data and includes all German establishments that are listed in the BeH on June 30th. Corresponding to the BeH data, I choose 2006 as the first year of the BHP for my project dataset. The BHP comprises data about establishment size, establishment years, location, sector affiliation, and worker compositions in terms of qualifications, age, gender and wages. Eberle/Schmucker (2017) provide further information about this comprehensive dataset. I link these data to the BeH employee data. After aggregating BHP data at occupational level, I use these data to generate several dummy variables representing the typical composition of firm characteristics for each occupation.

4 The greenness-of-jobs index (*goji*): Measuring the greenness and greening of jobs

As in many other text mining cases, the decision about the central definition of the text mining subject is crucial for the entire project and had to be made at this stage of the project. For the present paper, the definition of the character of a 'green task' is particular important. The literature above revealed that there is no standard scientific definition for green tasks. This is my definition, which is used for the rest of the analysis, following the definition of general

[9] 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).

tasks by Acemoglu/Autor (2011): ***Green tasks*** are the explicitly *environmentally friendly* occupational requirements related to the production of output (goods and services) and to any other organizational process. These requirements may be related to all steps along the entire value chain. This includes knowledge areas, technologies and practices to reduce the use of fossil fuels, to decrease pollution and greenhouse gas emissions, to increase the efficiency of energy usage and material usage, to recycle materials, to develop and adopt renewable sources of energy, to protect and promote biodiversity. This definition is the basis for the entire text mining procedure. The text mining procedure and its resutls are described in detail in the online appendix.

Based on the green tasks identified by text mining, I create an occupations-tasks-matrix that allocates the number of green task to every individual occupation and groups them by categories, especially by core and additional tasks. This matrix facilitates the calculation of the (unweighted) greenness-of-jobs index, *goji*. The *goji* describes the proportion of green tasks in the total sum of requirements of an individual occupation occ8d (8-digit level) in year *t*.

$$goji_{core_{occ8d,t}} = \frac{\sum gr\_core_{occ8d,t}}{\sum r\_core_{occ8d,t}} \tag{4.1}$$

$$goji_{add_{occ8d,t}} = \frac{\sum gr\_add_{occ8d,t}}{\sum r\_add_{occ8d,t}} \tag{4.2}$$

$$goji_{total_{occ8d,t}} = \frac{\sum gr\_core_{occ8d,t} + \sum gr\_add_{occ8d,t}}{\sum r\_core_{occ8d,t} + \sum r\_add_{occ8d,t}} \tag{4.3}$$

where $goji_{core/add/total_{occ8d,t}}$ is the ‘green *core* tasks index’, ‘green *additional* tasks index’ or ‘green *total* tasks index’ (0…1) of occupation *occ8d* (8-digit level). Occupation *occ8d* is based on the index system of BERUFENET. This index system is called the “occupational code number” (Berufskennziffer—BKZ). $\sum gr\_core/add_{\ occ8d,t}$ is the number of green *core* requirements or green *additional* requirements for occupation *occ8d* (8-digit level) in year *t*, whereas $\sum r\_core/add_{occ8d,t}$ is the number of all core requirements or additional requirements for occupation *occ8d* (8-digit level) in year *t*

The $goji_{core}$ describes the proportion of green core tasks in the total of core requirements for occupation *occ8d (8-digit level)* in year *t*. Because the core requirements cover those activities that are most essential for practicing the occupation, this index has the highest generalizability for each job within this occupation. However, due to its stability the core requirements are relatively static and changes last longer than additional requirements. Hence, $goji_{core}$ is most helpful to measure green core occupations with green requirements at the center of their occupational conception. It is rather useful for long-term observations of the transition dynamics of the greening of jobs.

The $goji_{add}$ describes the proportion of green additional tasks in the total sum of additional requirements for occupation *occ8d (8-digit level)* in year *t*. The additional requirements are those that can be activities of an occupation but are not part of its core occupational conception. The time spent on additional requirements depends strongly on the specific job. The $goji_{add}$ is well-suited for analyzing short-term dynamics within the green requirements composition of occupations, because there is much higher fluctuation of BERUFENET contents in additional requirements than in core requirements.

The $goji_{total}$ facilitates the measurement of the share of green requirements in the total requirements. It describes the proportion of green core and additional requirements in the total sum of core and additional requirements for occupation *occ8d (8-digit level)* in year *t*. Administrative employment data are only available at higher aggregated levels, starting at the 5-digit level of the KldB2010. To link the *goji* values to administrative employment data, I have to aggregate the *goji* from the 8-digit level to the 5-digit level. For the transformation of $goji_{occ(8-digit)}$ into $goji_{occ(\geq 5-digit)}$, I use a procedure similar to that applied by Dengler et al. (2014): the *goji* of the 8-digit occupations is added up, and the total is divided by the number of 8-digit occupations within the 5-digit occupation, or as the following formula:

$$goji_{core,add,total_{occ5d,t}} = \frac{\sum goji_{core,add,total_{occ8d\in 5d,t}}}{N_{occ8d\in 5d,t}} \tag{4.4}$$

As the data of employees per occupation is only available at the 5-digit level, there is no way to apply an employment-weight at this stage of the process (see also Dengler et al. 2014). Therefore, we have to assume that the number of employees in individual 8-digit level occupations is equally distributed within the aggregate of the 5-digit level occupations ("equal distribution assumption"), as follows:

$$emp_{\,occ8d\in 5d} = \frac{emp_{occ5d}}{N_{\,occ8d\in 5d}} \tag{4.6}$$

where $emp_{occ8d\in 5d}$ is the estimated number of employees per 8-digit level occupation within the occupational group (5-digit level), emp_{occ5d} denotes the total number of employees within the occupational group (5-digit level) and $N_{occ8d\in 5d}$ stands for the number of occupations at the 8-digit level within the occupational group (5-digit level).
More details about the generation of the unweighted goji values as well as the calculation of employment weighted greenness-of-jobs indices and the resulting descriptive results are available in the online appendix.

5 Econometric analysis

5.1 Empirical approach

The empirical approach should support the third research question *'Do occupations with larger greenness/greening show larger employment and wage growth?'* Two steps are necessary to answer this question: First, cross-sectional data regressions analyze the associations between the ***greenness*** of occupations (level of *goji*) and employment/wage growth. Second, panel data regressions (here: yearly data from 2012 to 2016) examine the relation of the ***greening*** of occupations (growth of *goji*) and employment/wage growth. The estimates should serve as a first example for the application of the *goji* in empirical research. To estimate the associations between the *goji* and employment/wage growth, I apply employment growth regressions and Mincer-type wage regressions at occupational level. In all models presented below, $Y_{occ\,t}$ represents the specific response variable of the model. Depending of the labor market outcome of interest it covers either $EMP_{occ\,t}$ or $WAGE_{occ\,t}$, where $EMP_{occ\,t}$ is the natural logarithm of the total of full-time equivalents and $WAGE_{occ\,t}$ is the natural logarithm of the median of daily wages of male full-time workers in order to facilitate the comparison between occupations. The subscript *occ* stands for the occupational aggregate at *5*-digit level of KldB2010. ***t*** stands for time and comprises yearly values. The base year t for the cross-sectional analysis is 2012, whereas the years used in the panel data analysis cover 2012-2016.

$GOJI_{\ occ\,t}$ represents the variable of interest, i.e. the greenness-of-jobs index *goji* in three variations: $goji_{total}$ is based on both core and additional requirements, goji_{core} is based on core requirements and goji_{add} is based on additional requirements. As mentioned above, the ***greenness*** of occupations is measured by the level of *goji* (here: in 2012) and the ***greening*** of occupations comprises the change of *goji* over time (here: 2012-2016). $X_{occ\,t}$ covers the control variables including the composition of employment, employee, employer, tasks, tools, regional and sectoral characteristics for each occupation *occ* and year *t*. In models with employment growth as dependent variable, the lagged occupational wage level (represented by the median daily wage of full-time male workers) is also included. For the fixed effects regression I only include those control variables that vary over time. A comprehensive list of all control variables is part of the sample description (Table 2).

Greenness of occupations and labor market outcomes: cross-sectional data analysis

As equation 6.1 shows, I estimate the correlation between the greenness of occupations in 2012 and employment/wage growth of the time period from 2012 to 2016 based on OLS regressions. For these regressions, I estimate the following model:

$$\Delta Y_{occ\,2012-2016} = \beta_0 + \beta_1 GOJI_{occ\,2012} + \beta_2 X_{occ\,2012} + \varepsilon_{occ\,2012} \qquad (6.1)$$

where $\Delta Y_{occ\,2012-2016}$ is the difference of $Y_{occ\,2016} - Y_{occ\,2012}$. As $Y_{occ\,t}$ represents the specific response variable of the model, the model can be differentiated according to employment and wage growth:

$$\Delta EMP_{occ\,2012-2016} = \beta_0 + \beta_1 GOJI_{occ\,2012} + \beta_2 X_{occ\,2012} + \varepsilon_{occ\,2012} \qquad (6.1.1)$$

$$\Delta WAGE_{occ\,2012-2016} = \beta_0 + \beta_1 GOJI_{occ\,2012} + \beta_2 X_{occ\,2012} + \varepsilon_{occ\,2012} \qquad (6.1.2)$$

Greening of occupations and labor market outcomes: panel data analysis

The employment effects of the change of greenness (‘greening’) are estimated by a fixed effects (FE) estimation (equation 6.2). This approach uses yearly panel data between 2012 and 2016. I estimate

$$Y_{occ\,t} = \beta_0 + \beta_1\, GOJI_{occ\,t} + \beta_2 X_{occ\,t} + \gamma_{occ} + \delta_t + \varepsilon_{occ\,t} \tag{6.2}$$

where γ_{occ} and δ_t comprise the occupation- and time-fixed effects, and the error term $\varepsilon_{occ\,t}$ covers the residuals. The panel data model can also be differentiated according to employment and wage growth:

$$EMP_{occ\,t} = \beta_0 + \beta_1\, GOJI_{occ\,t} + \beta_2 X_{occ\,t} + \gamma_{occ} + \delta_t + \varepsilon_{occ\,t} \tag{6.2.1}$$

$$WAGE_{occ\,t} = \beta_0 + \beta_1\, GOJI_{occ\,t} + \beta_2 X_{occ\,t} + \gamma_{occ} + \delta_t + \varepsilon_{occ\,t} \tag{6.2.2}$$

5.2 The sample for econometric analysis

For the econometric analysis in this paper I use an occupational panel dataset for the years 2011 to 2016. As described in detail in the data section, this panel is based on a full sample of public-register data at worker level from the German IAB Employment History (BeH) dataset. To prepare the econometric analysis it is necessary to select a clearly defined sample. The 'non-green' sample group covers the occupations that have already existed since 2012 or longer and had a $goji_{total}$ value of 0 in 2012. In contrast, the *'green'* group comprises those occupations that have also existed since 2012 or longer but had a $goji_{total}$ value larger than zero in 2012. I drop all occupations with missing values in the dummy variable *Dgreen2012*. As Table 1 shows, this decision affects 39 of the 5,741 observations, which are dropped from the sample. Hence, the econometric analysis provides no information about the employment effects of new occupations. This might be a worthwhile issue for future research.

Table 1: Sample groups—Number of occupations with $goji_{total}$ = 0 ('Non-green') or $goji_{total}$ > 0 ('Green') in 2012

	Number of occupations—selection by: Dummy variable Dgreen2012 (Non-green = $goji_{total\ 2012}$ = 0; Green = $goji_{total\ 2012}$ >0)				
Year	**Non-green (0)**	**Green (1)**	**Sample (0+1)**	**Missing (.)**	**Total**
2012	784	362	1,146	1	1,147
2013	782	361	1,143	9	1,152
2014	777	361	1,138	11	1,149
2015	778	360	1,138	7	1,145
2016	777	360	1,137	11	1,148
Total	3,897	1,804	5,702	(to drop:) 39	5,741

Sources: BeH, BERUFENET, own calculations.

Table 2 describes the sample by comparing non-green and green occupations in 2012 and 2016, showing all available variables, including the absolute values and the delta values for 2012 to 2016 as percentages. As I restrict the analysis to the base year of 2012, the sample is not refilled if occupations disappear between 2012 and 2016. Consequently, both sample groups decrease slightly in number from 784 to 777 (non-green) and 362 to 360 (green). Both groups may experience greening or degreening between 2012 and 2016 or may just keep the same $goji_{total}$ value of 2012. The potential transitions of the $goji_{total}$ values and their relations to employment growth are covered by fixed effects regressions, which are presented in the next subsection.

Furthermore, Table 2 shows similarities and marked raw differences between characteristics of occupational sample groups: in terms of the number of employees (total of full-time equivalents FTE), in 2016 the non-green group accounts for 77.0 percent (21.037M FTE) of the sample and the green group 23.0 percent (6.290M FTE). In the context of FTE, the group of green occupations shows an overall raw employment growth of 4.5 percent between 2012 and 2016, which is 0.7 percentage points larger than the employment growth of the non-green group (5.2 percent). The larger difference in headcount growth between the green and the non-green groups (1.9 percentage points more in the non-green group) reflects the development of full-time employment: the green group has a larger share of full-time employees than the non-green group and the gap between the two groups even increased between 2012 and 2016.

Looking at wages—for comparison reasons I only use the imputed wages of full-time male workers here—both groups report an increase in wages between 2012 and 2016. The workers in the non-green occupation group saw a slightly larger raw wage growth than those in the green occupation group (delta value of median of imputed log wages: 0.1 percentage points). In general, there is a large raw wage gap between the groups: at 116.76 EUR, the median daily wage of male full-time workers in the non-green group in 2016 is about 15.7 percent larger than that of this employee group in green occupations (98.44 EUR). Obviously, this large raw wage gap is driven, among other things, by the larger share of highly educated employees, which was 21.0 percent in the non-green group and 11.4 percent in the green group in 2016.

Besides the data on employee numbers and wages, there are plenty of control variables that help to explain the differences between the groups of non-green and green occupations. In terms of the composition of employment characteristics, the green group has a larger share of full-time employees and of fixed-term contracts, but also a larger share of workers in marginal employment. However, the share of temporary agency work is smaller in green occupations than in non-green occupations.

There is also a pronounced heterogeneity in terms of employee characteristics of occupations: green occupations seem to have a good absorption capacity for older employees, as the proportion of this group in the green occupations is about 17 percent higher. In contrast, the non-green occupations employ about 22 percent more employees who are younger than 30. The share of middle-aged workers as well as the average tenure are at a similar level. The green occupations are so far relatively male-dominated, because the share of female workers is about 50 percent smaller than in the non-green occupations group. This is in line with the literature which also claims that institutional changes should be undertaken in order to motivate women to work in green occupations. This claim is supported by the results of Horbach/Jacob (2018), who find that a large proportion of highly educated women and a gender diverse board of directors is positively linked to the realization of eco-innovations.

There seems to be particularly strong demand not only for older workers but also for low-skilled workers in green occupations, as their share is substantially larger than it is in the group of non-green occupations. In turn, the latter have a larger share of highly educated workers (non-green: 21.0 percent; green: 11.4 percent in 2016). Of course—like any aggregated characteristic—these values vary between each individual occupation.

Looking at the composition of occupational characteristics, the requirement level corresponds to the distribution of the education level: the green group has more unskilled/semi-skilled occupations and specialist occupations, whereas in the non-green group more workers are employed in complex specialist occupations and highly complex occupations. In terms of the average number of tasks and tools, the groups are relatively similar, but the task types vary strongly. Non-green occupations involve larger shares of non-routine analytical tasks and non-routine interactive tasks, whereas the group of green occupations has a much higher share of non-routine manual tasks. Overall, the group of green occupations has about ten percent fewer routine tasks (cognitive and manual). This indicates that green occupations entail a lower risk of being replaced by computer algorithms and/or robots. So far, however, the group of green occupations has a far smaller share of IT-aided and IT-integrated ('industry 4.0') digital tools. The interactions of the three trends of digitalization, routine biased technological change and the greening of the economy raises several interesting questions that cannot be covered by this paper, but shall be analyzed in more detail in future research.

The composition of employer characteristics in the two groups also reveals pronounced differences and similarities: the largest share of small establishments is found in the group of green occupations, whereas the share of medium-sized firms is at the same level for green and non-green occupations. The share of larger establishments is greater in the group of non-green occupations. The establishment-age composition is similar in both groups, indicating the same trend towards a larger share of older establishments. Looking at the differences in establishment size, it is no surprise that workers in green occupations are employed in establishments that pay lower wages (about ten percent less than the average wages in non-green occupations).

The sectoral distributions vary considerably within and between the groups. In general, green occupations are more prevalent in the primary sector and to some extent in the secondary sector. In contrast, the non-green occupations are prevailing in the tertiary sector. Within the group of green occupations, the industries with the largest shares are manufacturing, construction, and administrative and support service activities. The green occupations have higher shares in in the following industry sections: 'agriculture, forestry and fishing', 'electricity, gas, steam and air conditioning supply, 'water supply, sewerage, waste management and remediation activities', 'construction', 'transportation and storage', 'real estate activities' as well as 'administrative and support service activities'.

In respect of the regional distribution of occupations, the non-green group is more prevalent in core cities, while the green group has larger shares in rural districts. The category between these, that of 'urbanized districts', is equally occupied by both groups. The comparison of the distribution across federal states shows that green occupations have a higher share of employees in northern and especially eastern Germany. However, the larger share of green occupations in the eastern part of Germany decreased between 2006 and 2012. This may be due to the strong drop in the number of jobs in the eastern German solar industry. Besides the eastern German states, there are three western states with higher shares of green than non-green occupations: Schleswig-Holstein, Lower Saxony and Rhineland-Palatinate. The other states generally have similar or slightly higher shares of non-green occupations. Only the city states of Berlin and Hamburg have far higher shares of non-green occupations.

Finally, the *goji* composition delivers some further insights: about two percent of occupations that were non-green in the base year of 2012 have since become green. Additionally, two percent of the occupations that were already green in 2012 became greener between 2012 and 2016. The occupations with a *goji* larger than zero can be also distinguished by their shares of core tasks and additional tasks as well as by their green tasks categories (links to more than one category are possible). In 2016, 60.2 percent of green occupations have $goji_{core}$ (covering only core tasks) larger than zero and 80.2 percent of green occupations have a $goji_{add}$ (covering only additional tasks) larger than zero. The green tasks categories of 'building', 'circular economy' and 'mobility and tourism' are the ones with the highest shares of green-task-specific $goji_{total}$ values larger than zero. To work out the relationship between the greenness and greening of jobs and employment growth, it is necessary to disentangle the different determinants by applying econometric methods. This last analytical step is described in the next section.

Table 2: Sample description: sample size, number of employees and sample means

	Non-green and green occupations 2012 and 2016 Non-green: $goji_{total\ 2012} = 0$; Green: $goji_{total\ 2012} > 0$					
	NON-GREEN	**GREEN**	**NON-G.**	**GREEN**	**NON-G.**	**GREEN**
	2012	**2012**	**2016**	**2016**	**∆2012-16**	**∆2012-16**
Variable (Label)	**abs.**	**abs.**	**abs.**	**abs.**	**∆in %**	**∆in %**
Sample size: Number of observations						
Occupations existing in 2012 (N)	784	362	777	360	-	-
Number of employees						
Total full-time equivalents	19.995M	6.020M	21.037M	6.290M	5.2%	4.5%
Total headcount	22.810M	6.978M	24.154M	7.260M	5.9%	4.0%
Wages of full-time male workers						
Imputed log wages of male full-time workers (median)	4.626	4.468	4.697	4.540	1.5%	1.6%
Imputed wages of male full-time workers (median)	108.397	91.444	116.759	98.443	7.7%	7.7%
Employment characteristics						
Normal employment	0.957	0.933	0.964	0.944	0.7%	1.1%
Marginal employment	0.043	0.067	0.036	0.056	-15.7%	-15.7%
Full-time	0.801	0.827	0.788	0.823	-1.7%	-0.5%

	Non-green and green occupations 2012 and 2016 Non-green: *goji*$_{total\ 2012}$ = 0; *Green: goji*$_{total\ 2012}$ > 0					
	NON-GREEN	**GREEN**	**NON-G.**	**GREEN**	**NON-G.**	**GREEN**
	2012	**2012**	**2016**	**2016**	**∆2012-16**	**∆2012-16**
Variable (Label)	**abs.**	**abs.**	**abs.**	**abs.**	**∆in %**	**∆in %**
Permanent contract	0.888	0.903	0.846	0.864	-4.7%	-4.4%
Fixed-term contract	0.112	0.097	0.154	0.136	37.6%	40.7%
Temporary agency work	0.034	0.025	0.034	0.023	-1.6%	-5.9%
Employee characteristics						
Employee age group: 16 to <30 years	0.198	0.149	0.192	0.149	-3.2%	-0.1%
Employee age group: >=30 to <50 y.	0.523	0.517	0.483	0.471	-7.5%	-9.0%
Employee age group: >=50 y.	0.279	0.334	0.325	0.380	16.3%	14.0%
Tenure (average years)	6.458	6.492	6.653	6.637	3.0%	2.2%
Women	0.488	0.230	0.487	0.226	-0.4%	-1.6%
Foreign nationality	0.077	0.095	0.098	0.132	27.0%	38.1%
Education level						
Low education	0.091	0.116	0.106	0.142	16.6%	22.6%
Medium education	0.717	0.778	0.684	0.744	-4.6%	-4.4%
High education	0.192	0.106	0.210	0.114	9.2%	7.9%
Occupational characteristics						
Requirement level						
Unskilled/semi-skilled occupation	0.155	0.172	0.157	0.174	1.2%	0.9%
Specialist occupation	0.572	0.635	0.560	0.627	-2.1%	-1.3%
Complex specialist occupation	0.134	0.116	0.137	0.117	2.5%	0.7%
Highly complex occupation	0.139	0.077	0.146	0.083	4.8%	7.5%
Tasks characteristics						
Tasks complexity / N of tasks	18.554	18.637	19.381	19.040	4.5%	2.2%
Number of core tasks	8.119	8.708	8.340	8.863	2.7%	1.8%
Number of additional tasks	10.435	9.928	11.041	10.178	5.8%	2.5%
Tasks-type: Non-routine analytical	0.269	0.166	0.279	0.172	3.5%	3.9%
Tasks-type: Non-routine interactive	0.150	0.037	0.151	0.037	0.5%	0.5%
Tasks-type: Routine cognitive	0.302	0.251	0.290	0.248	-3.7%	-1.4%
Tasks-type: Routine manual	0.125	0.120	0.125	0.127	-0.4%	5.5%
Tasks-type: Non-routine manual	0.154	0.426	0.155	0.416	1.0%	-2.3%
Tools characteristics						
Tools complexity: N of work tools	7.648	9.314	7.660	9.272	0.2%	-0.5%
Dig. tools share (total)	0.343	0.202	0.344	0.206	0.5%	1.8%
Dig. tools share 1: IT-aided tools	0.322	0.192	0.323	0.195	0.4%	1.8%
Dig. tools share 2: IT-integrated t.	0.021	0.010	0.021	0.010	1.9%	0.3%

	Non-green and green occupations 2012 and 2016 Non-green: $goji_{total\ 2012} = 0$; Green: $goji_{total\ 2012} > 0$					
	NON-GREEN	**GREEN**	**NON-G.**	**GREEN**	**NON-G.**	**GREEN**
	2012	**2012**	**2016**	**2016**	**∆2012-16**	**∆2012-16**
Variable (Label)	**abs.**	**abs.**	**abs.**	**abs.**	**∆in %**	**∆in %**
plus 27 variables for the *goji* composition—see appendix (Table A-1)						
Employer characteristics						
Establishment size 1-49	0.383	0.454	0.356	0.423	-7.2%	-6.8%
Establishment size 50-449	0.397	0.370	0.383	0.358	-3.5%	-3.4%
Establishment size >500	0.220	0.176	0.261	0.219	18.9%	24.7%
Establishment age 0-10	0.247	0.246	0.171	0.163	-30.8%	-33.8%
Establishment age 11-20	0.228	0.249	0.223	0.228	-2.3%	-8.5%
Establishment age >20	0.525	0.505	0.606	0.609	15.5%	20.7%
Average daily wage in establishment	99.741	89.901	105.898	94.914	6.2%	5.6%
Avg. age of workers in establishment	41.302	42.481	41.650	42.897	0.8%	1.0%
Sectoral composition						
Basic sectoral composition						
Primary sector	0.006	0.015	0.007	0.014	2.3%	-5.6%
Secondary sector	0.283	0.403	0.275	0.398	-2.9%	-1.3%
Tertiary sector	0.710	0.583	0.718	0.588	1.2%	1.0%
plus 21 variables for sector composition at WZ-1 level (industry sections)—see appendix (Table A-3)						
Regional composition						
Regional types						
Core cities	0.380	0.326	0.382	0.328	0.5%	0.8%
Urbanized districts	0.356	0.354	0.355	0.356	-0.2%	0.5%
Rural distr. with features of concentration	0.145	0.170	0.145	0.169	-0.4%	-0.5%
Rural districts-sparsely populated	0.119	0.150	0.118	0.147	-0.6%	-2.4%
Federal states groups						
North	0.156	0.165	0.156	0.168	0.5%	1.8%
West	0.350	0.338	0.346	0.335	-1.0%	-1.1%
East	0.181	0.211	0.180	0.204	-0.5%	-3.1%
South	0.314	0.285	0.317	0.293	1.2%	2.5%
plus 16 variables for the regional composition at NUTS-1 level (fed. states)—see appendix (Table A-1)						

Sources: BeH, BERUFENET, own calculations.

5.3 Estimation results

Table 3 presents the coefficients of greenness (OLS, Column 1 and 2) and greening (FE, Column 3 and 4) of occupations with employment growth as dependent variable. The variables of interest are $goji_{total\ 2012}$ (Column 1) or $goji_{core\ 2012}$ and $goji_{add\ 2012}$ (Column 2), respectively. The coefficient for $goji_{total\ 2012}$ in Column (1) is 0.223 and highly significant at the 1-percent level. The regression results reported in Column (2) contain $goji_{core\ 2012}$ and $goji_{add\ 2012}$, but in this case only the coefficient of 0.220 for $goji_{add\ 2012}$ is significantly different from zero (at 5 percent level). The goji covers continuous values between 0 and 1 that can be interpreted as percentage values. Hence, the results of Column (1) and (2) indicate if the $goji_{total}$ or $goji_{add}$ value rises by one percentage point, the employment development is related with an increase of employment growth by 0.22 percent . It is obvious that this—economically slightly—positive relation of $goji_{total}$ and employment growth is largely driven by the proportion related to green additional tasks, represented by the coefficient of $goji_{add}$.

Column (3) and (4) of Table 3 report the results of the fixed effects estimation using yearly panel data from 2012 to 2016. The coefficients of the goji variations indicate the associations between the growth of goji ('greening') and the employment growth. According to Table 3, the FE estimation gives statistically insignificant coefficients of $goji_{total}$ (Column 3) and $goji_{core}$ /$goji_{add}$ (Column 4). Since institutional changes at the professional level are often slow, the relatively short observation period does not seem to allow for representative findings. The development of data material for further years might improve this situation. This remains an open point for future research projects.

Table 3: *Goji* and employment growth: Estimation results

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
Dependent variables:	OLS Full-time equivalents (log, delta 2012-2016)		FE Full-time equivalents (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
Share of green tasks total	0.223***		-0.230	
goji_{total}	(2.60)		(-1.58)	
Share of green core tasks		0.003		-0.058
goji_{core}		(0.05)		(-1.31)
Share of green additional tasks		0.220***		-0.102
goji_{add}		(2.72)		(-1.05)
Constant	0.372	0.373	13.24***	13.25***
	(1.51)	(1.49)	(22.60)	(22.59)
Control variables of occupational characteristics are included (employee, employer, employment, tasks, tools, (lagged) wage, regional and sectoral characteristics). The FE regression also contains time dummies for the years 2013-2016. Full regression results: see appendix (Table A-2).				
N	1146	1146	5699	5699
R^2	0.495	0.497	0.613	0.613

Note: t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Full regression results: see Table A-2. Source: BeH, BERUFENET, own calculations.

Turning to the wage development, the OLS estimations in Table 4 report a statistically insignificant coefficient for $goji_{total}$ (Column 1), but show significant results for $goji_{core}$ and

$goji_{add}$. Interestingly, $goji_{core}$ returns a positive value of 0.070, whereas goj_{add} returns a negative value -0.079. In other words, a $goji_{core\ 2012}$ that is larger by 1 percent is associated with a slight increase of wage growth by 0.07 percent. Contrary, a $goji_{add\ 2012}$ larger by 1 percent is related with a slight decrease of wage growth by 0.08 percent. The difference between $goji_{core}$ and $goji_{add}$ might be explained by variations in productivity related to those tasks. As there is no data available about related productivity so far, the analysis of the exact reasons for the wage differences between core and additional requirements is left to future research projects.

Table 4: *Goji* and wage growth: Estimation results

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
Dependent variables:	OLS Daily Wage (log, delta 2012-2016)		FE Daily Wage (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
Share of green tasks total	-0.002		0.098**	
$goji_{total}$	(-0.04)		(2.01)	
Share of green core tasks		0.070**		0.001
$goji_{core}$		(2.11)		(0.01)
Share of green additional tasks		-0.079*		0.062
$goji_{add}$		(-1.95)		(1.35)
Constant	0.0222	0.0193	5.747***	5.733***
	(0.14)	(0.12)	(11.38)	(11.28)
Control variables of occupational characteristics are included (employee, employer, employment, tasks, tools, regional and sectoral characteristics). The FE regression also contains time dummies for the years 2013-2016. Full regression results: see appendix (Table A-3).				
N	1137	1137	5702	5702
R^2	0.473	0.477	0.694	0.694

Note: t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01. Full regression results: see Table A-3. Source: BeH, BERUFENET, own calculations.

Looking at the greening of occupations, Table 4 reports in Column (3) a positive $goji_{total}$ coefficient of 0.098 which is statistically significant at the five percent level, whereas the FE estimation results in Column (4) show coefficients of $goji_{core}$ and $goji_{add}$ which are not significantly different from zero. It can therefore be stated that growth of the $goji_{total}$ by 1 percent between 2012 and 2016 is accompanied by wage growth of 0.10 percentage points.

From a methodical point of view, this suggests that the set of $goji_{core}$ and $goji_{add}$ should be applied to measure wage developments related to the greenness of jobs, whereas $goji_{total}$ might be the better choice to measure the relation between the greening of occupations and employment growth. One possible explanation for the relatively small coefficients in the field of labor market outcomes might be the short time period from 2012 to 2016, which might be not long enough to identify larger effects. Furthermore in some fields of activity the argument put forward by Peters (2014) might play a role. He states that the numbers of jobs created on account of green energy should be rather small because energy technologies are generally capital-intensive. This might also rule for other technology-intensive field of activity, too. But this interesting aspect will also be reserved for future research. The results presented show that there is obviously a large potential of the new index and also a need for further empirical analyses.

6 Conclusions

This paper is the first that describes and analyzes the greening of jobs in Germany. The paper contributes to the literature in three ways: First, it introduces a novel approach that develops the greenness-of-jobs index *goji* based on text mining with data from the German BERUFENET. Second, it describes the greenness and greening of jobs using employment weighted *goji* aggregates. Third, it analyzes the associations between *goji* and employment outcomes by applying econometric analyses.

The first objective of the paper is to develop an index to measure both the extent of the greenness of jobs and the development of greenness over time, i.e. the greening of jobs. At the beginning of the project I conduct a comprehensive literature review to compile a 'green task dictionary'. Based on this dictionary I apply the text mining procedures to BERUFENET data for every year. After a two-step matching process, the green tasks and all other information on each occupation's requirements are used to compute the unweighted greenness-of-jobs index *goji*. The *goji* is a continuous value from 0 to 1 and is calculated for every occupation. There are three *goji* variations: core requirements ($goji_{core}$) and additional requirements ($goji_{add}$). The $goji_{total}$ lies between 0.024 and 0.889 with a median of 0.083. At the end of this step there are 785 individual occupations in 2016 with a $goji_{total}$ larger than zero. Compared to 2012, the share of occupations with a $goji_{total}$ larger than zero has risen from 18.6 percent to 19.9 percent. But not only the number of '*goji* occupations' has increased, also the *goji* level. 137 occupations have experienced an increase in their $goji_{total}$ between 2012 and 2016. This study does not claim to cover all green jobs, but it provides first evidence of all occupations with green requirements even if they are not necessarily associated with the production or provision of green goods and services. It might be worthwhile combining the *goji* with output-oriented approaches in a follow-up project.

The second objective is to describe the occupational, sectoral and regional distributions of the greenness and greening of jobs. To analyze the distribution of the *goji* in Germany and to prepare the data for record linkage, I calculate several occupational, sectoral and regional aggregates. The descriptive results show that there is an increase in the $goji_{total}$ at each level of aggregation. Even at the highest occupational aggregate, the overall German greenness-of-jobs index ($goji_{de}$), a slight growth is observable: the $goji_{de}$ has grown from 0.0196 in 2012 to 0.0198 in 2016, which is an increase of one percent. Noteworthy, at this level the differences between $goji_{core}$ and $goji_{add}$ come to light. Whereas the higher $goji_{add}$ value of 0.0199 shows a slight decrease of -1.7%, the smaller $goji_{core}$ value (0.0150 in 2016) grows by 4.6 percent. To measure the true magnitude of the greenness of jobs, I also introduce the 'full-green employment equivalent (FGE)'. According to the FGE in 2016, there were 590 thousand full-green employment equivalents in Germany. A comparison of the FGE reveals that between 2012 and 2016 there was an increase in FGE of 56,643, i.e. a plus of 10.6 percent. The *goji* aggregates at industry level show heterogeneous developments in terms of the *goji* and reveal many examples of greening and degreening sectors*:* the sector 'public administration and defense; compulsory social security' exhibits the largest growth in the absolute $goji_{total}$ value, whereas 'accommodation and food service activities' has the largest relative growth rate. The strongest reduction in $goji_{total}$—both as an absolute and relative value—can be observed for 'agriculture, forestry and fishing'. The same heterogeneity appears with respect to the regional distribution of the *goji*. Nevertheless, there are some patterns that are visible in each year: the eastern part of Germany has higher employment-weighted *goji* values, and larger cities have lower *goji* values than rural areas.

The third goal of this paper is to examine whether the greenness and greening of jobs influence labor market outcomes. In order to analyze these relationships, OLS and FE regressions are applied. The econometric analysis uses a novel data source, linking the *goji* with occupation panel data based on a full sample of individual employment data from 2011 to 2016. The estimation results show a small positive and statistically highly significant association between the total greenness of occupations (level of $goji_{total}$) and employment growth. The coefficient of $goji_{total}$ may be interpreted such that one percentage point higher $goji_{total}$ value is accompanied by a 0.22 percent increase in employment growth. When differentiating between the two sub-indices $goji_{core}$ and $goji_{add}$, the results show that the positive correlation between the greenness-of-jobs and employment growth is mainly driven by the shares of green additional tasks. The OLS analysis of greenness and wage growth reveals the importance of differentiating between core and additional requirements. A $goji_{core\ 2012}$ that is larger by 1 percent is associated with a slight increase of wage growth by 0.07. Contrary, a $goji_{add\ 2012}$ larger by 1 percent is related with a slight decrease of wage growth by 0.08 percent. The reasons for this mixed effects should be analyzed in future research. In terms of the relationship between greening of occupations and wage growth, the results from FE estimation are clearer: an increase of $goji_{total}$ by 1 percent between 2012 and 2016 is accompanied by wage growth of 0.10 percentage points. The econometric results also demonstrate the potential of the new index for empirical studies in general. For example, the *goji* can be applied to examine the impact of environmental regulation on the greenness of jobs, the effects of a firm's greenness composition on productivity, or the interplay between local economic development and the regional greenness of jobs.

The practical and political implications of the results of this paper are threefold: 1) As shown in the study, it is possible to identify the greenness and greening of jobs using existing administrative data without expensive surveys and new data sources. This approach might therefore be an efficient way to officially measure the green transitions of employment in Germany. If similar data sources exist in other countries, this approach can be adopted or used for international comparisons. Moreover, the combination of text mining, index development and aggregation has the potential to be applied to other societal transition processes, e.g. ongoing digitalization (see Genz et al. 2018 for a first application). A necessary prerequisite for every application is the availability of up-to-date information on occupations, especially about the current requirements. Although the BERUFENET is updated regularly, there is still room for institutional improvement. It seems that the job requirements of training occupations lag somewhat behind current developments. A more proactive role of the participating institutions, like the Chamber of Handicrafts and the Chamber of Industry and Commerce, who are responsible for the contents of the vocational trainings in Germany, could lead to a more up-to-date data basis for practice and research. For this reason the use of web crawling and machine-learning procedures to analyze online job offers might be a promising approach to anticipate current developments on the labor market (Hermes/Schandock 2016). Furthermore, a flag of 'green task' similar to that in the US-American O*NET database would be a helpful feature of the BERUFENET. 2) The descriptive analysis of the *goji* distribution revealed a large heterogeneity between occupational aggregates, industries and regions. This heterogeneity should be kept in mind especially before policy implications are drawn. If the promotion of green jobs is a policy target, the results of this paper suggest that it is more advisable to promote the transformation of existing occupations rather than to design new occupations, though this may be necessary in individual cases. Furthermore, the large heterogeneity of the distribution of the *goji* demands a precise alignment of policy instruments. 3) Finally, the results of the third objective of this paper also have the potential to guide policy decisions. The general message of the econometric results is that the greenness of jobs is related to a moderate increase of employment growth and the greening of jobs is associated with a moderate increase of wage growth. Only the level of $goji_{add}$ is conjoined with a slight slowdown of wage growth. An in-depth analysis of this phenomenon is an interesting issue for future research. The economic significance of the results is relatively small in the short time period observed. This is not bad news at all, because the overall results of this paper show that 'green' transitions and labor market outcomes can even positively interrelate with each other. Nevertheless, there is still a need to prevent threats of individuals to lose their employability through these transitions. Hence, the most important objective for labor market policy might be to support the green adaptation of occupations, employees and employers to the changing needs of the labor market. This includes both continuous structural reforms of occupational contents and institutions and the use of existing active labor market policy instruments such as the promotion of further training, retraining and life-long learning.

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Appendix

Table A-1: Extension for sample description: Sectoral composition and regional composition of non-green occupations and green occupations 2012 and 2016

	Selection by $goji_{total}$ in 2012 (Non-green: $goji_{total\ 2012}$=0; *Green:* $goji_{total\ 2012}$> 0)					
	NON-GREEN	GREEN	NON-G.	GREEN	NON-G.	GREEN
	2012	2012	2016	2016	Δ2012-16	Δ2012-16
Variable (Label)	abs.	abs.	abs.	abs.	Δin %	Δin %
Sectoral composition						
Agriculture, forestry and fishing	0.006	0.015	0.007	0.014	2.3%	-5.6%
Mining and quarrying	0.003	0.003	0.002	0.003	-24.0%	-12.0%
Manufacturing	0.244	0.199	0.237	0.196	-3.0%	-1.4%
Electricity, gas, steam and air conditioning supply	0.007	0.012	0.006	0.011	-6.8%	-7.8%
Water supply, sewerage, waste management and remediation	0.005	0.021	0.005	0.021	-0.5%	0.3%
Construction	0.025	0.168	0.025	0.167	0.5%	-0.6%
Wholesale and retail trade, repair of motor vehicles and motorcycles	0.161	0.089	0.156	0.084	-3.3%	-5.5%
Transportation and storage	0.034	0.123	0.035	0.128	2.3%	3.8%
Accommodation and food service	0.042	0.018	0.043	0.018	2.4%	5.4%
Information and communication	0.039	0.007	0.040	0.006	4.0%	-15.0%
Financial and insurance activities	0.041	0.003	0.039	0.003	-5.8%	-7.9%
Real estate activities	0.006	0.019	0.006	0.020	0.1%	1.7%
Professional, scientific and technical activities	0.067	0.044	0.072	0.046	8.3%	6.1%
Administrative and support service activities	0.056	0.139	0.056	0.145	-0.1%	4.1%
Public administration and defence, compulsory social security	0.052	0.052	0.053	0.052	1.2%	-1.0%
Education	0.036	0.021	0.038	0.021	5.8%	-0.5%
Human health and social work	0.136	0.036	0.143	0.036	4.7%	-0.4%
Arts, entertainment and recreation	0.011	0.006	0.011	0.006	0.8%	-3.3%
Other service activities	0.028	0.023	0.026	0.022	-7.1%	-4.2%
Activities of households as employers, undifferentiated goods and services	0.001	0.001	0.001	0.001	2.4%	-10.6%
Activities of extraterritorial organisations and bodies	0.001	0.001	0.001	0.001	-27.1%	-29.1%
Regional composition						
Schleswig Holstein	0.028	0.033	0.028	0.034	-0.5%	2.0%
Hamburg	0.031	0.025	0.031	0.025	0.7%	1.6%
Lower Saxony	0.086	0.098	0.087	0.100	0.8%	2.0%
Bremen	0.010	0.009	0.010	0.010	-0.3%	0.6%
Northrhine-Westphalia	0.214	0.205	0.212	0.202	-1.0%	-1.8%
Hesse	0.080	0.074	0.080	0.075	-0.6%	1.6%
Rhineland-Palatinate	0.043	0.046	0.042	0.046	-1.0%	-0.9%
Baden-Württemberg	0.144	0.129	0.145	0.132	0.5%	2.4%
Bavaria	0.169	0.156	0.172	0.161	1.7%	2.7%
Saarland	0.013	0.013	0.012	0.012	-3.6%	-5.9%
Berlin	0.041	0.037	0.044	0.038	5.6%	2.8%
Brandenburg	0.025	0.033	0.024	0.032	-2.2%	-4.4%

Variable (Label)	Selection by $goji_{total}$ in 2012 (Non-green: $goji_{total\ 2012}$=0; *Green:* $goji_{total\ 2012}$> 0) NON-GREEN 2012 abs.	GREEN 2012 abs.	NON-G. 2016 abs.	GREEN 2016 abs.	NON-G. Δ2012-16 Δin %	GREEN Δ2012-16 Δin %
Mecklenburg Western Pomerania	0.017	0.022	0.017	0.021	-2.6%	-4.1%
Saxony	0.048	0.056	0.048	0.055	-0.9%	-2.6%
Saxony-Anhalt	0.024	0.032	0.023	0.030	-4.6%	-5.9%
Thuringia	0.025	0.030	0.025	0.028	-2.6%	-6.3%
Goji composition						
goji0_0	0.000	0.072	0.002	0.072	N/A	-1.0%
goji0_1	0.000	0.053	0.000	0.056	N/A	5.6%
goji0_2	0.000	0.074	0.002	0.069	N/A	-7.0%
goji1_0	0.000	0.004	0.000	0.003	N/A	-18.9%
goji2_0	0.000	0.018	0.000	0.018	N/A	2.2%
goji3_0	0.000	0.015	0.000	0.015	N/A	4.8%
goji4_0	0.000	0.004	0.000	0.003	N/A	-7.4%
goji5_0	0.000	0.001	0.000	0.002	N/A	40.7%
goji6_0	0.000	0.007	0.000	0.007	N/A	-7.6%
goji7_0	0.000	0.017	0.000	0.016	N/A	-5.7%
goji8_0	0.000	0.007	0.000	0.007	N/A	2.9%
D1goji0_0	0.000	1.000	0.059	0.996	N/A	-0.4%
D1goji0_1	0.000	0.579	0.018	0.602	N/A	4.0%
D1goji0_2	0.000	0.816	0.057	0.802	N/A	-1.8%
D1goji1_0	0.000	0.117	0.004	0.115	N/A	-1.4%
D1goji2_0	0.000	0.265	0.015	0.283	N/A	6.8%
D1goji3_0	0.000	0.284	0.007	0.315	N/A	11.0%
D1goji4_0	0.000	0.081	0.030	0.079	N/A	-2.4%
D1goji5_0	0.000	0.062	0.012	0.103	N/A	67.9%
D1goji6_0	0.000	0.139	0.013	0.162	N/A	17.3%
D1goji7_0	0.000	0.332	0.001	0.314	N/A	-5.4%
D1goji8_0	0.000	0.166	0.019	0.178	N/A	7.3%
Dnongreensteady	0.939	0.000	0.940	0.000	0.1%	N/A
Dgreensteady	0.000	0.905	0.000	0.906	N/A	0.1%
Dgreening	0.019	0.020	0.019	0.020	3.8%	0.6%
Ddegreening	0.000	0.071	0.000	0.069	N/A	-1.7%
Dblsgreenenhanced	0.019	0.020	0.019	0.020	3.8%	0.6%

Source: BeH, own calculations.

Table A-2: *Goji* and employment growth: Full estimation results

Dependent variables:	GREENNESS 2012 (level) OLS Full-time equivalents (log, delta 2012-2016) (1)	(2)	GREENING 2012-2016 (growth) FE Full-time equivalents (log, yearly panel 2012-2016) (3)	(4)
Share of green tasks total *$goji_{total}$*	0.223*** (2.60)		-0.230 (-1.58)	
Share of green core tasks *$goji_{core}$*		0.003 (0.05)		-0.058 (-1.31)
Share of green additional tasks *$goji_{add}$*		0.220*** (2.72)		-0.102 (-1.05)

Dependent variables:	GREENNESS 2012 (level) OLS Full-time equivalents (log, delta 2012-2016)		GREENING 2012-2016 (growth) FE Full-time equivalents (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
Imputed log wages of male full-time workers—median (lagged)	0.007 (0.16)	0.007 (0.16)	-0.030 (-1.00)	-0.030 (-1.00)
Employment age group 16 - <30 years	0.065 (0.54)	0.076 (0.62)	0.536*** (2.71)	0.534*** (2.69)
Employment age group >= 50 years	-0.372*** (-2.96)	-0.364*** (-2.90)	-1.565*** (-8.36)	-1.561*** (-8.31)
Tenure	-0.021*** (-3.63)	-0.021*** (-3.68)	-0.059*** (-5.70)	-0.059*** (-5.73)
Women	-0.117*** (-3.82)	-0.115*** (-3.75)	0.324 (1.26)	0.322 (1.24)
Foreign nationality	-0.091 (-0.66)	-0.072 (-0.52)	0.084 (0.34)	0.089 (0.36)
Low education	0.209 (1.37)	0.203 (1.33)	-0.580** (-2.13)	-0.586** (-2.15)
High education	0.034 (0.90)	0.033 (0.86)	-0.250 (-1.05)	-0.248 (-1.04)
Establishment size 1-49	-0.198*** (-4.93)	-0.203*** (-4.96)	0.716*** (4.10)	0.719*** (4.12)
Establishment size >500	-0.206*** (-4.23)	-0.208*** (-4.20)	0.383*** (2.81)	0.385*** (2.82)
Establishment age 0-10 years	0.139 (1.01)	0.123 (0.90)	-0.187** (-2.30)	-0.189** (-2.31)
Establishment age > 20 years	0.125 (1.17)	0.117 (1.10)	0.131*** (2.95)	0.130*** (2.99)
Marginal Employment	-0.256* (-1.88)	-0.250* (-1.85)	0.640 (1.51)	0.639 (1.51)
Part-time work	0.141** (2.00)	0.142** (2.01)	0.555** (2.08)	0.557** (2.09)
Fixed-term contract	-0.248*** (-2.84)	-0.264*** (-3.06)	0.068 (0.35)	0.072 (0.37)
Unskilled/semi-skilled occupation	0.026 (1.34)	0.029 (1.47)	N/A	N/A
Complex specialist occupation	-0.020 (-1.24)	-0.021 (-1.28)	N/A	N/A
Highly complex occupation	-0.034 (-1.37)	-0.035 (-1.41)	N/A	N/A
Tasks complexity (Number of tasks$_{total}$)	-0.002** (-2.50)	-0.002** (-2.34)	-0.001 (-0.91)	-0.001 (-0.91)
Share of non-routine analytical tasks	0.220*** (6.42)	0.222*** (6.43)	0.161** (2.24)	0.159** (2.21)
Share of non-routine interactive tasks	0.137*** (3.07)	0.138*** (3.10)	0.065 (0.75)	0.063 (0.72)
Share of routine cognitive tasks	0.099*** (3.29)	0.098*** (3.22)	0.010* (1.90)	0.097* (1.86)
Share of non-routine manual tasks	0.124*** (3.98)	0.126*** (4.02)	0.186*** (4.27)	0.185*** (4.25)
Tools complexity (Number of tools$_{total}$)	0.001 (1.09)	0.001 (1.12)	N/A	N/A
dtox$_{IT\text{-}add}$: share of IT-aided digital tools	-0.0211 (-0.33)	-0.015 (-0.24)	N/A	N/A
dtox$_{IT\text{-}int}$: share of IT-integrated digital tools	0.117 (0.85)	0.107 (0.78)	N/A	N/A
Mining and quarrying	-0.414*** (-2.80)	-0.408*** (-2.78)	0.595 (0.75)	0.555 (0.70)
Manufacturing	-0.036 (-0.71)	-0.030 (-0.59)	-0.790 (-1.52)	-0.804 (-1.54)
Electricity, gas, steam and air conditioning supply	-0.014 (-0.14)	-0.035 (-0.35)	-2.382** (-2.23)	-2.382** (-2.22)
Water supply, sewerage, waste	-0.249*** (-2.79)	-0.175** (-2.04)	-1.723 (-1.38)	-1.736 (-1.39)

Dependent variables:	GREENNESS 2012 (level) OLS Full-time equivalents (log, delta 2012-2016)		GREENING 2012-2016 (growth) FE Full-time equivalents (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
management and remediation activities				
Construction	-0.130***	-0.128***	-0.950	-0.977
	(-2.66)	(-2.64)	(-1.50)	(-1.54)
Wholesale and retail trade, repair of motor vehicles and motorcycles	-0.126**	-0.122**	-0.766	-0.782
	(-2.47)	(-2.39)	(-1.31)	(-1.33)
Transportation and storage	-0.095	-0.095	-0.492	-0.510
	(-1.47)	(-1.48)	(-0.89)	(-0.91)
Accommodation and food service activities	-0.131**	-0.133**	-0.480	-0.496
	(-2.27)	(-2.33)	(-0.60)	(-0.62)
Information and communication	-0.138*	-0.137*	-0.862*	-0.878*
	(-1.79)	(-1.78)	(-1.65)	(-1.67)
Financial and insurance activities	-0.168***	-0.166***	-2.170***	-2.190***
	(-2.79)	(-2.77)	(-3.08)	(-3.09)
Real estate activities	0.203**	0.200**	-0.698	-0.711
	(2.45)	(2.47)	(-0.95)	(-0.97)
Professional, scientific and technical activities	-0.046	-0.044	-0.742	-0.758
	(-0.65)	(-0.62)	(-1.43)	(-1.45)
Administrative and support service activities	-0.151***	-0.152**	-0.824*	-0.843*
	(-2.59)	(-2.56)	(-1.65)	(-1.67)
Public administration and defence, compulsory social security	0.001	0.004	-1.068**	-1.080**
	(0.03)	(0.08)	(-1.98)	(-2.00)
Education	0.069	0.074	-1.849***	-1.867***
	(1.15)	(1.25)	(-3.16)	(-3.17)
Human health and social work activities	-0.007	-0.004	0.030	0.019
	(-0.15)	(-0.08)	(0.05)	(0.03)
Arts, entertainment and recreation	-0.131**	-0.126**	-2.038***	-2.056***
	(-2.06)	(-1.97)	(-2.95)	(-2.96)
Other service activities	-0.088	-0.086	-2.389***	-2.391***
	(-1.43)	(-1.40)	(-3.45)	(-3.45)
Activities of households as employers, undifferentiated goods and services	0.168	0.158	-0.409	-0.421
	(0.79)	(0.75)	(-0.25)	(-0.26)
Activities of extraterritorial organisations and bodies	1.658*	1.606	2.343	2.396
	(1.68)	(1.61)	(0.91)	(0.93)
Urbanized districts	-0.028	-0.057	-1.168***	-1.166***
	(-0.32)	(-0.65)	(-5.55)	(-5.53)
Rural districts with features of concentration	-0.142	-0.154	-1.365***	-1.364***
	(-1.19)	(-1.28)	(-3.92)	(-3.90)
Rural districts-sparsely populated	0.033	0.044	-2.217***	-2.221***
	(0.27)	(0.36)	(-5.76)	(-5.76)
Western fed. states: Northrine-Westphalia, Hesse, Rhineland-Palatinate, Saarland	-0.198*	-0.184	0.455*	0.456*
	(-1.68)	(-1.56)	(1.95)	(1.95)
Eastern fed. states: Berlin, Brandenburg, Mecklenburg Western Pomerania, Saxony,	-0.061	-0.057	0.189	0.198
	(-0.58)	(-0.54)	(0.73)	(0.76)
Southern fed states: Baden-Wuertemberg, Bavaria	0.071	0.088	0.306	0.310
	(0.71)	(0.88)	(1.13)	(1.15)
Dummy 2013	N/A	N/A	0.039***	0.039***
			(8.15)	(8.09)
Dummy 2014	N/A	N/A	0.080***	0.080***
			(8.96)	(8.88)
Dummy 2015	N/A	N/A	0.102***	0.102***
			(8.14)	(8.06)
Dummy 2016	N/A	N/A	0.125***	0.124***
			(7.81)	(7.73)
Constant	0.372	0.373	13.24***	13.25***
	(1.51)	(1.49)	(22.60)	(22.59)

Dependent variables:	GREENNESS 2012 (level) OLS Full-time equivalents (log, delta 2012-2016)		GREENING 2012-2016 (growth) FE Full-time equivalents (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
N	1146	1146	5699	5699
R^2	0.495	0.497	0.613	0.613

Note: t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Reference groups: Employee age group: >=30-<50 years; Medium education; Establishment size 50-499; Establishment age 11-20 years; Specialist occupation; Share of routine manual tasks; Agriculture, forestry and fishing; Core cities; Dummy 2012.

Source: BeH, own calculations.

Table A-3: *Goji* and wage growth: Full estimation results

Dependent variables:	GREENNESS 2012 (level) OLS Daily Wage (log, delta 2012-2016)		GREENING 2012-2016 (growth) FE Daily Wage (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
Share of green tasks total $goji_{total}$	-0.002 (-0.04)		0.098** (2.01)	
Share of green core tasks $goji_{core}$		0.070** (2.11)		0.001 (0.01)
Share of green additional tasks $goji_{add}$		-0.079* (-1.95)		0.062 (1.35)
Employment age group 16 - <30 years	-0.111* (-1.90)	-0.121** (-2.11)	0.179 (1.46)	0.181 (1.48)
Employment age group >= 50 years	-0.097 (-1.59)	-0.105* (-1.78)	0.123 (1.24)	0.122 (1.24)
Tenure	0.007*** (3.08)	0.007*** (3.16)	0.005 (0.90)	0.005 (0.91)
Women	-0.059*** (-3.80)	-0.061*** (-3.97)	0.047 (0.27)	0.047 (0.27)
Foreign nationality	0.084 (1.04)	0.073 (0.91)	-0.318** (-2.35)	-0.320** (-2.37)
Low education	-0.022 (-0.30)	-0.013 (-0.17)	-0.223 (-1.32)	-0.220 (-1.31)
High education	0.000 (0.02)	0.000 (0.01)	0.235** (2.41)	0.234** (2.40)
Establishment size 1-49	0.047** (2.17)	0.051** (2.36)	-0.417*** (-4.01)	-0.418*** (-3.99)
Establishment size >500	0.0170 (0.74)	0.021 (0.92)	0.086 (1.34)	0.086 (1.32)
Establishment age 0-10 years	0.129* (1.72)	0.139* (1.92)	-0.066 (-1.20)	-0.065 (-1.18)
Establishment age > 20 years	0.084 (1.54)	0.090* (1.76)	-0.066** (-2.22)	-0.065** (-2.19)
Marginal Employment	0.059 (0.93)	0.053 (0.84)	-0.254 (-1.22)	-0.252 (-1.21)
Part-time work	0.101*** (2.79)	0.103*** (2.84)	0.495*** (3.50)	0.494*** (3.49)
Fixed-term contract	0.012 (0.31)	0.019 (0.54)	-0.152** (-2.12)	-0.154** (-2.15)
Unskilled/semi-skilled occupation	-0.037*** (-3.57)	-0.040*** (-3.70)	N/A	N/A
Complex specialist occupation	-0.008 (-1.02)	-0.007 (-0.95)	N/A	N/A

Dependent variables:	GREENNESS 2012 (level) OLS Daily Wage (log, delta 2012-2016)		GREENING 2012-2016 (growth) FE Daily Wage (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
Highly complex occupation	-0.000 (-0.01)	0.001 (0.07)	N/A	N/A
Tasks complexity (Number of tasks$_{total}$)	0.000 (0.78)	0.000 (0.58)	0.000 (0.83)	0.000 (0.86)
Share of non-routine analytical tasks	0.047** (2.37)	0.047** (2.39)	-0.111 (-0.99)	-0.108 (-0.95)
Share of non-routine interactive tasks	0.082*** (3.65)	0.082*** (3.69)	-0.187** (-2.07)	-0.186** (-2.06)
Share of routine cognitive tasks	0.053*** (3.15)	0.055*** (3.33)	-0.129 (-1.49)	-0.128 (-1.47)
Share of non-routine manual tasks	0.057*** (3.14)	0.057*** (3.15)	-0.013 (-0.32)	-0.014 (-0.37)
Tools complexity (Number of tools$_{total}$)	0.000 (0.14)	0.000 (0.16)	N/A	N/A
$dtox_{IT\text{-}add}$: share of IT-aided digital tools	0.009 (0.30)	0.005 (0.19)	N/A	N/A
$dtox_{IT\text{-}int}$: share of IT-integrated digital tools	-0.027 (-0.35)	-0.021 (-0.28)	N/A	N/A
Mining and quarrying	-0.050 (-1.40)	-0.056 (-1.56)	-0.218 (-0.47)	-0.193 (-0.41)
Manufacturing	-0.077*** (-3.15)	-0.079*** (-3.17)	0.164 (0.52)	0.179 (0.56)
Electricity, gas, steam and air conditioning supply	-0.086** (-2.05)	-0.071* (-1.70)	0.329 (0.85)	0.336 (0.86)
Water supply, sewerage, waste management and remediation activities	-0.032 (-0.99)	-0.055* (-1.69)	0.192 (0.46)	0.201 (0.48)
Construction	-0.105*** (-4.98)	-0.103*** (-4.82)	-0.213 (-0.62)	-0.193 (-0.56)
Wholesale and retail trade, repair of motor vehicles and motorcycles	-0.120*** (-4.85)	-0.122*** (-4.87)	0.048 (0.14)	0.065 (0.19)
Transportation and storage	-0.147*** (-4.58)	-0.146*** (-4.57)	-0.678* (-1.94)	-0.659* (-1.86)
Accommodation and food service activities	-0.047* (-1.82)	-0.045* (-1.78)	0.010 (0.02)	0.0228 (0.04)
Information and communication	-0.146*** (-3.95)	-0.145*** (-3.95)	0.007 (0.02)	0.021 (0.07)
Financial and insurance activities	-0.103*** (-4.10)	-0.103*** (-4.09)	-0.293 (-0.78)	-0.276 (-0.73)
Real estate activities	-0.196*** (-3.69)	-0.187*** (-3.76)	-0.005 (-0.01)	0.02 (0.05)
Professional, scientific and technical activities	-0.117*** (-3.93)	-0.116*** (-3.89)	-0.111 (-0.36)	-0.096 (-0.31)
Administrative and support service activities	-0.119*** (-4.12)	-0.116*** (-4.08)	-0.172 (-0.55)	-0.156 (-0.49)
Public administration & defence, compulsory soc.security	-0.085*** (-3.32)	-0.085*** (-3.35)	-0.587* (-1.75)	-0.577* (-1.70)
Education	-0.111*** (-3.53)	-0.113*** (-3.58)	-0.572 (-1.58)	-0.557 (-1.52)
Human health and social work activities	-0.089*** (-3.09)	-0.090*** (-3.10)	-0.725* (-1.86)	-0.715* (-1.82)
Arts, entertainment and recreation	-0.070** (-2.15)	-0.073** (-2.22)	-1.000** (-2.10)	-0.984** (-2.06)

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
Dependent variables:	OLS Daily Wage (log, delta 2012-2016)		FE Daily Wage (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
Other service activities	-0.049* (-1.72)	-0.049* (-1.70)	-0.625 (-1.55)	-0.622 (-1.54)
Activities of households as employers, undifferentiated goods and services	0.077 (0.32)	0.080 (0.33)	0.116 (0.14)	0.132 (0.16)
Activities of extraterritorial organisations and bodies	-1.177 (-1.45)	-1.155 (-1.43)	-1.583 (-0.70)	-1.555 (-0.69)
Urbanized districts	0.002 (0.05)	0.024 (0.53)	-0.186** (-2.01)	-0.186** (-2.01)
Rural districts with features of concentration	0.012 (0.21)	0.023 (0.40)	0.151 (0.83)	0.152 (0.83)
Rural districts-sparsely populated	0.073 (0.94)	0.061 (0.78)	-0.542*** (-2.81)	-0.541*** (-2.81)
Hamburg	0.172 (0.95)	0.175 (0.97)	-0.426 (-0.94)	-0.428 (-0.95)
Lower Saxony	-0.029 (-0.18)	-0.026 (-0.16)	-0.898** (-2.09)	-0.897** (-2.09)
Bremen	-0.070 (-0.24)	-0.076 (-0.26)	-0.921** (-2.05)	-0.927** (-2.07)
Northrhine-Westphalia	-0.054 (-0.35)	-0.061 (-0.40)	-0.849** (-2.28)	-0.848** (-2.29)
Hesse	0.050 (0.30)	0.041 (0.25)	-0.479 (-1.27)	-0.480 (-1.27)
Rhineland-Palatinate	-0.067 (-0.43)	-0.076 (-0.49)	-0.747** (-2.05)	-0.748** (-2.06)
Baden-Wuerttemberg	-0.059 (-0.39)	-0.075 (-0.50)	-0.572 (-1.50)	-0.575 (-1.51)
Bavaria	-0.018 (-0.12)	-0.029 (-0.20)	-0.676* (-1.84)	-0.679* (-1.85)
Saarland	-0.251 (-0.87)	-0.288 (-1.00)	-0.230 (-0.29)	-0.230 (-0.29)
Berlin	0.416** (2.21)	0.415** (2.22)	-1.425*** (-3.39)	-1.432*** (-3.42)
Brandenburg	-0.113 (-0.61)	-0.131 (-0.72)	-0.565 (-1.19)	-0.560 (-1.18)
Mecklenburg Western Pomerania	-0.279 (-1.26)	-0.267 (-1.20)	-0.824 (-1.27)	-0.816 (-1.26)
Saxony	0.090 (0.56)	0.085 (0.53)	-1.153*** (-3.03)	-1.154*** (-3.04)
Saxony-Anhalt	0.031 (0.15)	0.035 (0.16)	-1.389*** (-2.84)	-1.399*** (-2.87)
Thuringia	-0.281 (-1.50)	-0.261 (-1.40)	-1.196** (-2.23)	-1.201** (-2.24)
Dummy 2013	N/A	N/A	0.019*** (7.57)	0.019*** (7.59)
Dummy 2014	N/A	N/A	0.042*** (10.23)	0.042*** (10.25)
Dummy 2015	N/A	N/A	0.059*** (9.66)	0.059*** (9.67)
Dummy 2016	N/A	N/A	0.057*** (6.99)	0.057*** (7.02)
Constant	0.022 (0.14)	0.019 (0.12)	5.747*** (11.38)	5.733*** (11.28)
N	1137	1137	5702	5702

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
Dependent variables:	OLS Daily Wage (log, delta 2012-2016)		FE Daily Wage (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
R^2	0.473	0.477	0.694	0.694

Note: t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Reference groups: Employee age group: >=30-<50 years; Medium education; Establishment size 50-499; Establishment age 11-20 years; Specialist occupation; Share of routine manual tasks; Agriculture, forestry and fishing; Core cities; Schleswig Holstein; Dummy 2012.

Source: BeH, own calculations.

See also Online Appendix “The greenness-of-jobs index (goji)”