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The greening of jobs in Germany

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

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Content

Abstract

The transition towards a greener, less carbon-intensive economy leads to a growing demand for green products, services and business processes. In theory, this trend should 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). Due to a lack of measures, there is no empirical evidence on the relationship between the greening of jobs and the real labor market development so far. To fill this gap, the 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*). The *goji* is derived by performing text mining algorithms on yearly data from 2006 and 2011 to 2016 of BERUFENET, an occupational 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.

Zusammenfassung

Der Übergang zu einer grüneren, weniger kohlenstoffintensiven Wirtschaft führt zu einer wachsenden Nachfrage nach umweltfreundlichen Produkten, Dienstleistungen und Prozessen. Theoretisch sollte dieser Trend zu einem *Greening of Jobs* führen, d.h. zu einem steigenden Anteil an umweltfreundlichen Tätigkeitsanforderungen innerhalb von Berufen (*Greening of Occupations*) und zu einer steigenden Nachfrage nach Beschäftigten, die diese Berufe ausüben (Greening of Employment). Mangels geeigneter Indikatoren gibt es jedoch bislang keine empirischen Belege für einen Zusammenhang zwischen dem *Greening of Jobs* und der realen Arbeitsmarktentwicklung. Um diese Forschungslücke zu schließen analysiert dieses Papier das *Greening of Jobs* und dessen Wechselbeziehung mit dem Beschäftigungs- und Lohnwachstum. Der Grundstein des Papiers ist der neue *Greenness-of-Jobs Index* (*goji*), der durch Text Mining erschlossen wird. Die Datengrundlage hierfür ist die Online-Datenbank BERUFENET der Bundesagentur für Arbeit. Die deskriptiven Ergebnisse des Papiers zeigen, dass es ein messbares *Greening-of-Jobs* gibt, das zwischen Sektoren und Regionen stark variiert. Die ökonometrische Analyse basiert auf den administrativen Beschäftigtendaten von 2011 bis 2016. Die Ergebnisse der Schätzungen zeigen, dass der Anteil umweltschutzrelevanter Tätigkeitsinhalte (*Greenness*) von Berufen positiv mit deren Beschäftigungswachstum korreliert ist. Darüber hinaus ist das Wachstum dieses Anteils mit einem leichten Anstieg des Lohnwachstums verbunden.

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

Keywords: human capital, occupational tasks, structural change, labor market outcomes, green jobs, text mining

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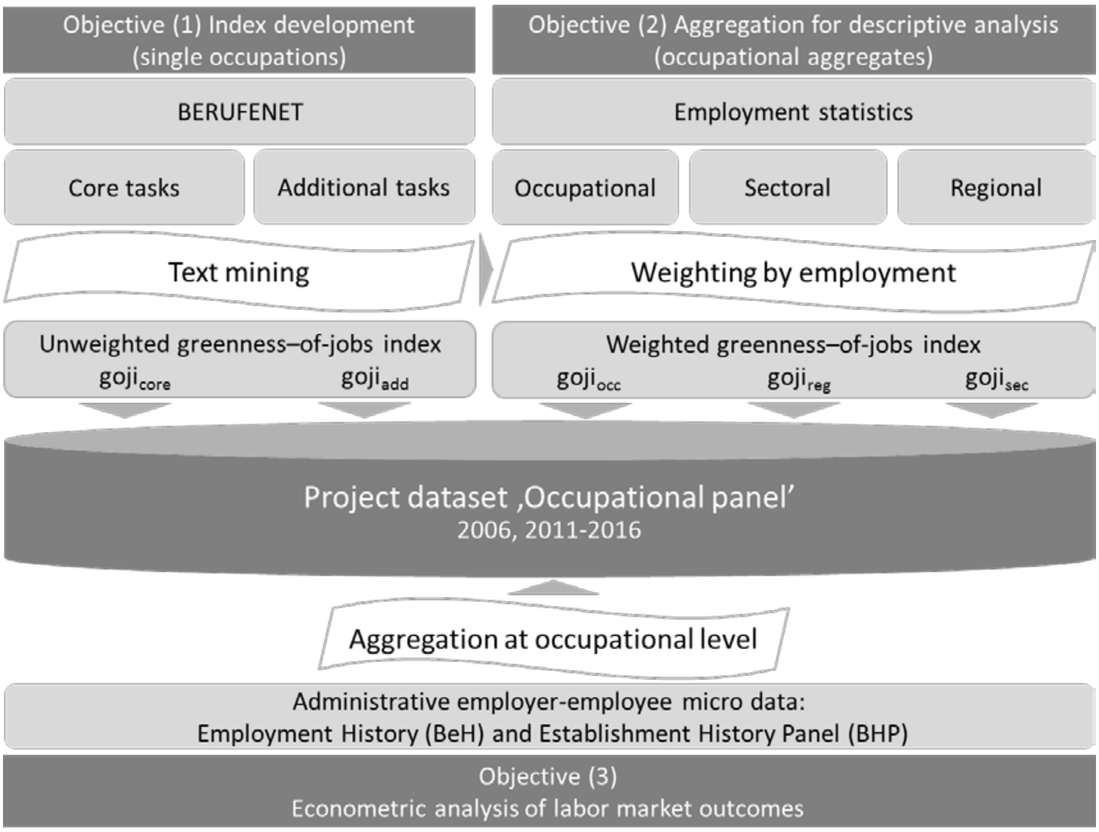
1 Introduction

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.

Whereas some studies have already measured the greenness of occupations (as a static parameter) 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), 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. Figure 1 provides an overview of the research objectives and the associated data sources.

Figure 1
Research objectives and the associated project dataset



Source: own illustration.

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. Janser 2018, Janser/Lehmer 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).

The paper is organized as follows: Section 2 contains an overview of related literature. The different data sources used in this paper are presented in section 3. Section 4 introduces the greenness-of-jobs index (*goji*) and shows the development stages from text mining to the employment-weighted *goji* variations. The occupational, sectoral and regional distribution of greenness and greening is described in section 5. Section 6 covers the econometric analysis of the associations between the greenness / greening of jobs and labor market outcomes. Section 7 concludes with a summary and reflections on possible practical or political implications. An online appendix provides further results of the text mining procedure and further descriptive findings.[1]

2 Literature review

2.1 Definitions and measurement approaches

In both science and public statistics, the topic of green jobs has been discussed widely in recent years. However, there is still no common definition and measurement concept but, instead, several coexisting approaches. The different concepts can be differentiated by output-, process- and occupation-based paradigms.

[1] A selection of csv files with aggregated goji values is available on request from the author.

Output-based approach: identification by goods and services

The most common approaches used so far to define and measure green jobs are related to the goods and services of firms or – at an aggregated level – of sectors. Up to now, there are no theoretical papers with a scientific definition of green jobs. Hence, in accordance to empirical green jobs papers (e.g. Deschenes 2013, Peters 2014, Vona et al. 2015, Consoli et al. 2016) I also refer to the common statistical definitions. According to the international System of Environmental-Economic Accounting, the environmental goods and services sector (EGSS) *"… consists of a heterogeneous set of enterprises which produce environmental goods and services. Historically, the production of environmental goods and services focused on the demand for basic services, such as wastewater treatment and the collection of solid waste. However, with the drive towards cleaner and more resource-efficient processes, products and materials, the activities of the sector have expanded to also include resource management activities." (UN et al. 2017: 25 in connection with UN et al. 2014).* This conception is in line with the EGSS as defined by Eurostat (2016: 8): The EGSS "*… comprises all entities in their capacity as 'environmental producers', i.e., undertaking the economic activities that result in products for environmental protection and resource management. Producers in the EGSS may or may not be specialised in the production of environmental goods and services, and may produce them as principal or secondary activities or produce these products for own use."* As already mentioned in the Eurostat definition, the main problem of the output-oriented approach is that many firms do not produce or deliver only environmental goods and services. They often follow a multi-purpose strategy (e.g. technical facilities like pump systems that can be applied both in biogas plants and in coal-fired power plants). Here the core question is: Where exactly should the line be drawn between environmental and non-environmental firms, or between environmental and non-environmental employment? It is also difficult to identify the environmental share of employment, as many employees are not only involved in the production of environmental goods and services but also perform work for non-environmental goods and services (in the case of multi-purpose firms). Moreover, the environmental impact of products and services may differ. Nevertheless, most publications identify labor market outcomes of the greening of the economy based on environmental goods and services (see also US DOL/BLS 2013b, US DOC 2010, and OECD/Cedefop 2014). Most research papers also use output-oriented identification strategies. For instance, Antoni et al. (2015) use the membership data of renewable-energy business associations to identify firms that are active in renewable-energy value chains. They regard all workers in those firms as renewable-energy workers. Also Lehr et al. (2012), Hillebrand et al. (2006) and others focus on firms related to renewable energies. Becker/Shadbegian (2009) analyze a broader group of firms, namely manufacturers of environmental products, and measure employment in terms of total employment. Horbach/Janser (2016) and Rennings/Zwick (2002) analyze employment in the entire environmental goods and services sector. Horbach/Janser (2016) identify green employment by equating the turnover in the field of green goods and services with the share of employees involved in the production of green goods and services. This approach helps to tackle the issue of multi-purpose firms, but still neglects a large part of integrated environmental protection.

Adding the process perspective

Using a process-based approach, it is possible to look beyond this limited goods and services perspective. Process-based perspectives focus on integrated environmental protection and the application of clean technologies and other environmentally friendly practices of business processes within firms. This approach is not regarded as an alternative approach but rather as an additional dimension sometimes included in definitions of green jobs. For example, an extended definition of green jobs has been developed by the Bureau of Labor Statistics of the U.S. Department of Labor (BLS/DOL 2013a). Their definition involves the basic distinction between output and process. Whereas the output-related approach covers the green goods and services, the process approach *"… identifies establishments that use environmentally friendly production processes and practices …"* (Sommers 2013: 5). Also Deschenes (2013) uses a mixed approach for his overview about green jobs. Based on the SEEA definition of environmental goods and services, the International Labour Organization (ILO) also emphasizes in their definition of employment in environmental activities the difference between employment in the production of environmental outputs and employment in environmental processes (ILO 2013a, 2013b, 2013c, 2015). The ILO introduces an even tighter definition of green jobs by adding a decent work dimension to the environmental dimension (ILO 2013a, 2013b, 2013c, 2015). In the sense of the ILO definition, green jobs include only employment in environmental activities that fulfill the conditions of decent work (decent work indicators according to ILO 2012). Because the issues of measuring decent work would go beyond the scope of this paper, I do not cover this aspect of green jobs here. However, the connection between green jobs and decent jobs remains a worthwhile issue for future research.

Task-based approaches: identification by occupational tasks

Peters (2014), Consoli et al. (2016) and Vona et al. (2015) were the first to apply the task-based approach to identify the greenness of jobs. They work with US-American data from the occupational database O*NET. Acemoglu/Autor (2011: 1045) define a *task as "… a unit of work activity that produces output (goods and services)."* Tasks have to be clearly distinguished from skills. According to Acemoglu/Autor (2011: 1045), a skill is *"… a worker's endowment of capabilities for performing various tasks. Workers apply their skill endowments to tasks in exchange for wages, and skills applied to tasks produce output*." Hence, both worker skills and job tasks can change over time and may be reallocated if skills and/or tasks change within the working context. In the remainder of this paper I use a task-based approach to identify the greenness of jobs in Germany. It is important to note that this paper focuses on the demand side of labor and thus on tasks rather than skills.

Dierdorff et al. (2009: 4), who work with US-American O*NET data, refer to the greening of occupations as *"… the extent to which green economy activities and technolo-*

gies increase the demand for existing occupations, shape the work and worker requirements needed for occupational performance, or generate unique work and worker requirements". They distinguish between the following types of greening occupations: (1) Green Increased Demand Occupations*:* the greening of the economy causes increasing demand for existing occupations without significant changes in occupational requirements, (2) Green Enhanced Skills Occupations: greening of the economy leads to significant changes in the occupational requirements of existing occupations – and may or may not lead to increasing labor demand, and (3) Green New and Emerging Occupations: greening of the economy triggers the need for new occupations. Both Green Enhanced Skills Occupations and Green New and Emerging Occupations can be identified by analyzing occupational contents, such as job requirements. The European Centre for the Development of Vocational Training has adopted this concept to a large extent (Cedefop 2012).

Similarly to the multi-purpose firms mentioned above, multi-purpose occupations are also a challenge for occupational concepts: most occupations do not include green tasks only. Instead, they include a certain share of environmental protection requirements as well as non-green tasks. Only a few scientific papers analyze in detail the extent of greenness of jobs (e.g. Peters 2016, Consoli et al 2016, Vona et al. 2015, 2017), whereas almost all the studies on the greenness of jobs look at the US labor market. The focus and main contribution of the paper in hand is to demonstrate a text mining approach to identify *Green Enhanced Skills Occupations* in Germany*,* to measure – for the first time – the related changes in occupational requirements over time and to analyze their impacts on employment growth*.*

2.2 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[2]. 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).[3]

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.[4]

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 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 that the proportion of green employment is between two and three percent and that

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2 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).

3 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.

4 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)

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.

2.3 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.

Considering the determinants of labor demand, I start with a standard production function. According to this function, initially formulated by Cobb/Douglas (1928), the labor market outcomes of labor demand and wages can be derived as follows:

$$Y = A * L^{a} * K^{(1-a)} \tag{2.1}$$

where Y is the output of production, A is the total factor productivity (i.e. the real output per unit of input), L is the measure of the flow of labor input, K is the measure of the flow of capital input, a is the output elasticity of labor (0 < a < 1).

In competitive equilibrium, production factors are paid according to the value of their marginal product. According to this assumption, the real wage (w) is equal to the marginal product of labor (MPL).

$$w \equiv MPL = \frac{dY}{dL} = a * A * L^{(a-1)} * K^{(1-a)} \tag{2.2}$$

After dissolving the equation to L, the labor demand function is

$$L = (a * A)^{-(1-a)} * K * w^{-1/(1-a)} \tag{2.3}$$

In addition, several economic papers (e.g. Neisser 1942, Appelbaum/Schettkat 1995, Möller 2001, Combes et al. 2004, Blien/Sanner 2004) emphasize the important role of demand elasticities in the production function: based on the studies mentioned before, Blien/Ludewig (2017) show that technological progress leads to an increase in employment when product demand is elastic. However, it is accompanied by a decline in employment if product demand is inelastic. So far, no demand elasticity data are available to support the econometric analysis of this paper with demand elasticities. As soon as detailed data on demand elasticities become available this might be a promising starting point for future research. Nevertheless, the decisive role of demand elasticities will be useful for interpreting the empirical results of this paper. Horbach et al. (2009) have already benefited from this opportunity by using the concept of demand elasticities to explain the partial decline in the environmental goods and services sector. Using data from the IAB Establishment Panel, they show a strong decline in employment in the environmental sub-sectors dominated by end-of-pipe technologies, which are at a stage in their product life cycle that is characterized by a low elasticity. On the other hand, their study also reveals positive employment trends and expectations for cleaner technologies, which – at least at the time of the study – were characterized by a high demand elasticity. According to their findings a similar result should be expected for the econometric analysis at the end of this paper. Smulders and Withagen (2012) also demonstrate how green growth can be integrated into dynamic general equilibrium models. They find that green growth is feasible if there is a good substitution, a clean backstop technology, a low proportion of natural resources in the gross domestic product or green directed technical change.

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 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. 2017 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 section 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.

As mentioned above, 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. All of these data sources are described in the remainder of this section.

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 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

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

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 achieve this goal, I use a text mining approach which is presented in the next section. Before moving on to this stage, I will briefly introduce the other data sources used for this project.

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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).

3.2 Statistical data to aggregate 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). Table A-1 illustrates the *goji* aggregation levels resulting from this procedure. Some of them are presented in the remainder of this paper.[8]

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

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[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.

[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).

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*)

4.1 Identification of green tasks by text mining

The source used for the semantic analysis of the present paper is the so-called 'requirements catalogue' of BERUFENET, which contains yearly text information about the three requirements dimensions mentioned above. For example, the requirements catalogue of 2014 contains 14,546 words, which are subjected to computational content analysis. This analysis is based on lexicometrics with a focus on frequency analysis and key term extraction (Wiedemann 2016). I apply a deductive approach (Ignatow/Mihalcea 2016) combining qualitative and quantitative content analysis. The aim of this step is to extract key terms associated with typical areas of activities, products and services in the green economy from national and international studies. Due to the explorative nature of this early stage I use qualitative content analysis methods (see Mayring 2014). After an extensive literature review[10], I created a 'green tasks dictionary' in the sense of a controlled list of relevant words. This dictionary is the basis of the quantitative content analysis of the BERUFENET data.

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 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.

The decisive criterion in this context is the explicitly *environmentally friendly* specific task content. It was necessary to choose this rigid 'explicit' approach to avoid the definition of 'green' becoming a matter of subjective decision. Either the process of production or the products and services included in the title of the specific tasks can

[10] The list of studies taken into account is documented in the Online Appendix 1 'Text Mining'

be used as an indicator for green tasks. Environmentally friendly covers all products and actions that actively foster the ecologically sustainable development goals of *green economy* principles. There are many different definitions of a green economy. I have adopted the definition of Dierdorff et al. (2009: 3) and extended it to include further green economy aspects which were stressed in literature (see literature review): the *green economy* comprises all economic activities 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. To distinguish between green tasks and green skills, I adapt the general skills definition by Acemoglu/Autor (2011): *green skills* are a worker's endowment with capabilities for performing various green tasks. Workers apply their green skill endowments to green tasks in exchange for wages, and green skills applied to green tasks produce output. The output need not necessarily be explicitly environmentally friendly. In the remainder of this paper, I focuses on green tasks to pursue my research objectives.

In accordance with the extended definition of green tasks, I worked with different thesauri[11] in order to define a basic set of keywords, which I extended using the literature review. The goal was to obtain a list with a wide range of different topics but a focus on the most relevant keywords. This strategy was adopted to avoid a too broad range of matches that might lead to less plausible results. Additionally, I aggregated words with the same root by reducing the words to their word stem ('stemming'). At the end of this process, I had obtained a **'green tasks dictionary'** by collecting the most frequently used key words in a structured list. Furthermore, I grouped the dictionary words by categories of keywords (see Table 1). This allocation to categories was derived from the main topic areas of the green economy literature. Each keyword was allocated to only one category (the one with the most frequent references).

[11] I use the German and English versions of the multilingual thesaurus of the European Union: http://eurovoc.europa.eu/drupal/?q=download/subject_oriented (e.g. parts from Subject 52 Environment, 66 Energy) as well as open content sources of http://www.openthesaurus.de and https://de.wiktionary.org/.

Table 1
List of keyword categories

	Category of Keywords	Category Code	Number of keywords
1	Energy production & storage	EN	19
2	Mobility & tourism	MOB	34
3	Building	BUILD	21
4	Farming, forestry, food, consumer goods	FFFC	19
5	Energy efficiency & further climate protection	CP	10
6	Emission protection (air, water, soil, noise)	EP	27
7	Circular economy, (raw) material efficiency & waste management	CE	13
8	Environmental protection (general)	EPGEN	10
	Total number of green tasks keywords	GT	153

Source: BERUFENET, own calculations.

On the basis of the green tasks dictionary I used the method of regular expressions to identify those job requirements in BERUFENET that contain key words from the dictionary. Those requirements were coded as ‘green tasks’. For the computational content analysis and automatic coding I used textmining packages of the statistical software R. The subject of the semi-automatic coding was job requirements in the requirements catalog generated from BERUFENET. The coding led to one class of ‘green tasks’ codes, comprising nine sub-codes for the main topic areas of the green economy introduced in the green tasks dictionary. I applied this process for the year 2006 and for 2011 to 2016. The results of the frequency analysis after the coding procedure are presented in section 5 (*'Descriptive analysis'*).

4.2 From green tasks to the employment weighted greenness-of-jobs index *goji*

Unweighted greenness-of-jobs index

To measure the share of environment-related requirements (‘green tasks’) involved in a specific occupation, I develop a greenness-of-jobs index (*goji*). The index exploits the information provided in BERUFENET’s ‘requirements’ section to shed light on the state and development of the greenness of occupations. Rather than simply distinguishing between green (‘1’) and non-green (‘0’), *goji* facilitates analyses of occupations within a huge range of different ‘shades of green’.

The basis of *goji* is a ‘*green tasks-occupations matrix’* to allocate the number of green tasks to each individual occupation. The matrix is grouped by two requirement dimensions of core and additional requirements. To use the total number of (both green and non-green) requirements as the denominator, I expand the matrix to include the total count of requirements per individual occupation, which is also grouped by core and additional requirements. Occupations with a higher requirements level usually contain a larger number of requirements and thus have a higher probability of containing more green tasks than occupations with lower requirements. To avoid this bias the relative greenness-of-jobs index (*goji*) always reports the number of green requirements as a proportion of the total number of requirements.

By means of the *green tasks-occupations matrices* for 2006 and 2011 to 2016, I calculate the greenness of occupations for each year. To calculate the shares per year, I apply a similar approach to that used by Consoli et al. (2016). However, their approach works only with cross-sectional data. Furthermore, it does not include the division into core and additional requirements or identify green tasks by themselves. They instead use the O*NET information of 'green task', which is not available for the German occupational classification system. Hence, I have to adapt the models and develop additional approaches due to the different data sources and the structure of BERUFENET:

$$\boldsymbol{goji}_{core_{occ8d,t}} = \frac{\sum \boldsymbol{gr\_core}_{occ8d,t}}{\sum \boldsymbol{r\_core}_{occ8d,t}}$$

where

$\boldsymbol{goji}_{core_{occ8d,t}}$	is the 'green core tasks index' *(0…1)* of occupation *occ8d* (8-digit level). Occupation *occ8d* is based on the index system of BERUFENET. This index is called the "occupational code number" (Berufskennziffer - BKZ).
$\sum \boldsymbol{gr\_core}_{occ8d,t}$	is the number of green core requirements for occupation *occ8d* (8-digit level) in year *t*
$\sum \boldsymbol{r\_core}_{occ8d,t}$	is the number of all core requirements for occupation *occ8d* (8-digit level) in year *t*

The $\boldsymbol{goji}_{core}$ 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 $\boldsymbol{goji}_{add}$ describes the proportion of green additional tasks in the total sum of additional requirements for occupation *occ8d (8-digit level)* in year *t*:

$$\boldsymbol{goji}_{add_{occ8d,t}} = \frac{\sum \boldsymbol{gr\_add}_{occ8d,t}}{\sum \boldsymbol{r\_add}_{occ8d,t}}$$

where

$goji_{add_{occ8d,t}}$	is the 'green additional tasks index' *(0…1)* of occupation *occ8d* (8-digit level).
$\sum gr\_add_{occ8d,t}$	is the number of green additional requirements for occupation *occ8d* (8-digit level) in year *t*
$\sum r\_add_{occ8d,t}$	is the number of all 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 $\boldsymbol{goji_{total}}$ 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*.

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

where

$goji_{total_{occ8d,t}}$	is the unweighted 'green total index' *(0…1)* of occupation *occ8d (8-digit level).*
$\sum gr\_core_{occ8d,t}$	is the number of green core requirements for occupation *occ8d (8-digit level)* in year *t*
$\sum r\_core_{occ8d,t}$	is the number of all core requirements for occupation *occ8d (8-digit level)* in year *t*
$\sum gr\_add_{occ8d,t}$	is the number of green additional requirements for occupation *occ8d (8-digit level)* in year *t*
$\sum r\_add_{occ8d,t}$	is the number of all additional requirements for occupation *occ8d (8-digit level)* in year *t*

The $goji_{total}$ is based on the assumption that the requirements are equally distributed in terms of working time on average. An alternative assumption might be that the core requirements take up a larger part of the working time than the additional requirements. For this reason, I also introduce and test a weighted index $\boldsymbol{goji_{wtotal}}$ that takes this assumption into account. As the time component of core requirements should theoretically be larger than that of additional requirements, I choose a weight of 2/3 for core requirements and 1/3 for additional requirements.

$$\boldsymbol{goji}_{\boldsymbol{wtotal}_{\boldsymbol{occ8d,t}}} = \boldsymbol{w}_{\boldsymbol{core}} \frac{\sum \boldsymbol{gr\_core}_{\boldsymbol{occ8d,t}}}{\sum \boldsymbol{r\_core}_{\boldsymbol{occ8d,t}}} + \boldsymbol{w}_{\boldsymbol{add}} \frac{\sum \boldsymbol{gr\_add}_{\boldsymbol{occ8d,t}}}{\sum \boldsymbol{r\_add}_{\boldsymbol{occ8d,t}}}$$

where

$\boldsymbol{goji}_{\boldsymbol{wtotal}_{\boldsymbol{occ8d,t}}}$	is the weighted 'green total index' *(0…1)* of occupation *occ8d (8-digit level).*
$\boldsymbol{w}_{\boldsymbol{core}}$; $\boldsymbol{w}_{\boldsymbol{add}}$	are the weights for the specific requirement types 'core requirements' and 'additional requirements'. The weights are defined as follows: $\boldsymbol{w}_{\boldsymbol{core}}$ **: 2/3,** $\boldsymbol{w}_{\boldsymbol{add}}$ **: 1/3**
Other variables:	See above.

Using the example of the occupation *chimney sweep*[12], Table 2 illustrates the calculation of the *goji* values. This occupation has five core requirements and sixteen additional requirements. The codes of text mining include the associated category of green tasks keywords.

[12] Occupational title in German: Schornsteinfeger. Administrative identifiers: 42212100 (KldB2010 8-digit level) / 8211 (BKZ). Source: https://berufenet.arbeitsagentur.de/berufenet/faces/index?path=null/suchergebnisse/kurzbeschreibung/berufkompetenzen&dkz=8211 .

Table 2
Example of (unweighted) greenness of jobs index: Occupation 'chimney sweep' (c.s.) 2016

Requirements	Codes (after text mining)	Elements of greenness-of-jobs index (goji)		
Core requirements (N_{core}=5)		$gr\_core_{c.s.2016}$	$r\_core_{c.s.2016}$	$goji_{core_{c.s.2016}}$
Fire safety			1	
Emission/Immis. control	green (gt03_APM)	1	1	
Fireplace inspection			1	
Customer advisory service, customer care			1	
Measurement			1	
		1	5	0.200
Additional requirements (N_{add}=16)		$gr\_add_{c.s.2016}$	$r\_add_{c.s.2016}$	$goji_{add_{c.s.2016}}$
Energy consulting	green (gt02_EEFF)	1	1	
Energy saving order (EnEV)	green (gt02_EEFF)	1	1	
Energy savings technology	green (gt02_EEFF)	1	1	
Heating and chimney construction			1	
Gas firings			1	
Danger defense (prevention)			1	
Heating technology			1	
Tiled stove construction			1	
Chimney stoves			1	
Sweep			1	
Ventilation systems	green (gt02_EEFF)	1	1	
Ventilation technology	green (gt02_EEFF)	1	1	
Oil heatings			1	
Pellet heating systems, woodchip heating systems	green (gt01_EPES)	1	1	
Environmental law	green (gt09_ECP)	1	1	
Environment protection, env. technology	green (gt09_ECP)	1	1	
		8	16	0.500
$\boldsymbol{goji_{total_{c.s.2016}}} = \dfrac{\sum \boldsymbol{gr\_core_{c.s.2016}} + \sum \boldsymbol{gr\_add_{c.s.2016}}}{\sum \boldsymbol{r\_core_{c.s.2016}} + \sum \boldsymbol{r\_add_{c.s.2016}}}$		$gr\_total_{c.s.2016}$ 9	$r\_total_{c.s.2016}$ 21	$goji_{total_{c.s.2016}}$ 0.429
$\boldsymbol{goji_{wtotal_{c.s2016}}} = \dfrac{2}{3} * \boldsymbol{goji_{core_{c.s.2016}}} + \dfrac{1}{3} * \boldsymbol{goji_{add_{c.s.2016}}}$				$goji_{wtotal_{c.s.20}}$ 0.300

Source: BERUFENET, own calculations

Employment-weighted greenness-of-jobs index $goji_x$ at aggregated occupational level

a) Occupational aggregation from 8-digit level to 5-digit level

Both administrative employment data and statistical employment data are only available at higher aggregated levels, beginning with the 5-digit level of KldB2010. For example, the BeH includes information on the last occupation of every employee at the 5-digit level of the KldB2010, but not at the 8-digit level. So far, the *goji* is only based on the individual occupation level (BKZ-/'8-digit-level' of KldB2010). To achieve the goal of this paper – analyzing employment impacts of the greening of jobs – it is necessary to link employment data with the *goji*. Therefore, $\boldsymbol{goji_{o(bkz)}}$ has to be aggregated to the next level, which is the 5-digit level of the German classification of occupations (Klassifikation der Berufe 2010 – KldB2010). To transform $\boldsymbol{goji_{occ(8-digit)}}$ into $\boldsymbol{goji_{occ(\geq 5-digit)}}$, I use a procedure similar to that used by Dengler et al. (2014): the greenness index 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.

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

A weakness of this procedure is caused by a structural difference between occupational data and employment data. As Dengler et al. (2014) point out, the general problem with aggregating occupational data from the 8-digit to the 5-digit-level is that there is no information available about how many people are employed in individual occupations at the 8-digit-level. This information is only available at the 5-digit level. Thus the employment share of every 8-digit level occupation in a 5-digit level aggregate has to be estimated. The assumption of this approach is that the number of employees in individual occupations is equally distributed. This might lead to some bias in the remaining steps. As there is no pattern to explain which 5-digit occupations comprise more individual occupations and which comprise less, I assume that the bias is randomly distributed and averages out in total. The same applies to the aggregation of the *goji.* If employment data were available at the 8-digit level this would be a natural basis for a weighting scheme. As this is not the case, I again apply the approach used by Dengler et al. (2014) and divide the total sum of the *goji* within each 5-digit level occupation by the number of individual occupations within the 5-digit occupational type. Taking the occupational group of '*Occupations in renewable energy technology - complex tasks*' as an example, Table 3 illustrates how this aggregation procedure is implemented in the *goji* data.

Table 3
Aggregation to occupational-type-level (KldB 2010, from 8- to 5-digit level): Example of 'Occupations in renewable energy technology - complex tasks' 2014

Individual Occupation 8-digit level of KldB 2010 (ID + Title)	Occupational type 5-digit level of KldB 2010 (ID + Title)	Number of employees 5-digit level	Number of employees 8-digit level	$goji_{core}$ 8-digit level	$goji_{core}$ 5-digit level (aggregate)
26243-100 Solar technician	26243 Occupations in renewable energy tech. - complex tasks	2,671	Equal distribution assump-tion: 2,671:3= 890.33	0.200	(0.200+ 0.100+ 0.333) : 3 = 0.211
26243-101 Wind energy technician				0.100	
26243-108 Specialist solar tech.				0.333	

Source: BERUFENET, employment statistics of the Federal Employment Agency, own calculations.

In the example of '*chimney sweep*' the aggregation to the 5-digit level is less challenging, because the 5-digit level of this occupation covers only one single occupation (here: # 42212 of KldB2010).

b) Occupational aggregation from 5-digit level to higher aggregated levels

The following step uses the employment data at the 5-digit level as starting point for the weighting. Employment weights $\boldsymbol{w}$ are based on the number of employees of occupational type *occ5d (5-digit level of KldB2010)* as a proportion of the total number of employees working in the X*d* digit-level of the KldB 2010 occupational classification:

$$\boldsymbol{w_{occ5dtoXd,t}} = \frac{\boldsymbol{emp_{occ5d\,\in d\,,t}}}{\sum \boldsymbol{emp_{occ5d\,\in Xd,t}}}$$

where $\boldsymbol{emp_{occ5d\,\in d\,,t}}$ is the number of employees in the individual 5-digit group within the x-digit group and $\sum \boldsymbol{emp_{occ5d\,\in Xd,t}}$ is the sum of employees (5-digit group) within the x-digit. In the next step, the products of weights and *goji* are added and lead to the *goji* at x-digit level (employment-weighted):

Goji at aggregated occupational levels (employment-weighted at X d(igit) level of KldB2010)

$$\boldsymbol{goji_{core,add,(w)total_{occXd,t}}} = \sum_{\boldsymbol{occ5d \in Xd=1}}^{\boldsymbol{n}} \boldsymbol{w_{occ5dtoXd,t}} * \boldsymbol{goji_{core,add,(w)total_{occ5d,t}}}$$

The example of 'chimney sweep' demonstrates the weighting by employment (Table 4).

Table 4
Aggregation from 8digit to 5digit level: Example of goji weighted by employment: Occupation 'chimney sweep'

Example of	Index	Operation	Result
Weight	$\boldsymbol{w_{\#42212to\#422,2014}}$	$\frac{\boldsymbol{emp_{\#42212\,,2014}}}{\sum \boldsymbol{emp_{occ5d\,\in\#422d,2014}}} = \frac{\boldsymbol{6525}}{\boldsymbol{13959}} =$	$= \boldsymbol{0.467}$
Greenness of jobs index (*goji*) (here: aggregation to 3-digit-level)	$\boldsymbol{goji_{core_{\#422,2014}}}$	$\sum_{\boldsymbol{\#42202}}^{\boldsymbol{\#42293}} \boldsymbol{w_{occ5dto3d,2014}} * \boldsymbol{goji_{core_{occ5d,2014}}}$ = 0.365*0.074+0.258*0.154+0.25*0.215+**0.200*0.467**+0.384*0.013+0.100*0.077= ⇩ = 0.0269 + 0.040 + 0.054 + **0.093** + 0.005 + 0.008 =	$= \boldsymbol{0.226}$

Note: As an example, I use the occupation 'chimney sweep'. This occupation has the classification number 42212 (5-digit level) and 433 (3-digit level), respectively. The title of the 3-digit level is 'Occupations in environmental protection engineering'.

Source: BERUFENET, employment statistics of the Federal Employment Agency, own calculations."

Conversion of goji from occupational 5-digit level to sectoral and regional level

The aggregations of occupational and employment data from the 5-digit level to higher aggregated levels (e.g. from 5-digit to 3-digit level) is also applicable in analogy for calculating the sectoral and regional distribution of employees with green occupations. I also use the employment data at the five-digit level as the base for the weight.

Weights $\boldsymbol{w}$ are based on the employees of occupational type occ5d (5-digit level of KldB2010) as a proportion of the total number of employees working in industry WZ-x or region NUTS-x.

Calculation of weight 'employment share of occupational type occ5d in industry WZx in year t':

$$w_{occ5dtoWZx,t} = \frac{\boldsymbol{emp}_{occ5d \in WZx,t}}{\sum \boldsymbol{emp}_{occ5d \in WZx,t}}$$

where $\boldsymbol{emp}_{occ5d \in WZx,t}$ is the number of employees of the specific occupational type (5-digit group) $\boldsymbol{occ5d}$ within the WZ-x industry in year t and $\sum \boldsymbol{emp}_{occ5d \in WZx,t}$ is the sum of employees of all occupational types (5-digit group) within the WZ-x industry.

The weight is now applied to the corresponding goji:

Greenness-of-jobs index at sectoral level (employment-weighted WZ-x level)

$$\boldsymbol{goji}_{core,add,(w)total_{WZx,t}} = \sum_{occ5d \in WZx=1}^{n} w_{occ5dtoWZx,t} * \boldsymbol{goji}_{core,add,(w)total_{occ5d,t}}$$

Calculation of weight 'employment share of occupational type occ5d in region NUTSx in year t:

$$w_{occ5dtoNUTSx,t} = \frac{\boldsymbol{emp}_{occ5d \in NUTSx,t}}{\sum \boldsymbol{emp}_{occ5d \in NUTSx,t}}$$

where $\boldsymbol{emp}_{occ5d \in NUTSx,t}$ is the number of employees of the specific occupational type $occ5d$ (5-digit group) within the NUTS-x region in year t and $\sum \boldsymbol{emp}_{occ5d \in NUTSx,t}$ is the sum of employees of all occupational types $occ5d$ (5-digit group) within the NUTS-x region. The weight is now applied to the corresponding goji:

Greenness-of-jobs index at regional level (employment-weighted NUTS-x level)

$$\boldsymbol{goji}_{core,add,(w)total_{NUTSx,t}} = \sum_{occ5d \in NUTSx=1}^{n} w_{occ5dtoNUTSx,t} * \boldsymbol{goji}_{core,add,(w)total_{occ5d,t}}$$

5 Descriptive analysis

This section provides unique descriptive evidence about the greenness and greening of jobs along all dimensions of the research objectives: it contains information about the prevalence of green tasks in the BERUFENET and about the greenness and greening of occupations at the level of individual occupations to describe both the input and output of measuring the greenness of occupations. Furthermore, the section presents the occupational, sectoral and regional distribution of the greenness and greening of jobs. The section ends with details about the sample prepared for econometric analysis, including information about sample size and sample means.

5.1 The greenness-of-jobs index at individual occupation level

Green tasks – the main components for measuring the greenness of jobs

As mentioned above, measuring the greenness of jobs starts with applying text mining procedures to the BERUEFENET data. Including both core and additional requirements, the yearly occupations-requirements matrices from the BERUFENET result in the following quantity structure (see Table 5):

Table 5
Quantity structure of occupations-requirements matrices derived from BERUFENET

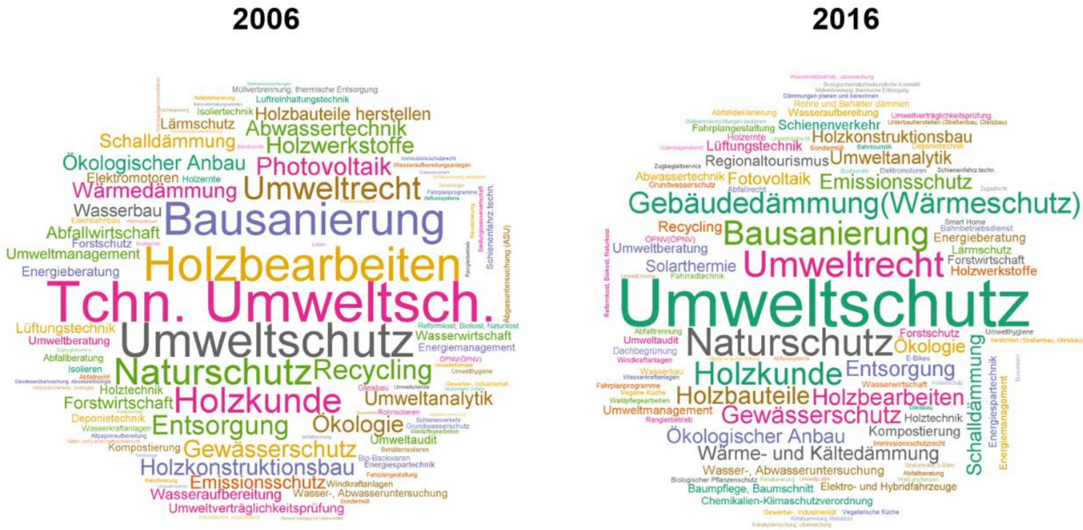
Year / Occ.classif.	Number of indiv. occupations	Number of requirements('tasks')	Cells of n:n occupations-requirements matrices
2006 KldB1988	6,423	5,724	36.8M
2012 KldB2010	3,926	6,670	26.2M
2013	3,952	6,709	26.5M
2014	3,961	6,745	26.7M
2015	3,953	6,819	27.0M
2016	4,251	7,325	31.1M
∆ 2012-2016	325	655	5.0M
as %	8.3%	9.8%	18.9%

Note: The decrease in the number of occupations between 2006 and 2011 is a technical effect due to the change in the occ. classification from KldB1988 to KldB2010. Therefore the total numbers of occupations in 2006 and 2011 et seq. cannot be compared, although the total number of requirements is still comparable.

Sources: BERUFENET, Classifications: KldB2010 (2011-2016) and KldB1988 (2006), own calculations.

Table 5 reveals a considerable increase in the number of occupations and requirements between 2012 and 2016: the number of individual occupations rose by 8.3 percent and the number of requirements by 9.8 percent. The resulting n:n-matrix, with about 26.2 to 36.8 million cells per year, is the basis for the text mining and the calculation of the greenness-of-jobs index. The content and relative frequency of the green tasks keywords identified by text mining procedures can be visualized by word clouds. For example, Figure 2 illustrates the changes between 2006 and 2016 in terms of the relative frequencies of the green tasks keywords weighted by their appearance in the requirements section of the BERUFENET. The size of the terms represents their weighted frequency, i.e. the larger the word the higher the frequency. The key words are presented in the original German language.

Figure 2
Word cloud of the relative frequency of green tasks weighted by their appearance in the BERUFENET requirements 2006 and 2016



Source: BERUFENET, own calculations.

The comparison of 2006 and 2016 in Figure 2 shows that there are changes in terms of the quantity and content of green tasks. The most obvious transition takes place in terms of 'technical environmental protection' (In German: 'Technischer Umweltschutz' / Abbreviation: 'Tchn. Umweltsch.'). This concept has been replaced entirely either by the more general term of 'environmental protection' (In German: 'Umweltschutz') or by more specific key terms. This might also represent the decreasing relevance of end-of-pipe technologies which used to be more strongly – but not solely – associated with technical environmental protection. As Horbach et al. (2009) report, end-of-pipe technologies have lost significance in contrast to integrated environmental protection. Other keywords exhibit increased frequencies of occurrence, for example 'building insulation (heat insulation)' (In German: 'Gebäudedämmung (Wärmeschutz)'), which might have been triggered by the more stringent requirements of the Energy Saving Ordinance (Energieeinsparverordnung, EnEV) and other regulations covered by the German CO_2 Building Modernization Program (In German: 'Gebäudesanierungsprogramm', for further details see Kuckshinrichs et al. 2010 and Rosenow 2012). Sometimes just the spelling was changed, such as in the case of photovoltaics (from 'Photovoltaik' to 'Fotovoltaik'), which shows the importance of fuzzy logic features of the text mining algorithm. In 2016, we also see genuine new terms, such as 'electric and hybrid vehicles' (In German: 'Elekro- und Hybridfahrzeuge') or 'smart home': these two examples refer to new technological trends in the fields of mobility and energy efficiency in buildings. For further information, the online appendix 'Text Mining' also includes the complete time series of word clouds from 2006 and 2012 to 2016 (Figure OA-TM-1) as well as word clouds from 2016 grouped by each of the keyword categories (Figure OA-TM-2). Table 6 contains the results of the frequency analysis after the semi-automatic coding, showing especially how many BERUFENET requirements are identified as 'green' and how many occupations contain those green tasks.

Table 6
Frequency table of matches from keywords to green tasks and occupations, 2012/ 2016

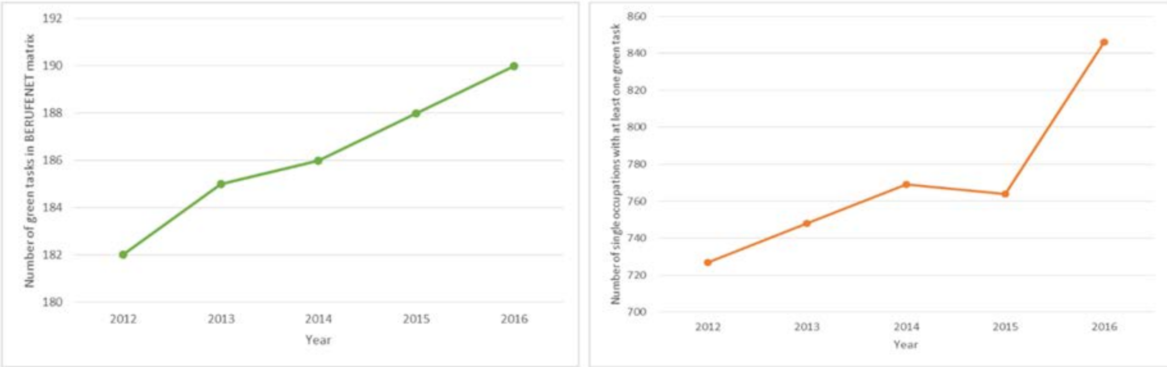
Green tasks category	Number of keywords	1st step: Keyword-requirements matches		2nd step: Green tasks-occupations matches	
		2012	2016	2012	2016
Energy production & storage	20	14	15	58	71
Mobility & tourism	34	50	53	106	131
Building	21	19	21	268	295
Farming, forestry, food, consumer goods	19	15	16	91	107
Energy efficiency & further climate protection	9	10	11	42	75
Emission protection (air, water, soil, noise)	27	26	26	146	168
Circular economy, (raw) material efficiency & waste management	13	24	24	87	92
Environmental protection (gen.)	10	25	25	256	306
Green tasks (total)	153	**182**	**190**	**727**	**846**
Share of total number of requirements		2.7%	2.6%	18.5%	19.9%
Note: Total number of …		… requirements		… indiv. occupations	
		6,670	7,325	3,926	4,251

Source: BERUFENET, own calculations.

According to Table 6, 190 requirements were environment-related ('green tasks') in 2016. This represents 2.6 percent of all the requirements in BERUFENET. In that year, the 190 green tasks were included in 846 occupations, i.e. 19.9 percent of all individual occupations had at least one green task in their requirements profile. Considering the mid-term period 2012 to 2016, it can be seen that the number of green tasks increased from 182 to 190 (+4.4 percent). However, the relative share of matched requirements remained the same or even decreased slightly in 2016 (from 2.7 percent to 2.6 percent), as the overall number of requirements increased more strongly during this period (+9.8 percent). In contrast, the total number of matched 'green occupations' – occupations containing at least one green task – grew faster than 'non-green occupations': between 2012 and 2016, the total number of green occupations rose by 16.4 percent from 727 to 846, whereas the remaining occupations increased by 8.3 percent. Consequently the share of green occupations increased more than average from 18.4 percent to 19.9 percent during this period. With regard to the mid-term perspective from 2012 to 2016, Figure 3 illustrates the slight tendency towards a greening of requirements ('green tasks') and occupations.

Figure 3
Number of hits after matching keywords with green tasks in BERUFENET 2012-2016

3a) Number of green tasks **3b) Occupations with at least one green task**



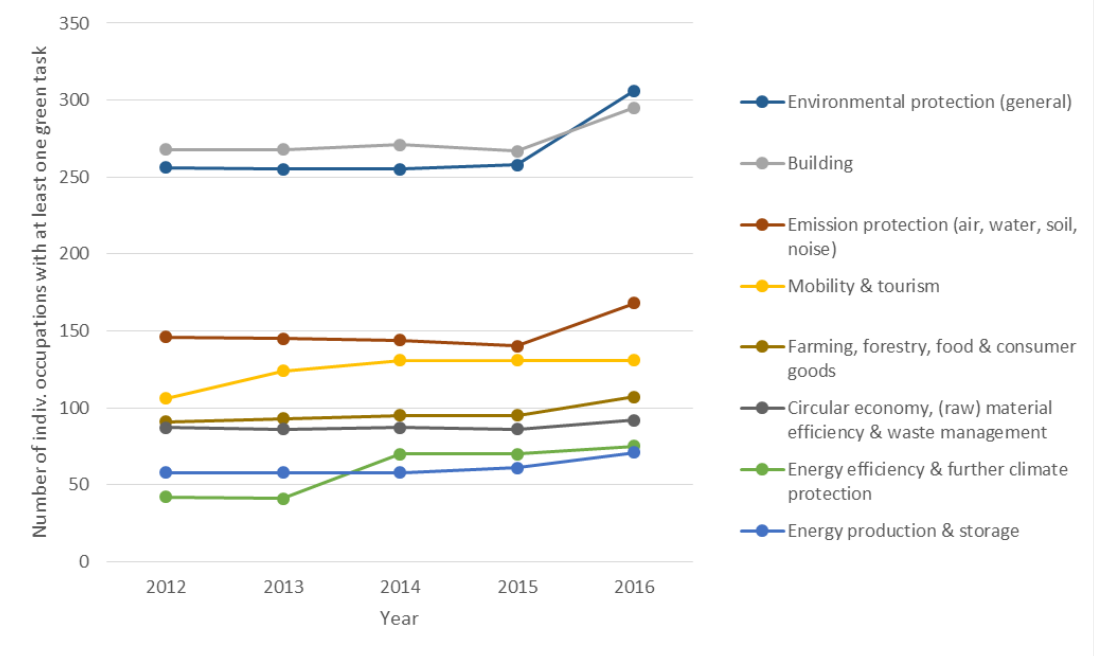
Source: BERUFENET, own calculations.

The additional use of green-task categories makes it possible to identify those green environmental fields that cause the overall change in requirements and occupations.

Table 6 also shows the distribution of matches in BERUFENET across the green tasks categories and their development between 2012 and 2016. In the first step, i.e. the keyword-requirements matches, the category of ‘building’ exhibits the largest growth, by 10.5 percent, whereas ‘mobility & tourism’ has the largest number of green tasks (2016: 53). ‘Emission protection’, ‘environmental protection (general)’ and ‘circular economy’ show a relatively large number of green tasks but no increase in tasks between 2012 and 2016. ‘Farming, forestry, food & consumer goods’, ‘energy production & storage’ and ‘energy efficiency & further climate protection’ have smaller shares of the total number of green tasks, but each of them exhibited a slight increase in their number of green tasks – gaining one new green task each.

Analyzing the second step of matching at the level of green tasks categories, Figure 4 confirms that this step leads to a considerable number of hits. For example, in 2016 the 25 green tasks of ‘environmental protection (general)’ are matched with 306 individual occupations (growth rate 2006-2012: 19.5 percent). This is also the largest share of all the occupations with at least one green task, followed by the green tasks category ‘building’, matched with 295 occupations (growth rate 2006-2012: 10.1 percent). The remaining green tasks categories have fewer hits (from 168 in ‘emission protection’ to 71 hits in ‘energy production’) but they all show a positive growth rate between 2012 and 2016 (from 5.7 percent in ‘circular economy’ to 78.6 percent in ‘energy efficiency’).

Figure 4
Number of hits after matching green tasks with occupations (8-digit level KldB2010): Individual occupations with at least one green task, grouped by green tasks categories



Source: BERUFENET, own calculations. Note: The online appendix comprises two corresponding tables with the time series of matches from green tasks to occupations.

The unweighted greenness-of-jobs index at individual occupation level

As explained in section 4, the unweighted greenness-of-jobs index (*goji*) is calculated as a ratio of the number of green tasks as described above and the total number of requirements. Table 7 provides a first idea of the distribution and values of *goji by* showing five occupations with maximum, medium and minimum $goji_{total}$ values respectively in 2016. For example, the occupation 'specialist in environmental protection' has the largest $goji_{total}$. For this occupation, the first value in the column $goji_{total}$ is 0.889, i.e. 88.9 percent of the tasks performed by a specialist in environmental protection are 'green' in the sense of this paper. The three columns on the right contain the *goji* specifications based on core and additional requirements ($goji_{core}$ and $goji_{add}$), or based on the total number of skill requirements weighted by the requirements-type ($goji_{wtotal}$). Table 7 indicates that occupations with the largest $goji_{total}$ values have both large $goji_{core}$ and large $goji_{add}$ values. Consequently, the difference between $goji_{total}$ and $goji_{wtotal}$ is relatively small. In contrast, the example occupations from the center of the distribution show relatively high $goji_{core}$ values but small or no $goji_{add}$ values. The smallest $goji_{total}$ values are 0.024. This group at the bottom of the distribution does not show a specific pattern: pos. 781 and 785 do not have any $goji_{core}$ values, pos. 782 to 784 only have $goji_{core}$ values but no $goji_{add}$ at all. Therefore, it can be concluded that the composition of green tasks within each 'green occupation' (with $goji_{total}$ > 0) differs considerably.

Table 7
Greenness-of-jobs ranking of individual occupations:
Top 5/Medium 5/Last 5 *goji*$_{total}$ values in 2016 (Kldb2010, 8-digit)

Pos.	Occupational title (English translation)	*goji*$_{total}$	*goji*$_{core}$	*goji*$_{add}$	*goji*$_{wtotal}$
	Top 5				
1	Specialist - Environmental protection	**0.889**	0.900	0.875	0.892
2	Environmental advisor	**0.850**	0.833	0.857	0.841
3	Recycling specialist	**0.769**	0.750	0.778	0.759
4	Environmental auditor	**0.765**	0.750	0.769	0.756
5	Environmental management officer	**0.750**	0.700	0.786	0.729
…	**Medium 5 (Median *goji*$_{total}$: 0.083)**				
388	Woodworking mechanic - Wood-based panel industry	**0.083**	0.250	0.042	0.183
389	Woodworking mechanic - Sawmill industry	**0.083**	0.250	0.050	0.183
390	Standardization expert	**0.083**	0.250	0.000	0.167
391	Master of hydraulic engineering	**0.083**	0.182	0.000	0.121
392	Technician - Machine tech. (process engineering)	**0.083**	0.167	0.000	0.111
…	**Last 5**				
781	Engineer - Viticulture	**0.025**	0.000	0.042	0.014
782	Motor mechanic	**0.024**	0.125	0.000	0.083
783	Engineer - Air-conditioning system technology	**0.024**	0.043	0.000	0.029
784	Engineer - Refrigeration system technology	**0.024**	0.037	0.000	0.025
785	Traffic construction engineer	**0.024**	0.000	0.043	0.014

Note: The decrease in the number of occupations between 2006 and 2011 is a technical effect due to the change in the occ. classification from KldB1988 to KldB2010. Therefore the total numbers of occupations in 2006 and 2011 et seq. cannot be compared, although the total number of requirements is still comparable.

Source: BERUFENET, own calculations.

To compare the general development of the *goji* values of occupations, I examine two groups: all occupations (also including occupations with a *goji* value of zero) and only occupations with a *goji*$_{total}$ larger than zero. Based on this distinction, Table 8 summarizes the development of different *goji* variations between 2012 and 2016. According to this table, the total number of occupations with *goji*$_{total}$ > 0 increases by 14.1 percent to 785 individual occupations. Relative to the total number of 3,946 individual occupations in 2016, this is a share of 19.9 percent 'green' occupations (2012: 18.6 percent). As a first interim result, I can state that a greening of occupations is occurring that amounts to 14.1 percent in terms of the growth of individual occupations that have an unweighted *goji*$_{total}$ larger than zero from 2012 to 2016. But does the level of *goji* also increase? Within the group of all occupations, the average *goji*$_{total}$ rises by 10.6 percent from 0.023 to 0.025. When distinguishing between requirement types, the growth of *goji*$_{core}$ is even higher (15.3 percent), whereas the growth of *goji*$_{add}$ is lower (6.2 percent). Because the core requirements have twice the weight of the additional requirements in the *goji*$_{wtotal}$, its growth is 1.2 percentage points larger than *goji*$_{total}$.

If these comparisons are restricted to the group of occupations with *goji*$_{total}$ > 0 ('*goji* occupations'), we see that the average values of *goji*$_{core}$ and *goji*$_{(w)total}$ also rise. With regard to *goji*$_{core}$ and *goji*$_{(w)total}$, the absolute growth of the *goji* value is even higher than in the overall group, whereas the relative growth as a percentage is lower than in the group of all occupations. Only the *goji*$_{add}$ values show a slight decrease in the group of *goji* occupations, probably because many other new requirements were included in these occupations, which leads to a reduction in the share of green tasks and thus to a drop in the *goji* value. Nevertheless, the second interim result is that there is also a greening of the extent of green tasks represented by $goji_{total}$ in individual occupations.

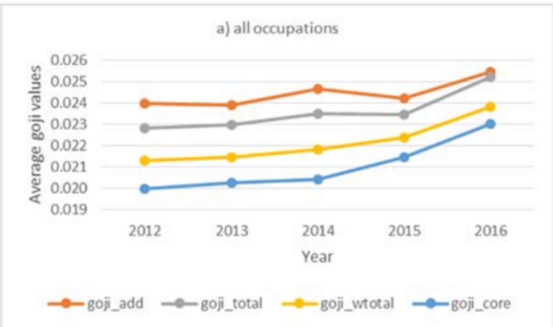
Table 8
Average *goji* values of individual occupations (8-digit level) – a) all occupations and b) *goji* occupations only (with $goji_{total}$ > 0), 2012-2016

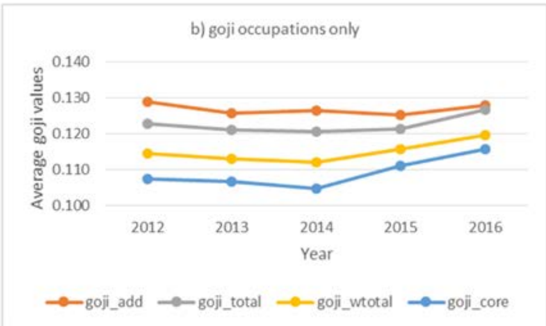
Year	Total number of occupations		Average *goji* values							
			all occupations				*goji* occupations ($goji_{total}$ > 0)			
	all	goji	$goji_{total}$	$goji_{core}$	$goji_{add}$	$goji_{wtotal}$	$goji_{total}$	$goji_{core}$	$goji_{add}$	$goji_{wtotal}$
2012	3,702	688	0.023	0.020	0.024	0.021	0.123	0.251	0.152	0.115
2016	3,946	785	0.025	0.023	0.025	0.024	0.127	0.254	0.153	0.120
∆2012-16	244	97	0.002	0.003	0.001	0.003	0.004	0.008	-0.001	0.005
in %	6.6%	14.1%	10.6%	15.3%	6.2%	11.8%	3.3%	7.7%	-0.8%	4.5%

Source: BERUFENET, own calculations.

The relative growth of *goji* levels between 2012 and 2016 is also illustrated in graphs a and b in Figure 5. Figure 5a covers all occupations and Figure 5b focuses on the occupations with a $goji_{total}$ larger than zero. Especially in the years between 2014 and 2016 one can see the stronger increase of $goji_{core}$, which by definition also leads to rises in $goji_{total}$ and $goji_{wtotal}$.

Figure 5
Average *goji* values of individual occupations (2012-2016, 8-digit level KldB2010) – a) all occupations and b) *goji* occupations only (with $goji_{total}$ > 0)

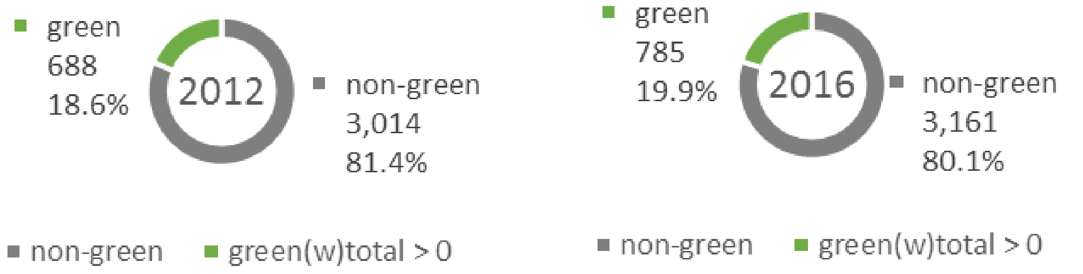




Source: BERUFENET, own calculations.

Figure 6 shows the growing share of occupations with $goji_{total}$ larger than zero. In 2016, 785 (19.9 percent) of the total of 3,946 occupations had a $goji_{total}$ value larger than zero, i.e. these '*goji* occupations' have green tasks in their requirements portfolio at least to certain extent.

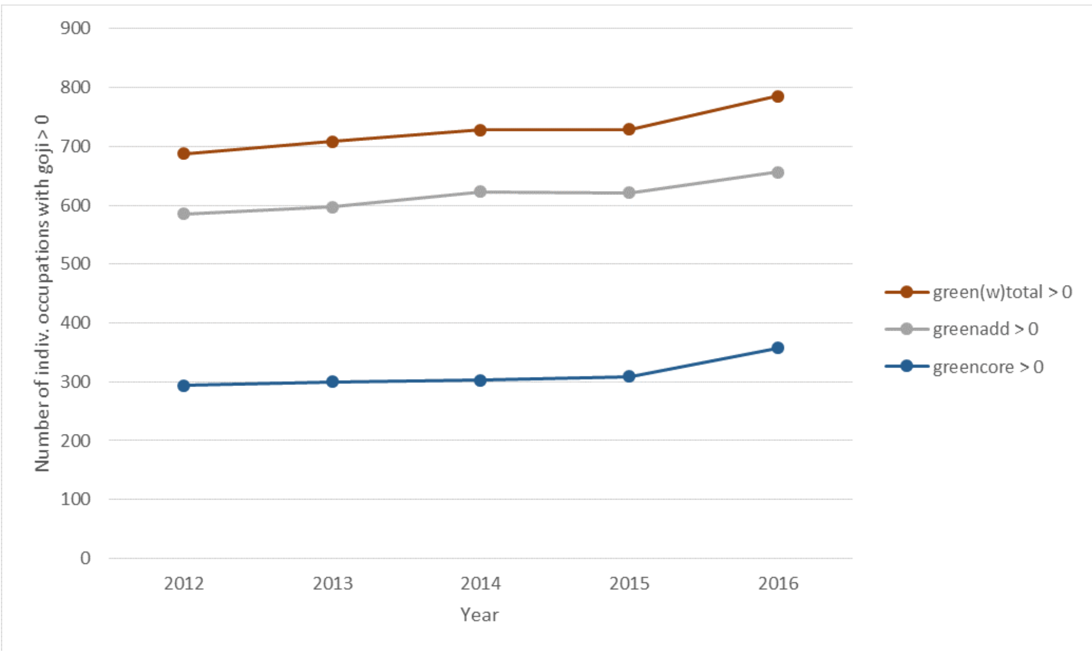
Figure 6
Share of individual occupations (8-digit level) with $goji_{total}$ > 0 in 2012 and 2016



Source: BERUFENET, own calculations.

Looking at the differences in terms of core and additional requirements, Figure 7 documents that the number of occupations with $goji_{add}$ > 0 have the highest absolute number of new arrivals. In contrast, the occupations with $goji_{core}$ > 0 include fewer new occupations (+63) but show the highest rate of increase (+21.4 percent). Nevertheless, the number of occupations with $goji_{add}$ > 0 (656) is still almost twice as high as the number of occupations with $goji_{core}$ > 0 (357). This indicates that up to now it is above all the large number of green additional tasks that is responsible for the large number of occupations with $goji_{total}$ > 0, whereas the strong increase in the number of green core tasks is responsible for the substantial growth of $goji_{total}$.

Figure 7
Number of individual occupations with goji > 0 (8-digit level KldB2010)



Source: BERUFENET, own calculations.

137 individual occupations experienced an increase in $goji_{total}$ between 2012 and 2016.

Table 9 lists examples of the top, median and end of the distribution of these greening occupations. The first section of Table 9 covers the five occupations with the largest growth in $goji_{total}$. For instance, between 2012 and 2016 the occupation of 'technician - environmental protection technology (landscape ecology)' increased from 0.300 to

0.520, thus representing a rise of 0.220 in $goji_{total}$ (i.e. the share of green tasks increased by 22 percentage points). In the center of the distribution we see occupations such as 'dietary cook' or 'body and vehicle construction mechanic – body maintenance', which exhibit a greening of 0.035 and 0.034, respectively. The latter occupation is also an example of an occupation that had no green task at all in 2012. The lowest level of greening can be observed in the occupation of 'agricultural laboratory technician' with a delta of 0.001. The entire list of greening occupations documents the wide range of different occupations that show an increase in *goji* between 2012 and 2016.

Table 9
Greening of jobs: ranking of individual occupations: Top/Medium/Last 5 of Δ $goji_{total}$ 2012 - 2016 (KldB2010, 8-digit)

		$goji_{total}$		
Pos.	**Occupational title (English translation)**	**Δ abs.**	**2012**	**2016**
	Top 5			
1	Technician – Environm. protection techn.(landscape ecology)	0.220	0.300	0.520
2	Technician - Waste technology	0.212	0.407	0.619
3	Extension specialist (heat, cold and sound insulation work)	0.199	0.176	0.375
4	Wood preservation expert	0.144	0.056	0.200
5	Two-wheeler mechatronic technician – Production	0.139	0.111	0.250
...	**Medium 5 (Median Δ$goji_{total}$: 0.035)**			
71	Dietary cook	0.035	0.080	0.115
72	Specialist agricultural farmer - Agricultural technology	0.035	0.056	0.091
73	Electronics technician - Energy & building services engineering	0.035	0.042	0.077
74	Master chimney sweep	0.035	0.238	0.273
75	Body and vehicle construction mechanic - Body maintenance	0.034	0.000	0.034
...	**Last 5**			
133	Food inspector	0.003	0.050	0.053
134	Helpers - Wood, wickerwork	0.002	0.048	0.050
135	Engineer - Interior design	0.002	0.040	0.042
136	Technician - Construction engineering	0.002	0.038	0.040
137	Agricultural laboratory technician	0.001	0.037	0.038

Source: BERUFENET, own calculations.

With regard to the unweighted *goji,* this subsection has shown that both the number of occupations with *goji* > 0 and the level of *goji* values increases between 2012 and 2016. The different values show that the level of greenness varies depending on the *goji* type examined (core/add/total/wtotal). It is therefore crucial to decide precisely which aspect of greenness should be considered for an in-depth analysis. The empirical example in section 'econometric analysis' shows the differences this decision yields in econometric analysis. As robustness checks prove, the results of models using $goji_{wtotal}$ show less statistically significant differences to $goji_{total}$. To reduce the complexity of the paper, I do not use the results for the *goji*$_{wtotal}$ in the remainder of this paper.[13]

At the individual-occupation (8-digit) level I can show that there is a greening of jobs in respect of the unweighted *goji*. However, at this stage it is not possible to consider the employment development associated with the greenness and greening of jobs, because in German employment statistics and administrative employment data, the occupational data are coded at the 5-digit level.

5.2 The employment-weighted distribution of the greenness and greening of jobs

The goji at aggregated occupational levels

As described in section 4, the use of employment statistics data facilitates an aggregation of the *goji* at every occupational, industrial and regional level. The only limitation is the availability of employment statistics at the relevant breakdown level. Table 10 illustrates the number of aggregates with a *goji* larger than zero within the hierarchical structure of KldB 2010. The table documents the aggregation levels available after the aggregation procedure. There is the unweighted *goji* at 5-digit level after applying an equal distribution assumption. Furthermore, there are five aggregates of KldB 2010 as well as these five aggregates plus the information about the requirement level (5th digit of Kldb2010). All in all the table corroborates the results of the descriptive analysis at individual-occupation (8-digit) level: between 2012 and 2016 the number of occupational *goji* aggregates increases – both after the aggregation to 5-digit level using an equal distribution assumption and after the aggregation to 3-digit level using weights derived from the specific employment share of the occupational groups.

[13] Employment-weighted aggregates of the *goji*$_{wtotal}$ as well as the results of all estimations and robustness checks using *goji*$_{wtotal}$ are available from the author on request.

Table 10
The hierarchical structure of the classification of occupations 2010 (KldB 2010) and their number of aggregates with *goji* > 0

Breakdown level (Digit level KldB 2010)	Year	Number of breakd. levels	Number of aggregates with *goji* > 0		
			$goji_{total}$>0	$goji_{core}$>0	$goji_{add}$>0
Unweighted *goji* at 5-digit level (equal distribution assumption)					
Occupational type	2012	1,174	355	166	311
5-digit level	2016	1,192	376	184	329
	∆2012-16	18	21	18	18
	in %	1.5%	5.9%	10.8%	5.8%
Employment-weighted goji					
Occupational groups, main groups and areas					
Occupational group	2012	140	82	49	78
3-digit level	2016	140	84	53	80
	∆2012-16	0	2	4	2
	in %	0.0%	2.4%	8.2%	2.6%
Occupational main group	2012	36	34	28	33
2-digit level	2016	36	34	30	33
Occupational areas	2012	9	9	9	9
1-digit level	2016	9	9	9	9
Occupational segments and sectors					
Occupational segments	2012	14	14	13	14
S2-digit level	2016	14	14	14	14
Occupational sectors	2012	5	5	5	5
S1-digit level	2016	5	5	5	5
Occupational aggregates plus requirement level (5th digit)					
Occ. areas + req. level	2012	422	170	96	149
3-digit level + 5th digit	2016	424	173	106	151
Occ. main group + req. level	2012	131	90	62	80
2-digit level + 5th digit	2016	132	90	66	80
Occ. group + req. level	2012	36	31	29	28
1-digit level + 5th digit	2016	36	31	29	27
Occ. segments + req. level	2012	54	44	36	39
S2-digit level + 5th digit	2016	55	44	37	39
Occ. sectors + req. level	2012	20	17	16	16
S1-digit level + 5th digit	2016	20	17	16	15

Note: I do not use the 4-digit level, because the number of sub-groups included there is 700, which is relatively close to the 5-digit level (1,286 breakdown levels).

Source: BERUFENET, employment statistics data from the Federal Employment Agency, own calculations.

At the 2-digit level and higher levels the greening of jobs in absolute numbers of aggregates with *goji* larger than zero becomes less obvious. In Table 10, only little development of the *goji* values is discernible. However, a look at the development of *goji* values within these higher aggregated levels reveals that a greening of jobs is still visible even at this level. For example, Table 11 presents the $goji_{total}$ values at the level of occupational sectors (S1-digit level). These values show a growth in $goji_{total}$ of 0.002 in the occupational sector concerning the production of goods, and a growth of 0.001 in the occupational sectors comprising occupations in personal services as well as occupations in business administration and other business-related services. This detailed view also reveals the occurrence of 'degreening' (-0.002) in service occupations in the IT sector and the natural sciences as well as in 'S5: Other occupations in commercial services'. This development is caused by a more substantial increase in non-green requirements and/or a loss of green tasks in individual occupations within these occupational sectors. The reduction in the number of jobs within occupations with $goji_{total}$ > 0 may also contribute to this phenomenon.

Table 11
Occupational sectors and their greenness of jobs 2012-2016

	$goji_{total}$		
Occupational sectors (S1-digit level of KldB2010)	**2012**	**2016**	**∆2012-16**
S1: Occupations in the production of goods	0.030	0.032	0.002
S2: Occ. in personal services	0.001	0.002	0.001
S3: Occ. in business administration and other business-related services	0.001	0.002	0.001
S4: Service occupations in the IT sector and the natural sciences	0.020	0.018	-0.002
S5: Other occupations in commercial services	0.046	0.044	-0.002

Sources: BERUFENET, employment statistics data from the Federal Employment Agency, own calculations.

Looking at the less highly aggregated level of occupational segments (S2-digit level of KldB2010, see Table 12) it becomes clear that the developments of (de)greening differ within occupational sectors. For example, the occupational sector ‘S1: Occupations in the production of goods’ (∆2012-16: 0.002) covers ‘S11: Occupations in agriculture, forestry and horticulture’ which experiences a drop of -0.014, as well as ‘S12: Manufacturing occupations’ and ‘S13: Occupations concerned with production technology’, each of which rise by 0.002.

Table 12
The employment-weighted *goji* of occupational segments 2012-2016

	$goji_{total}$		
Occupational segments (S2-digit level of KldB2010)	**2012**	**2016**	**∆2012-16**
S11: Occupations in agriculture, forestry and horticulture	0.080	0.066	-0.014
S12: Manufacturing occupations	0.008	0.010	0.002
S13: Occupations concerned with production technology	0.012	0.014	0.002
S14: Occupations in building and interior construction	0.088	0.089	0.001
S21: Occupations in the food industry, in gastronomy and in tourism	0.004	0.006	0.002
S22: Medical and non-medical health care occupations	0.000	0.001	0.001
S23: Service occupations in social sector and cultural work	0.001	0.001	0.000
S31: Occupations in commerce and trade	0.002	0.002	0.000
S32: Occupations in business management and organization	0.000	0.000	0.000
S33: Business-related service occupations	0.000	0.005	0.005
S41: Service occupations in the IT sector and the natural sciences	0.020	0.018	-0.002
S51: Safety and security occupations	0.020	0.022	0.002
S52: Occupations in traffic and logistics	0.048	0.046	-0.002
S53: Occupations in cleaning services	0.050	0.048	-0.002

Sources: BERUFENET, employment statistics data from the Federal Employment Agency, own calculations.

Another informative perspective is the *goji* aggregated to the requirement level. Table 13 shows that occupations with the requirement level of ‘2: Skilled tasks’ have the highest $goji_{total}$ value (0.021), which is driven in particular by the high value of $goji_{add}$ (0.024). The second largest group in $goji_{total}$, occupations with the requirement level of ‘1: Unskilled/semiskilled tasks’ (0.015) has seen a decrease of -7.3 percent (-0.001). In this group, *goji*$_{add}$ even fell to zero. Exhibiting a 15.9 percent increase (+ 0.002), occupations with the requirement level of ‘3: Complex tasks’ have the largest increase in *goji*$_{total}$ values, with both level and growth being driven mainly by the *goji*$_{add}$ values (2016: 0.015). These developments described in Table 13 suggest that the greening of jobs is mainly driven by the increase in occupations with complex tasks, skilled tasks and highly complex tasks. The occupations with unskilled/semiskilled tasks still have a relatively large *goji*$_{core}$ value, but they are the only group that show decreasing *goji* values. With regard to the level of greenness-of-jobs, Table 12 also provides an overview of the substantial differences between the occupational aggregates. At the highest level of aggregation, occupational sectors (S1-digit level), the occupational sector ‘S5: Other occupations in commercial services’ has the highest *goji* value in 2016 (0.044). Looking at the level below that, occupational segments (S2-digit level), it becomes obvious that this high value is driven mainly by the two occupational segments ‘S52: Occupations in traffic and logistics’ (0.046) and ‘S53: Occupations in cleaning services’ (0.048). However there are even higher values at this level, e.g. ‘S14: Occupations in building and interior construction’ is the occupational segment with the highest *goji* value in 2016 (0.089). With a *goji*$_{core}$ of 0.046, the occupational area ‘(3) construction, architecture, surveying and technical building services’ shows the highest value at this level, closely followed by ‘(1) Agriculture, forestry, farming, and gardening’ with a value of 0.042. After the third largest value of 0.020 (‘(5) Traffic, logistics, safety and security’), the only areas remaining have a very small *goji*$_{core}$. Three occupational areas show a value of 0.000 due to rounding to three decimal places. In fact, they all have shares larger than zero, but with very low values.

Table 13
Employment-weighted *goji* grouped by requirement level

Requirement level (5th digit of KldB 2010)	*goji*$_{total}$ 2016	*goji*$_{total}$ ∆2012-16	*goji*$_{core}$ 2016	*goji*$_{add}$ 2016
1: Unskilled/semiskilled tasks	0.015	-0.001	0.015	0.000
2: Skilled tasks	0.021	0.001	0.015	0.024
3: Complex tasks	0.011	0.002	0.006	0.015
4: Highly complex tasks	0.007	0.001	0.003	0.009

Source: BERUFENET, statistics data from the Federal Employment Agency, own calculations.

As mentioned above, I apply the aggregation procedure for the 5-digit level, and – as employment-weighted *goji* – for every breakdown level for the 3-, 2-, 1-, S1- and S2-digit-levels of the occupational classification KldB 2010. Furthermore, I calculate employment-weighted *goji* values for each of these breakdown levels differentiated according to the requirement level (5th digit) of KldB 2010. The online appendix presents some of these employment-weighted aggregates. The aggregation procedure also facilitates the calculation of an employment-weighted overall *goji* for Germany, which may be regarded as an overall indicator for the greening of jobs in Germany. Table 14 provides an overview of the development of this ‘German greening of jobs index (*goji*$_{.de}$)’ between 2012 and 2016.

Table 14
The employment-weighted overall goji$_{.de}$ (KldB 2010) 2012-2016

Year	$goji_{total}$	$goji_{core}$	$goji_{add}$	Total employment	Full-green employment equivalents
2012	0.0196	0.0143	0.0202	27,168,448	532,946
2016	0.0198	0.0150	0.0199	29,772,496	589,589
∆2012-16	0.0002	0.0007	-0.0003	2,604,048	56,643
in %	1.0%	4.6%	-1.7%	9.6%	10.6%

Source: BERUFENET, statistics data from the Federal Employment Agency, own calculations.

In order to calculate the total employment development relative to $goji_{total}$, ('full-green employment equivalents'), I add up the individual employment data in relation to goj_{total}. After this step I obtain the hypothetical number of employees with a pseudo $goji_{total}$ of 1. Using these 'full-green equivalents', we see from Table 14 that in 2016 there are 0.59 million persons employed in occupations with a hypothetical $goji_{total}$ of 1 (all $goji_{total}$ of the 29.77 million employment relationships with $goji_{total} > 0$ are added together). Between 2012 and 2016, the full-green equivalents increased by 10.6 percent. As this describes only the raw employment development grouped by levels of $goji_{total}$, the econometric analysis is going to disentangle the association between the greenness of jobs and employment growth.

The sectoral distribution of the goji

The sectoral distribution of the *goji* identifies the industries in which the greening takes place. Table 15 presents the industry sections (1-digit level) of the Classification of Economic Activities, Edition 2008 (WZ 2008). Considering the greenness of industries in 2016, the table shows industry section 'E. Water supply; sewerage, waste management, remediation activities' as being the one with the largest $goji_{total}$ (0.108), followed by 'H. Transportation and storage' (0.063) and 'F. Construction' (0.057). In terms of the greening of jobs within industries, section 'O. Public administration and defense; compulsory social security' reports the largest growth in the absolute $goji_{total}$ value by +0.006, whereas 'I. Accommodation and food service activities' has the largest relative growth rate (+69 percent) with an increase in $goji_{total}$ of 0.003. With -0.008 (-15.8 percent), the strongest loss of $goji_{total}$ – in both the absolute value and the percentage share – can be observed for 'A. Agriculture, forestry and fishing'. This corroborates the finding in the occupational aggregates presented above (Table 12), where occupations in 'S 11. Occupations in agriculture, forestry and horticulture' show a strong decrease.

Table 15
Industry sections and their employment-weighted greenness-of-jobs index (ISIC Rev. 4 / WZ 2008, 1-digit level), 2012-2016

	$\mathbf{goji}_{total}$			
***Goji* distribution in industry sections**	**2012**	**2016**	**∆2012-16**	**in %**
A. Agriculture, forestry and fishing	0.052	0.044	-0.008	-15.8%
B. Mining and quarrying	0.020	0.022	0.002	9.0%
C. Manufacturing	0.010	0.009	0.000	-1.6%
D. Electricity, gas, steam and air conditioning supply	0.027	0.031	0.004	13.9%
E. Water supply; sewerage, waste management, remediation activities	0.107	0.108	0.001	1.1%
F. Construction	0.054	0.057	0.003	5.8%
G. Wholesale and retail trade; repair of motor vehicles / motorcycles	0.006	0.008	0.002	37.9%
H. Transportation and storage	0.066	0.063	-0.003	-3.8%
I. Accommodation and food service activities	0.004	0.008	0.003	69.0%
J. Information and communication	0.002	0.002	0.000	18.2%
K. Financial and insurance activities	0.001	0.001	0.000	14.6%
L. Real estate activities	0.026	0.029	0.003	10.9%
M. Professional, scientific and technical activities	0.008	0.009	0.001	12.8%
N. Administrative and support service activities	0.028	0.027	-0.001	-2.6%
O. Public administration and defense; compulsory social security	0.016	0.022	0.006	36.5%
P. Education	0.005	0.006	0.001	13.6%
Q. Human health and social work activities	0.003	0.004	0.000	15.0%
R. Arts, entertainment and recreation	0.008	0.009	0.001	9.1%
S. Other service activities	0.010	0.011	0.001	9.6%
T. Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	0.007	0.007	0.000	0.1%
U. Activities of extraterritorial organizations and bodies	0.014	0.017	0.003	20.8%

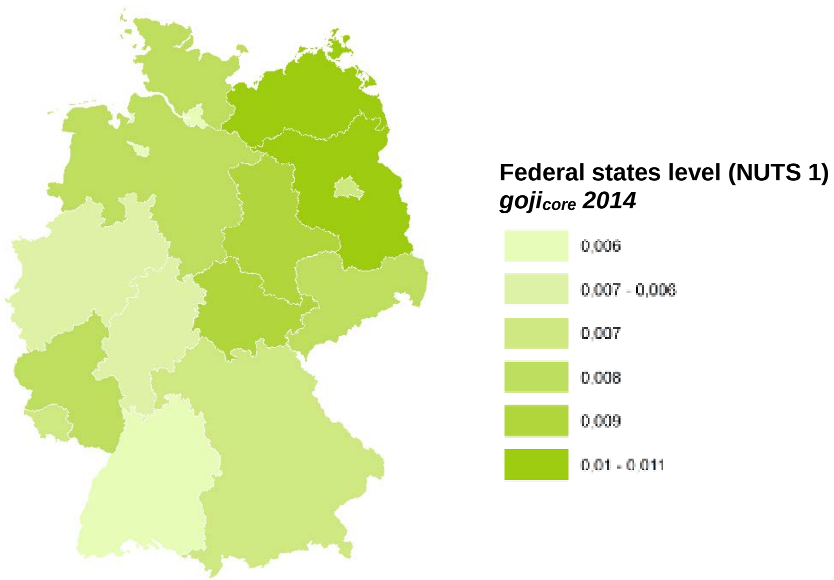
Note: Industry sections according to the International Standard Industrial Classification of All Economic Activities, Rev.4 (ISIC Rev. 4) and Classification of Economic Activities, Edition 2008 (WZ 2008).

Sources: BERUFENET, employment statistics data from the Federal Employment Agency, own calculations.

The regional distribution of the goji

Analogous to the industry aggregates, I also apply the weighting procedure to NUTS-1 level (federal state level) and NUTS-3 level (county level). As part of the results of this conversion, the following two maps should give an example of $goji_{core}$ at NUTS-1 / federal state level (Figure 8) and at NUTS-3 /county level (Figure 9). The two maps reveal pronounced differences between federal states and between counties. In the first place, this reflects the spatial disparities in terms of occupational distributions between regions. Figure 8 shows relatively high *goji* values in the north-eastern states of Mecklenburg-Vorpommern and Brandenburg, as well as in the states of Saxony-Anhalt, Thuringia and Rhineland-Palatinate, which might reflect to some extent the relatively large share of agricultural and other ‘green-by-nature’ occupations. Meanwhile, however, renewable energy production also influences this distribution. For example, several manufacturers of wind power plants are located in Mecklenburg-Vorpommern[14] and there is a considerable amount of biogas production in Brandenburg[15]. Some states, such as Bavaria and Baden-Wuerttemberg, have lower *goji* values despite the fact that many people work in green occupations there. This is probably due to a greater heterogeneity of occupations (many green occupations, but also many/more non-green occupations). This reason might also hold for the city states of Berlin, Hamburg and Bremen. Moreover, these and other large cities do not have many ‘green-by-nature’ occupations, e.g. in the context of agriculture. The reflections on federal states (Figure 8) can be applied to a large extent to the county level, too. Interestingly, Figure 9 reveals that within some federal states there is considerably more heterogeneity between counties (e.g. in Bavaria or Baden-Wuerttemberg). Hence, the greenness of specific counties seems to stem partly from county-level characteristics, which should be taken into account in future analyses.

Figure 8
Gojicore 2014 at federal state level (NUTS-1), weighted by employment



Note: Federal states and county codes: NUTS Classification (NUTS 1 and 3).

Sources: BERUFENET, employment statistics data from the Federal Employment Agency, own calculations.

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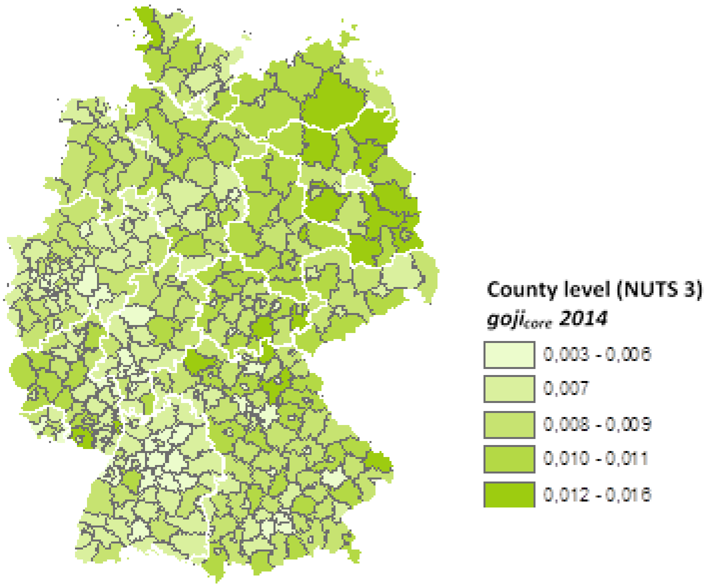
[14] Report on the wind energy industry in Mecklenburg-Vorpommern (German language): https://www.energie-und-management.de/nachrichten/alle/detail/mecklenburg-vorpommern-vorwaerts-mit-dem-wind-101817

[15] Statistics about renewable energies in the federal states of Germany (German language) https://www.foederal-erneuerbar.de/landesinfo/bundesland/BB/kategorie/bioenergie/auswahl/189-anzahl_und_dichte_vo

Figure 9
Gojicore at county level (NUTS-3), weighted by employment



Note: Federal states and county codes: NUTS Classification (NUTS 1 and 3).
Sources: BERUFENET, employment statistics data from the Federal Employment Agency, own calculations.

5.3 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 16 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 16
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 17 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 de-greening 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 17 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 17
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%
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%

Variable (Label)	NON-GREEN 2012 abs.	GREEN 2012 abs.	NON-G. 2016 abs.	GREEN 2016 abs.	NON-G. ∆2012-16 ∆in %	GREEN ∆2012-16 ∆in %
	Non-green and green occupations 2012 and 2016					
	Non-green: *goji*$_{total\ 2012}$ = 0; Green: *goji*$_{total\ 2012}$ > 0					
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%
plus 27 variables for the *goji* composition – see Appendix (Table A-3)						
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-3)						

Sources: BeH, BERUFENET, own calculations.

6 Econometric analysis

6.1 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 17).

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

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

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:

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

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

6.2 Estimation results

Table 18 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 18 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 18, 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 18
***Goji* and employment growth: Estimation results**

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)
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)
Constant	0.372 (1.51)	0.373 (1.49)	13.24*** (22.60)	13.25*** (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-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. Full regression results: see Table A-4.

Source: BeH, BERUFENET, own calculations.

Turning to the wage development, the OLS estimations in Table 19 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 19
***Goji* and wage growth: 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)
Constant	0.0222 (0.14)	0.0193 (0.12)	5.747*** (11.38)	5.733*** (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-5)				
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-5.

Source: BeH, BERUFENET, own calculations.

Looking at the greening of occupations, Table 19 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.

7 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 Janser 2018, Janser/Lehmer 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
Goji aggregation levels

Aggregation dimension	Aggregation level: Digit level	Aggregation level: Level name	Number of breakdown levels (here: 2016)
Occupational (Classification of Occupations, KldB2010 / 2006: KldB1988)	5	Occupational type	1,192
	3	Occupational group	140
	(3plus5)	*(extension: plus 5th digit)*	*(424)*
	2	Occupational main group	36
	(2plus5)	*(extension: plus 5th digit)*	*(132)*
	1	Occupational areas	9
	(1plus5)	*(extension: plus 5th digit)*	*(36)*
	S2	Occupational segment	14
	(S2plus5)	*(extension: plus 5th digit)*	*(20)*
	S1	Occupational sector	5
	(2plus5)	*(extension: plus 5th digit)*	*(55)*
	5th digit	Requirements level	4
Sectoral (Classification of Economic Activities, WZ 2008)	2	Divisions	88
	1	Sections	21
Regional (Nomenclature of Territorial Units for Statistics, NUTS)	NUTS 3	Districts	429
	NUTS 1	Federal States	16

Note: The 5th digit of KldB2010 provides additional information about the requirements level.

Source: Employment Statistics of the Federal Employment Agency, own calculations.

Table A-2
Greenness-of-jobs ranking of single occupations grouped by green tasks categories: Examples for top 5 of gojigtcat,total values in 2016 (KldB2010, 8-digit)

Pos.	Occupational title grouped by green tasks category (gtcat)	$goji_{gtcat,total}$	$goji_{gtcat,core}$	$goji_{gtcat,add}$	$goji_{gtcat,wtotal}$
	Top 5 – Energy production & storage				
1	Specialist - solar technology	**0.250**	0.364	0.000	0.242
2	Climate protection manager	**0.250**	0.200	0.263	0.221
3	Energy consultant	**0.188**	0.250	0.167	0.222
4	Engineer - renewable energies	**0.171**	0.222	0.118	0.187
5	Tech. assistant - renewable raw materials	**0.167**	0.071	0.300	0.148
	Top 5 - Circular economy, (raw) material efficiency & waste management				
1	Recycling specialist	**0.692**	0.750	0.667	0.722
2	Specialist in recycling & waste mgmt.	**0.526**	0.667	0.462	0.598
3	Waste advisor	**0.526**	0.667	0.462	0.598
4	Waste manager	**0.421**	0.857	0.167	0.627
5	Technician for waste technology	**0.381**	0.667	0.267	0.533
	Top 5 - Environmental protection (general)				
1	Environmental management officer	**0.417**	0.300	0.500	0.367
2	Environmental expert	**0.412**	0.444	0.375	0.421
3	Environmental auditor	**0.412**	0.750	0.308	0.603
4	Head of expert office for the environment	**0.320**	0.214	0.455	0.294
5	Water pollution control officer	**0.308**	0.167	0.429	0.254

Note: Each occupation may appear in different groups of green tasks categories, because each $goji_{gtcat}$ value represents only the share of green tasks from the specific green tasks category in the total number of requirements. For example, the occupation 'Water pollution control officer' contains four tasks related to environmental protection (one green core task and three green additional tasks) and is thus ranked in the green tasks list of 'Environmental protection (general)' with $goji_{gtcat,total}$ = 0.308). It is also ranked in the green tasks list of 'Emission protection (…, water, …)' with $goji_{gtcat,total}$ = 0.231, of which this occupation contains three green (core) tasks.

Source: BERUFENET, own calculations.

Table A-3
Extension for sample description: 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 2012	GREEN 2012	NON-G. 2016	GREEN 2016	NON-G. Δ2012-16	GREEN 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%
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%

	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 %
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-4
***Goji* and employment growth: Full estimation results**

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
	OLS		FE	
Dependent variables:	Full-time equivalents (log, delta 2012-2016)		Full-time equivalents (log, yearly panel 2012-2016)	
	(1)	(2)	(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)
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

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)
Mining and quarrying	-0.414***	-0.408***	0.595	0.555
	(-2.80)	(-2.78)	(0.75)	(0.70)
Manufacturing	-0.036	-0.030	-0.790	-0.804
	(-0.71)	(-0.59)	(-1.52)	(-1.54)
Electricity, gas, steam and air conditioning supply	-0.014	-0.035	-2.382**	-2.382**
	(-0.14)	(-0.35)	(-2.23)	(-2.22)
Water supply, sewerage, waste management and remediation activities	-0.249***	-0.175**	-1.723	-1.736
	(-2.79)	(-2.04)	(-1.38)	(-1.39)
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***

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
	OLS		FE	
Dependent variables:	Full-time equivalents (log, delta 2012-2016)		Full-time equivalents (log, yearly panel 2012-2016)	
	(1)	(2)	(3)	(4)
			(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)
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-5
***Goji* and wage growth: Full estimation results**

	GREENNESS 2012 (level)		GREENING 2012-2016 (growth)	
	OLS		FE	
Dependent variables:	Daily Wage (log, delta 2012-2016)		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
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

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)
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)
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)

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)
Lower Saxony	-0.029	-0.026	-0.898**	-0.897**
	(-0.18)	(-0.16)	(-2.09)	(-2.09)
Bremen	-0.070	-0.076	-0.921**	-0.927**
	(-0.24)	(-0.26)	(-2.05)	(-2.07)
Northrhine-Westphalia	-0.054	-0.061	-0.849**	-0.848**
	(-0.35)	(-0.40)	(-2.28)	(-2.29)
Hesse	0.050	0.041	-0.479	-0.480
	(0.30)	(0.25)	(-1.27)	(-1.27)
Rhineland-Palatinate	-0.067	-0.076	-0.747**	-0.748**
	(-0.43)	(-0.49)	(-2.05)	(-2.06)
Baden-Wuerttemberg	-0.059	-0.075	-0.572	-0.575
	(-0.39)	(-0.50)	(-1.50)	(-1.51)
Bavaria	-0.018	-0.029	-0.676*	-0.679*
	(-0.12)	(-0.20)	(-1.84)	(-1.85)
Saarland	-0.251	-0.288	-0.230	-0.230
	(-0.87)	(-1.00)	(-0.29)	(-0.29)
Berlin	0.416**	0.415**	-1.425***	-1.432***
	(2.21)	(2.22)	(-3.39)	(-3.42)
Brandenburg	-0.113	-0.131	-0.565	-0.560
	(-0.61)	(-0.72)	(-1.19)	(-1.18)
Mecklenburg	-0.279	-0.267	-0.824	-0.816
Western Pomerania	(-1.26)	(-1.20)	(-1.27)	(-1.26)
Saxony	0.090	0.085	-1.153***	-1.154***
	(0.56)	(0.53)	(-3.03)	(-3.04)
Saxony-Anhalt	0.031	0.035	-1.389***	-1.399***
	(0.15)	(0.16)	(-2.84)	(-2.87)
Thuringia	-0.281	-0.261	-1.196**	-1.201**
	(-1.50)	(-1.40)	(-2.23)	(-2.24)
Dummy 2013	N/A	N/A	0.019***	0.019***
			(7.57)	(7.59)
Dummy 2014	N/A	N/A	0.042***	0.042***
			(10.23)	(10.25)
Dummy 2015	N/A	N/A	0.059***	0.059***
			(9.66)	(9.67)
Dummy 2016	N/A	N/A	0.057***	0.057***
			(6.99)	(7.02)
Constant	0.022	0.019	5.747***	5.733***
	(0.14)	(0.12)	(11.38)	(11.28)
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.

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 "Text mining and descriptives"

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