I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14028

Eco-Innovation and Employment: A Task-Based Analysis

Robert J. R. Elliott
Wenjing Kuai
David Maddison
Ceren Ozgen

JANUARY 2021

I Z A Institute
of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 14028

Eco-Innovation and Employment: A Task-Based Analysis

Robert J. R. Elliott
University of Birmingham

Wenjing Kuai
University of Birmingham

David Maddison
University of Birmingham

Ceren Ozgen
University of Birmingham and IZA

JANUARY 2021

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Eco-Innovation and Employment: A Task-Based Analysis*

This paper provides some of the first evidence of the relationship between eco-innovation and employment. Adopting a O*NET based task approach, in a study of the Dutch firms, we show that eco-innovation has no impact on overall employment. However, compared to non- eco-innovators there is an 18.2% increase in the number of green jobs (equivalent to 12 new green workers for the average firm). This means an average increase in the share of green workers of around 3.3%. Broadly speaking, the increase in the share of green jobs was driven by a reduction in non-green workers and a smaller but still significant increase in the number of green workers. We further show that subsidy-driven policies, rather than regulation-driven policies positively correlate with the number of green workers.

JEL Classification: Q52, Q55, J23
Keywords: eco-innovation, green jobs, subsidies

Corresponding author:
Ceren Ozgen
Department of Economics
University of Birmingham
JG Smith Building, Room 239
Edgbaston, B15 2TT
United Kingdom
E-mail: c.ozgen@bham.ac.uk

* We wish to thank Matthew Cole and Eric Strobl for useful comments. We also thank seminar participants at 5th Geography of innovation conference (Stavanger). Ceren gratefully acknowledges the Marie-Skłodowska Curie Individual Grant for MAStErS project (H2020-MSCA-IF- 2015, No. 705366) from the European Commission. All errors are our own.

1 Introduction

The global economy was already facing a period of increased uncertainty with policy-makers and firms worried about sluggish economic growth, persistent unemployment and growing environmental concerns. The Covid-19 pandemic has magnified these concerns for both governments and firms. A popular governmental response to the current uncertainties is to use the crisis as an opportunity to move their economies to a more sustainable development path. Already, prior to the Covid-19 crisis, a central part of the Europe 2020 strategy called for the region to become greener so as to achieve smart, sustainable and inclusive growth. Similarly, the United Nations conference (Rio+20) concluded that a green growth transition is one of the most important routes by which an economy can achieve a sustainable development path. A central tenet of these policy recommendations is that a consequence of the development of the technologies required for a successful green transition will be a commensurate impact on the number, type, and quality of jobs associated with a new greener economy. However, despite the popular belief that an employment positive green transition is possible, there is little research that investigates this relationship empirically.

The purpose of this paper is to examine the relationship between eco-innovation and firm-level employment patterns and to understand whether the increasing emphasis placed by policy-makers on eco-innovation as a way to create jobs and to green the labour market at the same time is justified. This paper contributes to the existing literature in the following ways. First, we introduce a task-based approach to the firm level analysis of relationship between eco-innovation and firm-level employment and second, we are the first, to the best of our knowledge, to examine how eco-innovation (total, product and process eco-innovation) impacts the number and share of green employees within a firm. Third, we estimate the impact of different policies (subsidies versus environmental regulations) on eco-innovation and their subsequent employment effect.[1]

A number of institutions hypothesise that there should be a strong link between eco-innovation and employment. For example, OECD (2012) state that one of the main drivers of the transition processes is through the promotion of eco-innovation. In Europe, the Environmental Technologies Action Plan (ETAP) introduced a wide range of activities to promote eco-innovation

[1] In this paper we use the terms employee and job interchangeably as the final sample only records the main job of each individual in the data.

with the argument being that eco-innovation provides firms with a great opportunity to change what they produce or how they produce it, to enhance competitiveness, and ultimately create new and decent jobs (ETAP 2020). Likewise, in terms of employment, UNEP (2011) propose that investing in green activities has the potential to create a large number of decent jobs while ILO/UNEP (2012) argue that greening the economy, if accompanied by an appropriate policy mix, can create more and better jobs. However, others have argued that the job creation potential from greening the economy may simply be a beautiful fantasy of politicians, and that there are no sound economic arguments to support the premise that, holding macroeconomic conditions constant, total employment will increase (Hughes 2011). Given these contrasting views, it is important to understand how eco-innovation impacts different employment outcomes.

For our analysis we use data for the Netherlands for the period 2006-2010. The Netherlands is an ideal country to study the link between eco-innovation and employment for several reasons. First, as one of the most densely populated countries in the world, the Netherlands is currently facing increasing environmental pressures due to the consumption of fossil fuels and relatively high Greenhouse Gas (GHG) emissions (UN 2017). Second, the Netherlands is an active eco-innovator, ranked 7th in the EU27 eco-innovation scoreboard in 2010 (EIO 2010), and hence places considerable emphasis on the importance of eco-innovation.

To this end, we merge the Dutch Community Innovation Survey (CIS), Tax Register Data (TRD), and Labour Force Survey (LFS). The creation of a linked employer-employee dataset allows us, for the first time, to examine a number of different aspects of the relationship between eco-innovation and employment at the firm level adopting a task-based measure of green jobs.

To briefly summarise our results, we find that during our sample period, although firms that engaged in eco-innovation did not, on average, see any change in the total number of employees, they did increase the proportion of those employees that are considered to be green workers. On average, eco-innovators had 12 more green employees than non-eco-innovating firms which is the equivalent to a 3.3% higher share of green workers per firm. However, a careful analysis shows that the increase in the share of green workers was due more to a falling number of non-green workers rather than a rise in the number of green employees. Subsequent analysis indicates that the differences in hiring of the two types of firm is driven primarily by green product innovation and not green process innovation. Additional analysis reveals that it is policy-driven eco-innovation, primarily subsidies, that led to the increase in the number and share of green workers, rather than environmental regulations.

The remainder of the paper is organized as follows: Section 2 explains how we a define green jobs and reviews the existing literature. Sections 3 and 4 describes the data and econometric approach used for our analysis, respectively. Results are presented in Section 5 while our sensitivity analysis reserved for Section 6. The final section concludes.

2 Literature review and definitions

2.1 What is a green job?

Central to our research question, and more broadly for the policy debate, is how we define what makes a job green or not green. The existing empirical literature has tended to take one of three main approaches. The first is to use an industry level definition where a sector, and hence all employees working in that sector (irrespective of occupation), are considered to be either green or non-green (e.g., Eurostat 2009, Yi 2014, Yi & Liu 2015). The second approach, used by the US Bureau of Statistics is to consider all employees that work in establishments that produce green goods and services, and those jobs that are located in environmentally friendly production processes, to be green(e.g., Deschenes 2013, Elliott & Lindley 2017). Both of these approaches have significant shortcomings as they discreetly assign all workers with given firms or sectors to be green or not green.

The third approach, and the one we use in this paper, defines green jobs according to the number of green tasks that a given occupation requires the worker to do and is the method used in the O*NET classification system (US Department of Labour).[2] The reason we are able to use the O*NET classification is that the National Centre for O*NET Development identifies the characteristics associated with each occupation. By analysing the different tasks associated with a given occupation it is possible to define an occupation as “green" (Dierdorff et al. 2009).

[2] O*NET is maintained by the US Department of Labour and provides data on occupations including a description of the tasks and skills associated with each occupation. In this paper we use the O*NET 23.0 Database released in August 2018.

Generally speaking, O*NET considers green jobs as those occupations that are affected by the greening of an economy. Based on this broad definition, O*Net goes on to describe three types of green occupation:

1. Green Increased Demand (Green ID) occupations are those occupations that are expected to experience an increase in demand because of a greening economy but do not involve changes to the content of work or the requirements of the job.

2. Green Enhanced Skills (Green ES) occupations are those occupations that will be affected by a greening economy through changes to the tasks, skills and the content of work or requirements of the job.

3. Green New and Emerging (Green NE) occupations are those occupations that will be newly generated because of a greening economy but currently do not exist.

It is generally understood in the existing literature that Green ID occupations should be considered as indirectly "green" as these jobs are only affected by demand and do not involve any green tasks as part of the content of work (Bowen et al. 2018, Vona et al. 2018). For other two types of green jobs, the Green Task Development Project of O*NET further divides the tasks associated with a given occupation into green tasks and non-green tasks. For these occupations, their tasks may include general tasks but also specific green tasks.

The benefit of using the O*NET classification is that it enables us to understand the changes in occupation and skill requirements that may be triggered when a country transitions to a greener economy. The O*NET definition is unique in a number of ways. First, green occupations, as defined by O*NET, can exist in different establishments across multiple industries. Second, the task-based definition does not limit an occupation to being given a binary "green" or not green label but captures a continuum of greenness within each occupation which can be considered as a proxy for the time an individual in a given occupation spends on green activities. Finally, each green occupation is given a corresponding O*NET-SOC code so we can use the US classification for our paper on the Netherlands.[3]

[3]SOC stands for the Standard Occupational Classification. One of the challenges of this paper was to match the US O*NET-SOC with the ISCO (International Standard Classification of Occupations) that is used in the Netherlands. To do this we match each O*NET-SOC code with a standard SOC code, where the latter is available only at the 6-digit level. We take a number of different steps. First, we treat green jobs as

Hence, we estimate the greenness of an occupation based on the task content associated with that occupation so that the term “green" is a continuous characteristic rather than a binary classification (Peters 2014, Bowen et al. 2018, Vona et al. 2018). Therefore, we follow Vona et al. (2019) and calculate the greenness of each occupation by an analysis of the tasks associated with it, weighted by importance scores, using information from the Green Task Development project within O*NET.[4]

$$Greenness_i = \sum_{j=1}^{n} w_{ij} * green_j \tag{1}$$

Where w_{ij} is the importance score that is attached to each task within occupation i, and $green_j$ is a dummy that takes the value of 1 if task j is a green task. Following the same methodology, we transform the O*NET-SOC greenness indices to ISCO greenness indices, based on task measurement which gives us 83 out of 436 occupations that record a greenness index greater than 0. Once we have a greenness value for each occupation based on tasks we define three type of green jobs: (1) A task-based green occupations measure that excludes Green ID occupations and is a continuous measure; (2) Broad green jobs that includes three types of green occupations and uses a binary measure; (3) Core green jobs that excludes Green ID occupations and uses a binary measure.[5] To provide a little background, of the 1,100

binary and assume that workers are equally distributed within each broader occupation group and take the average greenness for each associated broad code category. Using this approach, 156 out of 841 jobs are found to have greenness index of greater than 0, among which 61 are Green ID occupations, 59 are Green ES occupations, and 36 are Green NE occupations. Second, we use a cross-walk between the standard SOC and the ISCO to identify green occupations in the ISCO system. The crosswalks used in this paper can be found at http://ibs.org.pl/en/resources/occupation-classifications-crosswalks-from-onet-soc-to-isco/. There are fewer occupational categories in the ISCO system than the SOC as the former is only available at 4-digit level. In the crosswalk between SOC and ISCO, we have 839 unique SOC codes at the 6-digit level, and 436 unique ISCO codes at 4-digit level. Using the same methodology to calculate the average greenness within each SOC code, we find that 161 out of 436 occupations have a greenness index greater than 0, and 106 out of 436 occupations have a greenness index greater than 0, once we exclude Green ID occupations.

[4]Importance scores for all tasks are normalised to sum to one for each occupation.

[5]Details of matching O*NET-SOC with ISCO and a full list of green occupations and associated greenness scores can be found in Appendix A. To capture as much information as possible, if the occupation is only coded at a higher level of aggregation (e.g. Major occupation group) we also calculate the a greenness index at that level and use the corresponding green index for those individuals that only have more aggregated occupations recorded. The appendix also includes details on how we calculate a greenness index for

8-digit O*NET-SOC level occupations, 204 are defined as green occupations of which 64 are Green ID occupations, 62 are Green ES occupations, and 78 are Green NE occupations.

Although a number of studies have used the O*NET task-based definition of green occupations, none of these studies are at the firm level. For example, Peters (2014) used a task-based approach to show that green intensive jobs are high quality and tend to be full time, include health insurance, and pay higher than average wages. Similarly, Consoli et al. (2016) compare the skill and human capital requirements for green and non-green occupations and show that green occupations require: higher levels of abstract skill; higher levels of education; greater work experience; and more on-the-job training. Similarly, Vona et al. (2019) explore the characteristics of green occupations in the US between 2006 and 2014, and show that green occupations tend to be associated with higher skills which require more years of eduction and also have a wage premium over those working in non-green occupations. Finally, Vona et al. (2018) compare green jobs with so-called brown jobs, in terms of skill requirements, where the latter is defined as occupations that are more prevalent in pollution intensive industries. Although they find that the overall skills gap between green and brown occupations is relatively small, green occupations are still found to have a higher technical skill requirement (Vona et al. 2018). This largely descriptive evidence underpins the popular belief of policy-makers that green job creation is something to be actively encouraged.

2.2 Eco-innovation and (green) employment

Innovation, and by extension eco-innovation, is generally thought to be harder and more risky (Berrone et al. 2013), and can affect employment in a number of different ways, both positively and negatively. Innovation can destroy jobs through a substitution of capital for labour or a labour saving effect but it can also create employment through a compensation effect (Licht & Peters 2013). It is useful therefore to first define what we mean by eco-innovation. In this paper, we follow OECD (2008) and define eco-innovation as something that "*... leads to a new or significantly improved product (good or service), process, organizational method or marketing method that creates*

each level of aggregation. To this end, we construct a list of 580 ISCO occupations each of which has its own individual greenness index. Table A2 shows the average greenness index by different green job type for all 580 occupations. Around 80% of the occupations listed can be considered non-green jobs. This means that the average greenness index is relatively low and is at its lowest for the task-based measurement of greenness (0.034).

environmental benefits, and that such environmental benefits can occur during the production of goods or services, or during the after sales use of a good or service by the end users" (OECD 2008).

To understand the impact of eco-innovation on employment we turn first to the existing literature. Although there is a relatively well established literature that examines the relationship between innovation and employment using firm-level data (e.g., Van Reenen 1997, Evangelista & Savona 2003, Lachenmaier & Rottmann 2011, Dachs & Peters 2014, Harrison et al. 2014), and a smaller number of studies that use industry-level data (e.g., Antonucci & Pianta 2002, Bogliacino & Pianta 2010), there is very little research on the relationship between eco-innovation and employment, and even fewer that do so at the firm level and none that do so using a task-based approach.

The reason for the limited number of studies examining the relationship between eco-innovation and employment is due primarily to data limitations. Moreover, the empirical evidence to date is rather mixed. Early studies by Rennings & Zwick (2002), Rennings et al. (2004) investigate the employment effects of environmental innovation using telephone surveys in five European countries and show that generally speaking, green product innovation creates additional employment while the effect of green process innovation is unclear. More recently, and in stark contrast, Horbach & Rennings (2013) examine the employment effect of different types of eco-innovation using the German Community Innovation Survey (CIS), and show that, green product innovation does not stimulate employment growth, but green process innovation does have a positive employment effect.

At the industry level, in a study of Italian firms Cainelli et al. (2011) find a negative employment effect of environmentally oriented innovation in the service sector. On the other hand, for the same country, Gagliardi et al. (2016) show that for manufacturing firms, green innovation, measured by environmentally-related patents, has a positive effect on long-run employment growth. The approach taken by Kunapatarawong & Martínez-Ros (2016) is to make a distinction between dirty and clean industries based on pollution intensities when examining the impact of eco-innovation on employment after which they find a stronger positive effect of eco-innovation on employment for dirty industries.

There are also a small number of studies that ask whether the motives that firms declare as the reasons that they undertake eco-innovation have differential impacts on employment. Rennings & Zwick (2002) show that eco-innovation tends to reduce employment if the intended goal is cost reduction, while the employment effect is ambiguous if the eco-innovation is motivated by efforts to increase market share. To compare policy effects, Kunapatarawong & Martínez-Ros (2016) make a comparison between firms with policy-driven eco-innovation and those that undertake voluntary eco-innovation and show that there is a positive relationship between voluntary eco-innovation and employment but no effect between employment and policy driven eco-innovation.

Finally, there are a those studies that focus on the effect of various environmental policies on the creation of green jobs such as using *ex-ante* forecasting to analyse the job creation potential of different clean energy policies. For example, Cai et al. (2011) examine the direct and indirect employment effect of China's Greenhouse Gas (GHG) mitigation policy in the power generation sector and found a net loss of jobs if 2010 was not included while Wang et al. (2013) estimate the employment effect of China's Clean Development Mechanism (CDM) project in the power sector and find that the direct effect of the policy was job losses although there was a positive indirect effect.

There have also been a number of *ex-post* assessments on whether certain environmental policies led to the creation of green jobs. Based data for US metropolitan areas, Yi (2013) evaluate the effect of state and local clean energy and climate policies and find a moderate and positive effect on the number of green jobs from both. In later research Yi & Liu (2015) measure the number of green jobs in green industries at the city-level in China, where green industries are defined by a list of SIC codes provided by Pew Charitable Trust and show that green jobs are more prevalent in cities with clean energy policies.

Another strand of the literature links policy and green jobs using on an early O*NET classification. For example, Vona et al. (2019) measure and assess the drivers of green employment in US metropolitan and non-metropolitan areas and find that the American Recovery and Reinvestment Act (ARRA) subsidies were more efficient at stimulating green jobs than direct environmental regulation. More recently, Vona et al. (2018) use the O*NET green skills classification to examine the role of environmental regulation on the demand for green skillsin US metropolitan and non-metropolitan areas and find that environmental regulation has no effect on total employment, although it did trigger an increase in demand for green skills.

As Vona et al. (2019) shows, one of the most popular, and apparently successful, environmental policies is to subsidise eco-innovation. For example, the ETAP takes "green job creation" as a slogan by integrating eco-innovation into environmental policy (ETAP 2020). One of the few papers to directly link eco-innovation with green jobs is Cecere & Mazzanti (2017), who examine the role of eco-innovation on green job creation for European small and medium firms using a cross-section of EU27 countries. In this research their key dependent variable, the number of green jobs that firms aim to create in the next two years, is obtained through a special survey. Their main finding is that green innovation and service innovation is positively correlated with the creation of green jobs (Cecere & Mazzanti 2017).

Overall, the literature linking eco-innovation and employment is still relatively scarce despite the important policy implications and popular understanding that there is a positive correlation. Although the current literature has looked at different aspects of this relationship there has not been a comprehensive firm level study where the greenness of tasks within an occupation are used to measure the how occupations are becoming greener over time.

3 Data

3.1 Data and sample

Our data links three administrative datasets, the Dutch Community Innovation Survey (CIS2008), the Tax Register Data (TRD2010), and the Labour Force Survey (LFS2010). The community innovation survey (CIS) is a harmonised survey that covers the innovation behaviour of firms across different European countries through the use of identical surveys in each country and is frequently used to analyse the innovation activities of firms. The CIS2008 survey for the Netherlands covers the period 2006 to 2008, includes information on over 11,000 firms, and crucially for this research, includes modules that collect data on the innovation activities of firms, including eco-innovation, product innovation, process innovation, organisational innovation and marketing innovation, consistent with the OECD (2008) definition of eco-innovation. A firm is defined as an innovator if it reports at least one of innovation activities mentioned above during the period of the survey.[6]

More specifically, in one of the CIS2008 modules, firms are asked whether they undertook an innovation that had environmental benefits. We therefore

[6] A firm in our analysis is defined as a production unit with autonomous decision making capacity.

consider a firm to be an eco-innovator if they answered yes to this question. Furthermore, if the environmental benefits are generated from the use of a product by an end user, we consider it as eco-product innovation, while if the environmental benefits occur during the production of goods and services within the firm, we consider it as eco-process innovation. In addition, in this special environmental module, firms are asked about their motivation for engaging in the eco-innovation process. In this paper we categorize firms into one of three groups: (1) if eco-innovation is undertaken in response to current environmental policy and further environmental regulation we define it as "regulation driven eco-innovation"; (2) if eco-innovation is triggered by governmental grants or subsidies eco-innovation is defined as "subsidy driven eco-innovation"; (3) if eco-innovation is driven by current or expected market demand or voluntary agreements, it is defined as "voluntary eco-innovation". Figure 1 presents a schematic representation of how we map the relationships between different innovation categories.

[Figure 1 about here]

One of the challenges faced by researchers in this area is how to accurately capture the employment effect of eco-innovation in the years following engagement with the eco-innovation process. This is partly due to the limitations with the CIS2008 data. One of the contributions of this paper, is rather than using self-reported employment data reported in the CIS2008 survey, we instead calculate the number of employees for each firm using the Dutch Tax Register (TRD) data that provides information on the population of employees (around 10 million employees per year). Crucially, the TRD also allows us to calculate the average wage of a firm from the aggregation of individual wage data. A further important benefit of using the TRD data is that we can calculate the number of employees for up to two years after the CIS2008 survey took place. This means we can take into account possible lags between the implementation of eco-innovation and changes in employment patterns.

It is generally well understood that it can take time to both hire and fire workers and for the effects to feed through to firm performance indicators such as productivity and exporting (Lachenmaier & Rottmann 2011, Isogawa et al. 2012, Elliott et al. 2019). Using employment and wage data from the TRD allows us to deal with the criticism that has plagued previous studies that use the CIS data, which is that researchers are only able to consider the impact of innovation on employment in the year of the survey. This inevitable restriction, when using the CIS surveys, means that there is very little time for the innovation to have any meaningful impact on sales, productivity or profits that would, in turn, feed through to employment changes.[7]

Finally, we link variables from the LFS2010. The LFS is a large survey that enables us to identify the occupation of each individual worker at the 4-digit ISCO classification level. The LFS2010 surveys more than 100,000 workers across 421 different occupations.[8] Matching the green occupation list with the LFS2010 means that all of the occupations listed in the LFS2010 have an associated greenness index. At this stage, a consistent definition of a green occupation is required. If we consider that an occupation is green if it has a greenness index greater than 0, there will be a tendency to overestimate the number of green jobs at the firm-level. In this paper the solution is to define green jobs as those in occupations with a greenness index greater than the average greenness index for each category. In other words, broad green jobs are in those occupations with a greenness index greater than 0.189, core green jobs are in those occupations with a greenness index greater than 0.115, and task-based green jobs are those occupations with greenness index greater than 0.034.

Figure 2 plots average annual wage against the task-based greenness index for each occupation based on LFS2010. The size of each circle is proportional to the number of green employees in that occupation. The black dots indicates those occupations with a greenness index of zero (no green employees). The darkest area, where the greenness index is zero, is centred around 30,000 Euro, whereas the average wage of most of the occupations with a positive task-based index value is above that average level. The upward slope of the fitted lines is suggestive of a positive relationship between average annual wage and task-based greenness of an occupation.[9] Figure 3 plots the skill

[7]Matching the CIS2008 survey with the TRD2010 survey means our sample consists of those firms that existed in both 2006 and 2010. This means that firms that exited during this period were dropped from the sample (in our case almost 20% of firms from the CIS2008 survey were dropped).

[8]Before we aggregate individual information to the firm level, we also merge LFS2010 with TDR2010. Using the LFS means we can track people who are currently active in the labour market, i.e. who are currently paying tax and which firm they are working in.

[9]Similar figures for broad and core green jobs can be found in Appendix B. When we compare these wage graphs horizontally, we can see that the fitted line for task-based greenness is steeper than that of core greenness, and core greenness is steeper than that of broad greenness. This indicates the wage level of broad green occupations is reduced by adding indirect Green ID occupations while task-based measurement captures the jobs where the return to the green tasks in jobs is the highest.

intensity (average share of high skilled workers) of each occupation against the task-based greenness index. The circles in Figure 3 are less concentrated but nevertheless, the fitted line is upward sloping that suggests there is a positive correlation between the skill intensity and task-based greenness of an occupation. T statistics and P-value are reported.[10]

[Figure 2 about here]

[Figure 3 about here]

By merging the LFS, the TRD, and CIS2008, we are able to calculate the share of green workers per firm. If we multiply the share of green workers by the total number of workers in each firm we can calculate the number of green jobs in each firm.[11] Micro-firms with less than 10 employees and the top 1% and bottom 1% of firms by total turnover are dropped from the sample leaving a final sample of 4,511 firms.

In the final sample, the average number of workers per firm in 2010 was 313, and the average number of broad green workers, core green workers and task-based green workers are 118, 79, and 76, respectively. Medium sized firms, with 50 to 250 employees, account for 53.36% of firms. Small firms, with less than 50 employees, and large firms, with more than 250 employees, account for 21.8% and 24.83% of employees, respectively.

Our sample is based on the first two-digits of the Dutch Standard Industry Classification (SBI2008) which gives us 16 sectors.[12] The primary sector includes Agriculture, forestry and fishing (SBI01) and Mining and quarrying (SBI02) and accounts for 1.82% of the sample. The secondary sector, including manufacturing and economic activities that facilitate the production of tangible goods (SBI 03 to 06), accounts for 39.28%, and manufacturing (SBI 03) 27.49% of the sample. The service or tertiary sector (SBI 07 to 21) accounts for 58.90% of the sample. As a service based economy, in 2010, the service sector accounted for 68.28% of gross value added (WB 2018*b*). Of the rest, only 10.61% of gross value added came from the manufacturing sector

[10]Equivalent figures for broad and core green jobs can be found in Appendix B.

[11]Matching CIS2008 with LFS2010 reduces our sample by around 50%.

[12]The Dutch Standaard Bedrijfsindeling (SBI 2008) is compatible with the economic activity classification of the European Union (NACE) and the United Nations (International Standard Industrial Classification of All Economic Activities, ISIC). The first four digits of the SBI are identical to the first four digits of NACE and the first two digits of the SBI and NACE are the same as the first two digits of ISIC.

(WB 2018*a*), 19.90% from industry including construction (WB 2017*b*) and 1.72% from Agriculture, forestry, and fishing (WB 2017*a*).[13]

Before we describe the variables it is useful to briefly review the macroeconomic conditions in the Netherlands during our sample period. Most importantly, the years 2008 to 2010 cover the years most severely impacted by the global financial crisis when employment as a share of the total population was falling, in this case from 63.34% in 2008 to 61.81% in 2010 (WB 2019), and an increase in unemployment which rose from 3% in 2008 to 4.5% in 2010 (OECD 2018). The financial sector was particularly hard hit during this period. Given that our study period coincides with the global financial crisis, results should be interpreted in the context of a difficult business environment. We expect that the crisis would have slowed down any green transition such that our results could be considered to be conservative estimates.

3.2 Dependent Variables

Previous studies of looking at the impact of innovation on employment have tended to use either: (1) the employment growth rate (e.g., Horbach & Rennings 2013, Licht & Peters 2013, Harrison et al. 2014); (2) the log of the number of employees (e.g., Lachenmaier & Rottmann 2011, Kunapatarawong & Martínez-Ros 2016); or (3) a discrete variable to capture employment dynamics (e.g., Rennings et al. 2004, Horbach & Rennings 2013). As we are interested in the effect of eco-innovation on total employment and the share of green workers within a firm, we use the log of the total number of jobs (*Total employment*), the log of the number of green jobs (*Green employment*), and the share of green jobs (*Share of green jobs*). As the number of green jobs has a significant number of zero values we use an inverse hyperbolic sine transformation. In addition, we follow Kunapatarawong & Martínez-Ros (2016) and calculate our dependent variable two years into the future, in this case 2010, to mitigate endogeniety concerns.

3.3 Innovation Variables

Our key explanatory variables are all drawn from CIS2008. We consider a firm to be an eco-innovator (*Eco-innovator*) if it has introduced an inno-

[13]See Appendix C for details of the distribution of firms by size and sector.

vation with environmental benefits during the period 2006 to 2008. Benefits include: reducing material use; energy use or emissions during the production process; or benefits that are experienced after the product has been sold, for example, if the product can be more easily recycled at the end of its life. We are also able to differentiate between those environmental benefits then result from the use of a product by end users, that we call green product innovation (*Eco-product innovator*), and the environmental benefits generated from the production of goods and services within a firm, that we call green process innovation (*Eco-process innovator*). To control for the overall effect of innovation more generally on employment patterns we include variables to capture product innovation (*Product innovator*), process innovation (*Process innovator*), marketing innovation (*Marketing innovator*) and organisational innovation (*Organisational innovator*).

Figure 4 presents the share of eco-innovators at the 2-digit level and shows that there is greater variability across sectors for the number of eco-innovators as a share of all firms in a sector. The generally high percentages reflects the prevalence of innovating firms in our sample (that tend to be larger firms on average). In terms of sectors, both types of innovators are most prevalent in water supply; sewerage, waste management and re-mediation activities. General innovation happens most often in electricity; gas; steam; and air conditioning supply sectors. Manufacturing is also a highly innovative but only moderately eco-innovative.

[Figure 4 about here]

In the second stage we investigate whether and how employment patterns are influenced by a firm's motives for undertaking eco-innovation. To this end, we differentiate between policy driven (*Policy driven*) and voluntary (*Voluntary*) eco-innovation. In addition, we investigate whether there are employment differences as a result of eco-innovation that is undertaken in response to current environmental regulations; future expected environmental regulation; or government grants or subsidies. We define voluntary eco-innovation to be eco-innovation driven by current or expected market demand, or voluntary agreements. We are also able to split policy eco-innovation into regulation driven (*Regulation driven*) and subsidy driven (*Subsidy driven*) where the former is likely to increase costs to the firm and the latter to reduce them.

Table 1 shows the characteristics of innovators and eco-innovators in our sample, and the motives given for why they eco-innovate. Innovators (347 employees on average) are significantly larger than non-innovators (225 employees on average). Innovators also have a significantly higher share of green jobs (31.47% against 25.91%). In terms of eco-innovators, in our sample they are a little smaller than general innovators and they have a marginally higher share of green jobs (31.90%). Eco-innovators tend to be larger than non-eco-innovators (335 employees against 289) and they also have a higher share of green jobs (31.90% against 26.75%). Of the eco-innovators, eco-product innovators have a higher share of green jobs (34.33%) than eco-process innovators (32.83%). Table 1 also shows that firms who claim that their eco-innovation is policy driven have a high share of green jobs and this is especially true when the eco-innovation is supported by government subsidies (where the share of green jobs is 39.29%).

[Table 1 about here]

3.4 Control Variables

Our analysis includes a number of control variables. To control for firm size we include total turnover (*Turnover*) while *Export* takes value of 1 if a firm sells overseas. Average firm-level wage (*Wage*) is included to control for the average quality of workers. We also include dummy variables equal to 1 if a firm is part of an enterprise group (*Group*) or has an head office (*Headoffice*) outside of the Netherlands. Finally, we control for sector and regional level heterogeneity by including 2-digit level sector dummies, and nuts2 level province dummies. Tables D1 and D2 of Appendix D provide a description of our dependent and independent variables and a correlation matrix of our key variables of interest, respectively.

4 Econometric model

While the descriptive evidence suggests that eco-innovators have a higher share of green jobs, this does not mean the relationship is causal. However, estimating a causal relationship is a challenge due to a number of potential endogeneity concerns. On the one hand, innovation may be a result of a previous hiring decision to employ particular workers (potentially into green jobs), and on the other hand, innovation may cause a firm to become more competitive which increases demand for the firm's products which in turn means that the firm hires additional workers. Other unobservable factors that may also influence the propensity of a firm to innovate may also affect the hiring decisions of firms (such as management ability). To address these endogeneity concerns we estimate an endogenous switching model (Maddala 1986). Such an approach was used in a similar context by Horbach & Rennings (2013), Kunapatarawong & Martínez-Ros (2016). The estimating equation is given by:

Selection Equation:

$$inno_i = 1 \text{ if } \alpha Z_i + u_i > 0 \text{ (Innovators)}$$

$$inno_i = 0 \text{ if } \alpha Z_i + u_i \leqslant 0 \text{ (Non-Innovators)}$$

Continuous Equation:

$$\text{Regime 1: } Employment_{1i} = \beta_1 X_{1i} + \epsilon_{1i} \text{ if } inno_i = 1$$

$$\text{Regime 0: } Employment_{0i} = \beta_2 X_{0i} + \epsilon_{0i} \text{ if } inno_i = 0$$

The first step is to estimate a selection equation that estimates the determinants of a firm's innovation behaviour. Z_i is a vector of variables that may affect a firm's innovation behaviour and includes all of the exogenous variables from the continuous equation plus our instrumental variables that are included to help identification (Lokshin & Sajaia 2004). The two instrumental variables are: R&D expenditure (*R&D*); and a dummy variable that takes the value of 1 if a firm receives any public financial support for innovation (*Funding*). R&D expenditure includes capital expenditure on buildings and equipment needed to undertake R&D but not the hiring of R&D personnel or other personnel. The funding variable includes financial support, via tax credits or deductions, grants, subsides or loans, targeted at innovation activities, and also does not include job hires. Both R&D expenditure and funding can be thought of as inputs into the innovation process and should be correlated with technology improvements but are unrelated to changes to employment patterns.

In the second state, the continuous equation estimates the factors that affect employment patterns. There are two regimes in the continuous equation: Regime 1 for innovators, and regime 0 for non-innovators. The continuous equation is estimated based on the control variables previously described. u_i, $\epsilon_{1i}, \epsilon_{0i}$ are error terms, which are assumed to have a trivariate normal distribution with zero mean and covariance matrix as follows:

$$\Omega = \begin{bmatrix} \sigma_u^2 & \sigma_{1u} & \sigma_{0u} \\ \sigma_{1u} & \sigma_1^2 & . \\ \sigma_{0u} & . & \sigma_0^2 \end{bmatrix} \tag{2}$$

In equation (2) σ_u^2 is the variance of the error term in the selection equation, and σ_1^2 and σ_0^2 are the variance of the error term in the continuous equation for regime 1 and regime 0, respectively. σ_{1u} and σ_{0u} are the covariances between u_i and ϵ_{1i}, ϵ_{0i}, respectively. The covariance between ϵ_{0i} and ϵ_{1i} is defined as $Employment_{1i}$ and $Employemnt_{0i}$ can never be simultaneously observed. If the estimated covariances $\hat{\sigma_{1u}}$ and $\hat{\sigma_{0u}}$ are statistically significant, then this indicates that a firm's decision to innovate is correlated with its employment decisions. In other words, there is an evidence of endogenous switching and sample selection bias (Maddala 1986).

The most efficient method to estimate an endogenous switching model is to use full-information maximum likelihood (FIML) estimation. In order to obtain consistent standard errors, FIML simultaneously estimates the selection and continuous part of the model (Lokshin & Sajaia 2004).[14] The log likelihood function for regimes 0 and 1, given the assumption about the distribution of the error terms, is as follows:

$$\begin{aligned} \ln L = \sum_i (I_i \omega_i [\ln F(\eta_{1i}) + \ln f(\epsilon_{1i}/\sigma_1)/\sigma_1] + \\ (1 - I_i)\omega_i [\ln 1 - F(\eta_{0i}) + \ln f(\epsilon_{0i}/\sigma_0)/\sigma_0]) \end{aligned} \tag{3}$$

Where F is the standard normal cumulative distribution function and f is the standard normal density function, ω_i is an optional weight for observation i, and for j= 0,1 [15]

$$\eta_{ji} = \frac{(\alpha Z_i + \rho_j \epsilon_{ji}/\sigma_j)}{\sqrt{1 - \rho_j^2}} \tag{4}$$

Where $\rho_1 = \sigma_{1u}/\sigma_1\sigma_u$ and $\rho_0 = \sigma_{0u}/\sigma_0\sigma_u$ are the correlation coefficients between ϵ_{1i} and u_i and ϵ_{0i} and u_i, respectively. The signs on the correlation coefficients, ρ_j, are always the same as the sign of the covariance term σ_{ju}, as σ_j and σ_u are always positive.

[14]The estimation of FIML is done by using the 'movestay' command in Stata.

[15]The values are 0 for regime 0, and 1 for regime 1

After estimating the coefficients of the model, the following unconditional expectations can be obtained:

$$E(Employment_{1i} \mid X_{1i}) = \beta_1 X_{1i} \tag{5}$$

$$E(Employment_{0i} \mid X_{0i}) = \beta_2 X_{0i} \tag{6}$$

These expectations are unconditional on a firm's innovation decision. If we take expectations on the outcome equations, conditional on a firm's innovation decision, the expected outcome (log of employment) for an innovator who self-selected into innovation is given by:

$$\begin{aligned} E(Employment_{1i} \mid innovator = 1) &= E(Employment_{1i} \mid \alpha Z_i + u_i > 0) \\ &= E(Employment_{1i} \mid u_i > -\alpha Z_i) \\ &= \beta_1 X_{1i} + E(\epsilon_{1i} \mid u_i < \alpha Z_i) \\ &= \beta_1 X_{1i} + \sigma_{1u}[\frac{f(\alpha Z_i)}{F(\alpha Z_i)}] \end{aligned} \tag{7}$$

Similarly, taking expectations on the outcome of a non-innovator who self-selects into non-innovation gives:

$$\begin{aligned} E(Employment_{0i} \mid innovator = 0) &= E(Employment_{0i} \mid \alpha Z_i + u_i \leq 0) \\ &= E(Employment_{0i} \mid u_i \leq -\alpha Z_i) \\ &= \beta_2 X_{0i} + E(\epsilon_{0i} \mid u_i \leq -\alpha Z_i) \\ &= \beta_2 X_{0i} - \sigma_{0u}[\frac{f(\alpha Z_i)}{1 - F(\alpha Z_i)}] \end{aligned} \tag{8}$$

If the switching is endogenous, i.e. estimated $\hat{\sigma_{1u}}$ and $\hat{\sigma_{0u}}$ are statistically significantly different from zero, then the conditional and unconditional expectations are fundamentally different (Poirier & Ruud 1981). As an example, let x_{1i} be a variable that appears in the selection equation (Z_{1i}) and the continuous equation (X_{1i}). Then a partial derivative of equation (6) with respect to x_{1i} gives:

$$\frac{\partial E(Employment_{1i} \mid Innovator = 1)}{\partial x_{1i}} = \beta_{1i} - [\alpha_i \sigma_{1u} (\frac{f(\alpha Z_i)}{F(\alpha Z_i)})(\alpha Z_i + \frac{f(\alpha Z_i)}{F(\alpha Z_i)})] \tag{9}$$

Where the expression in the squared brackets is always positive. Therefore, the total marginal effect of x_{1i} on $Employment_{1i}$ is composed by two parts: (1) A direct effect of x_{1i} on $Employment_{1i}$; and (2) an indirect effect from a firm's innovation decision that is the result of the unobservable factors that affect both a firm's innovation decision and its employment (Poirier & Ruud 1981).

As pointed out by Maddala (1986), two type of inferences are permitted in this model: (1) a marginal distribution ($\partial E(Employment_{ji})/\partial X_{ji}$) and (2) a conditional distribution ($\partial E(Employment_{ji} \mid Innovator = j)/\partial X_{ji}$). Which type of inference is correct depends on the question being asked. If one only considers the marginal distribution, then the marginal effect can be interpreted from the coefficients β_{ji}. However, the interpretation should be based on "if a firm were to innovate" rather than "if firm is an innovator". If the conditional expectation is the focus of interest, then the total marginal effect on employment is a combination of the two parts discussed above.

5 Results

The main results are based on our task-based measure of green jobs. We also present the results using broad and core measures of green occupations as part of our sensitivity analysis.

The main results from the endogenous switching model are presented in Table 2 in five panels. The top panel is for regime 1 (innovators). The first three columns report the results for an estimation of the relationship between being an eco-innovator and (a) the total number of jobs, (b) the number of green jobs, and (c) share of green jobs, respectively. Columns (4), (5), and (6) split the eco-innovator variable into (a) eco-product innovators and (b) eco-process innovators. Endogenous switching is observed for the total number of jobs and the number of green jobs indicated by at least one of the ρs in the fifth (bottom) panel being significant in Columns (1), (2), (4) and (5). There is no evidence of endogenous switching when the dependent variable is share of green jobs. In the case where there is no endogenous switching, the estimation results will be almost identical to OLS results. For completeness the equivalent results using a standard OLS approach are presented in Table E1 of Appendix E.

[Table 2 about here]

The results in columns (1), (2), and (3) show that, although being an eco-innovator has no effect on total number jobs (a negative but insignificant coefficient), eco-innovators do have 18.2% more green workers than non-eco-innovators, which is equivalent to 12 more green workers per firm on average. Column (3) also suggests that eco-innovators have 3.3% higher share of green jobs on average than non-eco-innovating firms. What these results appear to tell us is that, generally speaking, the positive effect on the share of green jobs is driven by a small but positive increase in green jobs (as eco-innovators have more green workers but not necessarily more workers *per se*) suggesting a decrease in non-green workers (hence there is no significant effect on total jobs as there seems to be a substitution between green and non-green workers).

Making a distinction between eco-product innovators and eco-process innovators in columns (4), (5), and (6) suggests that neither eco-product nor eco-process has an effect on the total number of jobs (negative but insignificant coefficients). We also lose the effect on the number of green jobs where the coefficients are positive but insignificant. However, we do find a positive and significant effect of being an eco-product innovator on the share of green jobs. This suggests that it is eco-product innovation that is driving the results. One explanation is that there is a trade-off between green jobs and non-green jobs in green product innovating firms. In other words, producing new environmental goods and services may require firms to hire more green workers at the expense of non-green workers where the former is substituted for the latter.

Turning to the results for other non-eco-innovation activities, we find that being a product innovator and a organisation innovator is positively related to the total number of jobs in a firm. Notably, organisation innovators are also found to have positive effect on the number of green jobs, but no effect on the share of green jobs. This suggests that the increase in the total number of jobs is proportionate to the increase in the number of green jobs such that the share of green jobs does not change.

In terms of our controls, we find that firms with a higher average wage have lower total employment, but not fewer green workers (hence the share of green jobs is higher). This is true if a firm is an innovator or non-innovator (regime 1 and 0). This result suggests that higher wage firms have a similar number of green jobs to lower wages firms, but they have a lower number of non-green jobs which is why the share of green jobs is higher in high wage firms. Similar results are found for exporting firms.[16]

For both innovators and non-innovators, firms that are part of larger group (*Group*) are characterized by higher total employment and a higher level of green employment but only for innovators is there an increase in the share of green workers, suggesting that innovators that are part of a larger group have proportionally more green workers. Not surprisingly, larger firms measured by total turnover (*Turnover*) have more employees and more green workers but not a greater share of green workers. Finally, firms with head offices (*Headoffice*) outside of the Netherlands tend to have more employees in total but not more green workers.

Turning briefly to the selection equation (panel 3 of Table 2), we find that exporters (*Export*), and larger firms (*Turnover*), are more likely to innovate. More importantly, we find the expected results for our two instrumental variables, *R&D* and *Funding*, which indicates that firms who invest in R&D and who receive public funding have a higher probability of successfully innovating. Over-identification tests, under- and weak identification tests are performed on our instruments. We also perform an exogeneity test and a redundancy test for *R&D* and *Funding*, respectively using the orthorg and redundant options. The results confirm that our instruments are valid.[17] Test statistics and information on each test are provided in Appendix F.

The next step in our analysis is to investigate whether the motives a firms reports for undertaking eco-innovation have an impact on employment patterns. Table 3 presents the results. As the coefficients for the control variables are broadly similar, we only present the results for our key explanatory and instrumental variables. Columns (1), (2), and (3), differentiate between eco-innovation that is policy driven and that which is undertaken voluntarily. Policy-driven eco-innovation is positively correlated with green employment as shown by the significant and positive coefficient in column (2) of Table 3 (although only at the 10% significance level). We find no effect on employment (green or otherwise) for eco-innovation that is undertaken voluntarily.

[16]Our results show that exporters are smaller in size than non-exporters. Our descriptive statistics support this empirical result as it shows that exporter are indeed smaller on average than non-exporters. We also find that the maximum size for non-exporter is very large compared to exporter, this is not surprising as our sample includes firms in the service sector that can be labour intensive.

[17]Details of these tests can be found in Baum et al. (2010).

Data allows us to further investigate the effect of policy driven regulation by splitting regulations in to: (1) subsidy driven eco-innovation and (2) environmental regulation driven eco-innovation. These policies can be thought of as carrot and stick respectively. The results are shown in Columns (4), (5), and (6). Our results show that subsidy-driven eco-innovation has a strong positive effect on green employment, and hence a strong positive effect on share of green jobs although there is no impact on total employment. The previous literature has shown that the cost of eco-innovation has significant negative effect on the adoption of environmental initiatives and hence the subsequent effect on firm's performance (Dowell & Muthulingam 2017, Duanmu et al. 2018). Hence, one possible mechanism is that subsidies reduce the cost on eco-innovation and thus allow a firm to hire more green workers. In contrast, regulation induced eco-innovation appears to have no effect on total employment or green employment. This result is similar to those found in Vona et al. (2019), who show that subsidies were more successful in stimulating the creation of green jobs than direct environmental regulation.

[Table 3 about here]

6 Sensitivity checks

As part of our analysis we perform a series of sensitivity checks. First, Table 4 reports the results from a firm heterogeneity test where we divide our sample into manufacturing and non-manufacturing firms using a 1-digit classification (Sector C is for manufacturing firms). As we can see, it appears to be non-manufacturing firms that are driving our results[18].

[Table 4 about here]

The next step is to see whether the key results hold for different measures of green jobs. The results for core and broad green jobs are presented

[18]The descriptive of eco-innovator and employment by sectors shows that for manufacturing firms, they are very similar in size (eco-manufacturing innovator: 239.25 and non-eco-manufacturing innovator: 238.52), and eco-manufacturing innovator have slightly higher share of green jobs (57.75% vs 54.15%) and higher number of green jobs(130 vs 98). For most of non-manufacturing sectors, we find eco-innovators have high share of green jobs than non-eco-innovator. The negative effect on total jobs are mainly driven by energy supply, water and waste management, transportation and storage, accommodation and food services, renting, buying and selling of real estate, and other service activities sectors.

in Tables 5 and 6, respectively. Table 5 measures core green jobs and is a binary definition of a green job (excluding Green ID occupations). We do not report total jobs as they are same as the baseline model (see Table 2) and also for reasons of space. The results in Columns (1) and (2) show that being an eco-innovator is positively correlated with the number of core green jobs, and the share of core green jobs. More specifically, on average, an eco-innovator is found to have 14 more core green jobs than a non-eco-innovator which is equivalent to a 4.5% higher share of core green jobs. When we break eco-innovators into eco-product and eco-process innovators, we find similar results to using a task-based measure in that eco-product innovators are mainly driving the results. Columns (5) to (8) look again at the impact of different motives. Our results are generally consistent although we also find a positive relationship between policy driven eco-innovation and the share of core green jobs and a stronger effect from subsidy driven eco-innovation. The results for core green jobs are in some senses more significant than for our task-based measure.

[Table 5 about here]

Table 6 reports the results for the broader definition of green jobs is used with Green ID occupations included. The results are generally consistent and show that whichever of the three different measures of green jobs that are used there remains a positive impact of eco-innovation on the number and share of green jobs within a firm.

[Table 6 about here]

7 Conclusions

Eco-innovation is seen by many as a key mechanism by which an economy can transition to a more sustainable growth path and increase the quality of jobs. However, the employment effects of eco-innovation are not particularly well known, especially on the creation of so-called green jobs. In this paper we examine the relationship between eco-innovation and firm-level employment using the Dutch data from the CIS2008, TRD2010, and LFS2010 between 2006 and 2010. More specially, using a task-based measure and the green occupation list from O*NET we investigate how eco-innovation affects the total number of jobs as well as number of green jobs and share of green jobs within a firm.

Our econometric results, based on an endogenous switching model approach, show that eco-innovation has no statistically significant effect on total number of workers in a firm but does increase the number of green jobs and hence the share of green jobs. In further analysis we show that it is green product innovation that is driving the increase in the share of green jobs. This can be explained by the introduction of new green products that require occupations considered to be green to produce them but that these new green jobs substitute the non-green jobs which explains the overall finding of no change in total number of workers. When we consider the motives for undertaking eco-innovation we find that policy-induced eco-innovation is positively correlated with green jobs but that this is primarily due to subsidies given by the government to support eco-innovation and not through environmental regulation. Therefore, eco-innovations seem to lead to a compositional change of the labour force within the firms rather than an overall change in firms' employment, and this change is stimulated by the subsidy tool. We further show in sensitivity analysis that the results using task-based measurement provide a conservative estimate of the effect of eco-innovation as opposed to those based on binary definitions such as broad and core grenness measures of green jobs.

If the goal of the government is to create new greener jobs then the carrot of subsidies is more effective than using stricter environmental regulations that might result in firms taking other actions (e.g. relocating to more lenient regulatory environments consistent with the pollution haven hypothesis). However, a full welfare analysis on the cost of each new job based on the amount of subsidies given is beyond the scope of this study.

Finally, it is worth recalling that our sample period covers the years before and immediately after the global financial crisis which was categorized as a period of rising unemployment in general. Hence, our finding that eco-innovation has no effect the total employment of firms, but increases or has no effect on the number of green jobs does show that the Netherlands continued to transition towards a greener economic structure. The take away for policy-makers is that the encouragement of eco-innovation through subsidies or regulations may involve a trade off between the number of green jobs and the number of non-green jobs.

Table 1: Share of green jobs by different innovation activities

Characteristics	Ave. no. of jobs per firm	Share of green jobs (task-based measurement)	No. of firms
Innovation activties			
Innovator	347	31.47%	3,265
Non-innovator	225	25.91%	1,246
Eco-innovator	335	31.90%	2,377
Non-eco-innovator	289	26.75%	2,134
Eco-product innovator	362	34.33%	1,593
Eco-process innovator	347	32.83%	2,100
Motives			
Policy driven	337	33.56%	924
Environmental regulation	340	34.06%	802
Subsidy for eco-innovation	307	39.29%	364
Voluntary eco-innovation	357	34.91%	1058

Note: Firms can belong to more than one innovation category.

Table 2: Eco-innovation and employment: Baseline results (Task-based measurement)

	(1) Total employment	(2) Green employment	(3) Share of green jobs	(4) Total employment	(5) Green employment	(6) Share of green jobs
Regime 1						
Eco-innovator	-0.060	0.182*	0.033**			
	(-0.037)	(-0.105)	(0.015)			
Eco-product innovator				-0.020	0.137	0.027**
				(0.033)	(0.095)	(0.013)
Eco-process innovator				-0.020	0.143	0.014
				(0.036)	(0.103)	(0.015)
Product innovator	0.091**	0.184	0.014	0.093**	0.178	0.012
	(0.037)	(0.114)	(0.015)	(0.037)	(0.114)	(0.015)
Process innovator	0.025	-0.048	-0.014	0.026	-0.046	-0.014
	(0.036)	(0.106)	(0.015)	(0.036)	(0.106)	(0.015)
Organisation innovator	0.240***	0.379***	0.011	0.244***	0.381***	0.010
	(0.035)	(0.099)	(0.014)	(0.035)	(0.098)	(0.014)
Marketing innovator	0.053	-0.034	-0.024*	0.055	-0.036	-0.024*
	(0.035)	(0.099)	(0.014)	(0.035)	(0.099)	(0.014)
Wage	-0.755***	0.228	0.142***	-0.755***	0.229	0.141***
	(0.051)	(0.145)	(0.021)	(0.051)	(0.145)	(0.021)
Group	0.215***	0.371***	0.034**	0.215***	0.373***	0.034**
	(0.037)	(0.105)	(0.015)	(0.037)	(0.105)	(0.015)
Headoffice	0.089**	-0.029	-0.013	0.089**	-0.030	-0.013
	(0.043)	(0.122)	(0.017)	(0.043)	(0.122)	(0.017)
Export	-0.125***	0.043	0.042***	-0.124***	0.042	0.041***
	(0.038)	(0.111)	(0.015)	(0.038)	(0.111)	(0.015)
Turnover	0.439***	0.443***	-0.008*	0.438***	0.443***	-0.008*
	(0.011)	(0.034)	(0.005)	(0.011)	(0.034)	(0.005)
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes

Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regime 0						
Wage	-0.873***	0.171	0.161***	-0.873***	0.171	0.161***
	(0.080)	(0.181)	(0.027)	(0.080)	(0.181)	(0.027)
Group	0.226***	0.588***	0.034	0.226***	0.588***	0.034
	(0.067)	(0.156)	(0.023)	(0.067)	(0.156)	(0.023)
Headoffice	0.235***	-0.073	-0.038	0.235***	-0.073	-0.038
	(0.091)	(0.217)	(0.033)	(0.091)	(0.217)	(0.033)
Export	-0.264***	0.030	0.049*	-0.264***	0.030	0.049*
	(0.070)	(0.168)	(0.025)	(0.070)	(0.168)	(0.025)
Turnover	0.383***	0.478***	0.009	0.383***	0.478***	0.009
	(0.021)	(0.056)	(0.008)	(0.021)	(0.056)	(0.008)
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation						
R&D	0.249***	0.297***	0.300***	0.249***	0.297***	0.300***
	(0.019)	(0.023)	(0.023)	(0.019)	(0.023)	(0.023)
Funding	0.371***	0.608***	0.613***	0.371***	0.607***	0.613***
	(0.139)	(0.181)	(0.181)	(0.139)	(0.181)	(0.181)
Wage	-0.061	-0.063	-0.065	-0.061	-0.063	-0.065
	(0.064)	(0.065)	(0.065)	(0.064)	(0.065)	(0.065)
Group	0.070	0.097*	0.096*	0.070	0.097*	0.096*
	(0.050)	(0.051)	(0.051)	(0.050)	(0.051)	(0.051)
Headoffice	-0.058	-0.060	-0.051	-0.058	-0.060	-0.051
	(0.067)	(0.069)	(0.069)	(0.067)	(0.069)	(0.069)
Export	0.176***	0.191***	0.183***	0.176***	0.191***	0.183***
	(0.051)	(0.052)	(0.052)	(0.051)	(0.052)	(0.052)
Turnover	0.142***	0.119***	0.122***	0.142***	0.120***	0.122***

	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
rho_0	-1.344***	-0.012	0.068	-1.344***	-0.012	0.068
rho_1	-0.162***	-0.203*	-0.032	-0.160***	-0.197*	-0.031
N	4511	4511	4511	4511	4511	4511

Selection equation: Y = Innovator; firm is an innovator if it has introduced general product and process innovation, eco-innovation, marketing innovation and organisational innovation during the period 2006 to 2008.
Regime 1 for innovator; regime 0 for non-innovator. Standard errors in parentheses.
Rho_0 is the correlation coefficient between u_i and ϵ_{0i}, and rho_1 is the correlation coefficient between u_i and ϵ_{1i}
Group takes value of 1 if firm is part of an enterprise group. Headoffice takes value of 1 if the head office of firm is outside the Netherlands.
Constants are not reported. $^{***}p < 0.01;^{**}p < 0.05;^{*}p < 0.1$.

Table 3: Eco-innovation and employment: Different motives (Task-based measurement)

	(1) Total employment	(2) Green employment	(3) Share of green jobs	(4) Total employment	(5) Green employment	(6) Share of green jobs
Regime 1						
Policy driven	0.049	0.182*	0.033**			
	(0.039)	(0.105)	(0.015)			
Subsidy driven				0.069	0.293**	0.050**
				(0.052)	(0.150)	(0.021)
Regulation driven				0.023	0.068	-0.001
				(0.041)	(0.118)	(0.017)
Voluntary	0.025	0.096	-0.000	0.025	0.100	-0.000
	(0.037)	(0.107)	(0.015)	(0.037)	(0.106)	(0.015)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regime 0						
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation						
R&D	0.249***	0.297***	0.300***	0.249***	0.297***	0.300***
	(0.019)	(0.023)	(0.023)	(0.019)	(0.023)	(0.023)
Funding	0.370***	0.608***	0.613***	0.369***	0.607***	0.613***
	(0.139)	(0.181)	(0.181)	(0.139)	(0.181)	(0.181)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	Yes	Yes	Yes	Yes	Yes	Yes

Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
rho_0	-1.344***	-0.012	0.068	-1.344***	-0.012	0.068
rho_1	-0.154**	-0.201*	-0.036	-0.154**	-0.202*	-0.035
N	4511	4511	4511	4511	4511	4511

Selection equation: Y = Innovator; firm is an innovator if it has introduced general product and process innovation, eco-innovation, marketing innovation and organisational innovation during 2006 to 2008.
Regime 1 for innovator; regime 0 for non-innovator.Standard errors in parentheses.
Rho_0 is the correlation coefficient between u_i and ϵ_{0i}, and rho_1 is the correlation coefficient between u_i and ϵ_{1i}
Group takes value of 1 if firm is part of an enterprise group. Headoffice takes value of 1 if the head office of firm is outside the Netherlands.
Other controls are included but not reported as they are same as Table2. Constants are not reported. $^{***}p < 0.01;^{**}p < 0.05;^{*}p < 0.1$.

Table 4: Eco-innovation and employment: Heterogeneity tests (Task-based measurement)

	Manufacturing			Non-manufacturing		
	(1) Total employment	(2) Green employment	(3) Share of green jobs	(4) Total employment	(5) Green employment	(6) Share of green jobs
Regime 1						
Eco-innovator	-0.008	0.214	0.017	-0.086*	0.241*	0.055***
	(0.059)	(0.176)	(0.025)	(0.048)	(0.133)	(0.019)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	No	No	No	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Regime 0						
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	No	No	No	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation						
R&D	0.229***	0.285***	0.288***	0.268***	0.312***	0.314***
	(0.025)	(0.034)	(0.034)	(0.027)	(0.033)	(0.033)
Funding	0.089	0.492**	0.472**	0.825***	0.962***	0.957***
	(0.152)	(0.218)	(0.219)	(0.303)	(0.358)	(0.353)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral dummies	No	No	No	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
rho_0	-1.739***	0.196	0.183	-1.151***	-0.291	-0.069
rho_1	-0.142*	-0.211	-0.023	-0.188**	-0.201	-0.013

N	1772	1772	1772	2739	2739	2739

Selection equation: Y = Innovator; firm is an innovator if it has introduced general product and process innovation, eco-innovation, marketing innovation and organisational innovation during the period 2006 to 2008.
Regime 1 for innovator; regime 0 for non-innovator.Standard errors in parentheses.
Rho_0 is the correlation coefficient between u_i and ϵ_{0i}, and rho_1 is the correlation coefficient between u_i and ϵ_{1i}
Group takes value of 1 if firm is part of an enterprise group. Headoffice takes value of 1 if the head office of firm is outside the Netherlands.
Other controls are included but not reported as they are similar to Table2. Constants are not reported. $^{***}p < 0.01$;$^{**}p < 0.05$;$^{*}p < 0.1$.

Table 5: Eco-innovation and employment: Sensitivity check (1) (Core green jobs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Green employment	Share of green jobs	Green employment	Share of green jobs	Green employment	Share of green jobs	Green employment	Share of green jobs
Regime 1								
Eco-innovator	0.221**	0.045***						
	(0.106)	(0.015)						
Eco-product innovator			0.293***	0.048***				
			(0.095)	(0.014)				
Eco-process innovator			0.043	0.012				
			(0.103)	(0.015)				
Policy driven					0.245**	0.032*		
					(0.112)	(0.016)		
Subsidy driven							0.390***	0.069***
							(0.150)	(0.022)
Regulation driven							0.109	0.005
							(0.119)	(0.017)
Voluntary					0.126	0.006	0.122	0.006
					(0.107)	(0.016)	(0.106)	(0.016)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regime 0								
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection equation								

R&D	0.295***	0.300***	0.295***	0.300***	0.295***	0.300***	0.295***	0.300***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Funding	0.610***	0.618***	0.606***	0.617***	0.609***	0.619***	0.608***	0.618***
	(0.179)	(0.181)	(0.179)	(0.181)	(0.179)	(0.181)	(0.179)	(0.181)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rho_0	-0.034	0.054	-0.034	0.054	-0.034	0.054	-0.034	0.054
rho_1	-0.360***	-0.114	-0.358***	-0.112	-0.356***	-0.117	-0.358***	-0.116
N	4511	4511	4511	4511	4511	4511	4511	4511

Core green jobs are green occupations that exclude Green ID.
Selection equation: Y = Innovator; firm is an innovator if it has introduced general product and process innovation, eco-innovation, marketing innovation and organisational innovation during 2006 to 2008.
Regime 1 for innovator; regime 0 for non-innovator. Standard errors in parentheses.
Rho_0 is the correlation coefficient between u_i and ϵ_{0i}, and rho_1 is the correlation coefficient between u_i and ϵ_{1i}
Group takes value of 1 if firm is part of an enterprise group; headoffice takes value of 1 if the head office of firm is outside the Netherlands.
Total jobs are not reported as they are same to Table2, and also for space reason.
Other controls are included but not reported as they are similar to Table2. Constants are not reported. $^{***}p < 0.01;^{**} p < 0.05;^{*} p < 0.1$.

Table 6: Eco-innovation and employment: Sensitivity check (2) (Broad green jobs)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Green employment	Share of green jobs	Green employment	Share of green jobs	Green employment	Share of green jobs	Green employment	Share of green jobs
Regime 1								
Eco-innovator	0.202**	0.053***						
	(0.097)	(0.016)						
Eco-product innovator			0.209**	0.043***				
			(0.088)	(0.014)				
Eco-process innovator			0.088	0.024				
			(0.095)	(0.015)				
Policy driven					0.411***	0.057***		
					(0.103)	(0.017)		
Subsidy driven							0.539***	0.079***
							(0.138)	(0.022)
Regulation driven							0.192*	0.022
							(0.109)	(0.018)
Voluntary					-0.003	-0.003	0.007	-0.000
					(0.099)	(0.016)	(0.098)	(0.016)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regime 0								
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Selection equation								
R&D	0.299***	0.300***	0.299***	0.300***	0.299***	0.300***	0.299***	0.300***
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Funding	0.609***	0.592***	0.607***	0.591***	0.607***	0.591***	0.606***	0.591***
	(0.179)	(0.181)	(0.179)	(0.181)	(0.179)	(0.181)	(0.179)	(0.181)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
rho_0	-0.349**	-0.335*	-0.349**	-0.335*	-0.349**	-0.335*	-0.349**	-0.335*
rho_1	-0.205**	-0.097	-0.202**	-0.095	-0.189**	-0.096	-0.191**	-0.096
N	4511	4511	4511	4511	4511	4511	4511	4511

Broad green jobs are green occupations that include Green ID.
Selection equation: Y = Innovator; firm is an innovator if it has introduced general product and process innovation, eco-innovation, marketing innovation and organisational innovation during 2006 to 2008.
Regime 1 for innovator; regime 0 for non-innovator. Standard errors in parentheses.
Rho_0 is the correlation coefficient between u_i and ϵ_{0i}, and rho_1 is the correlation coefficient between u_i and ϵ_{1i}
Group takes value of 1 if firm is part of an enterprise group; headoffice takes value of 1 if the head office of firm is outside the Netherlands.
Total jobs are not reported as they are same to Table2, and also for space reason.
Other controls are included but not reported as they are similar to Table2. Constants are not reported. $^{***}p < 0.01; ^{**}p < 0.05; ^{*}p < 0.1$.

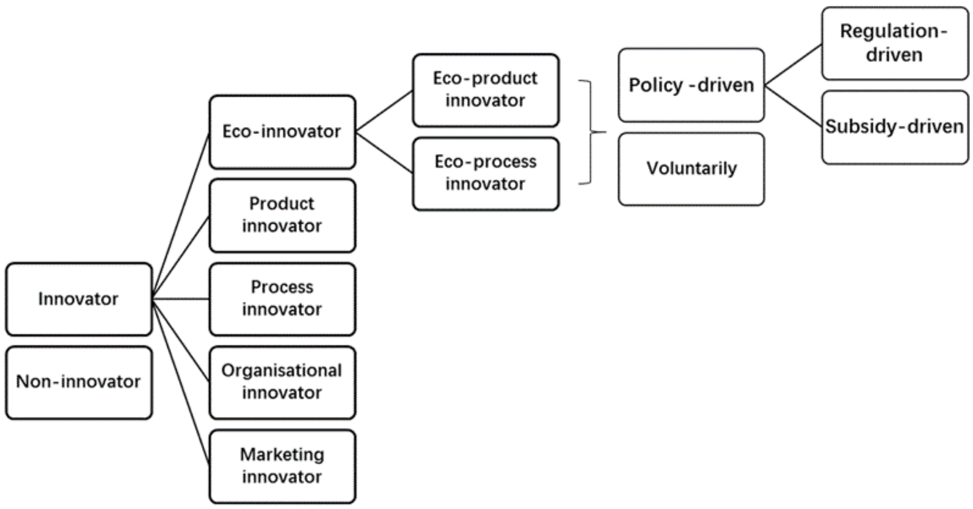

Figure 1: Relationship between different innovation categories

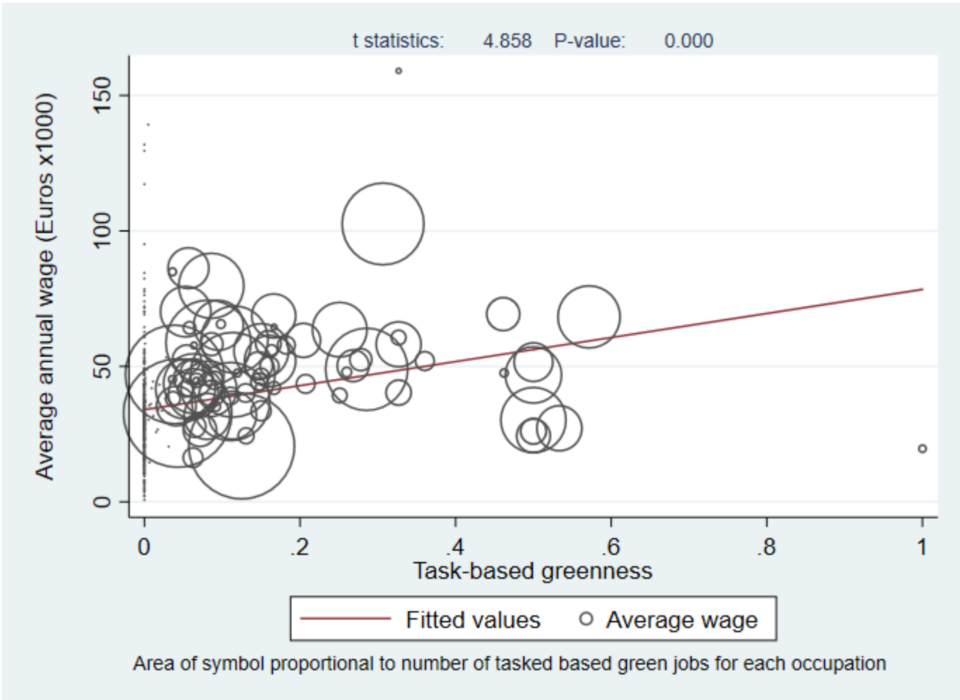

Figure 2: Wage and greenness for occupations

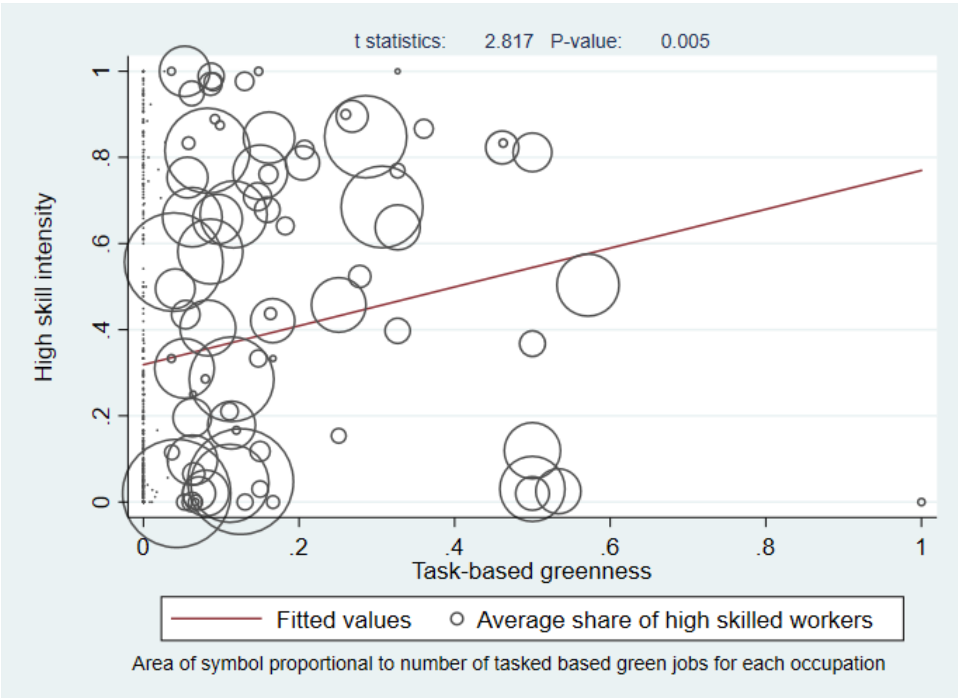

Figure 3: High skill intensity and greenness for occupations

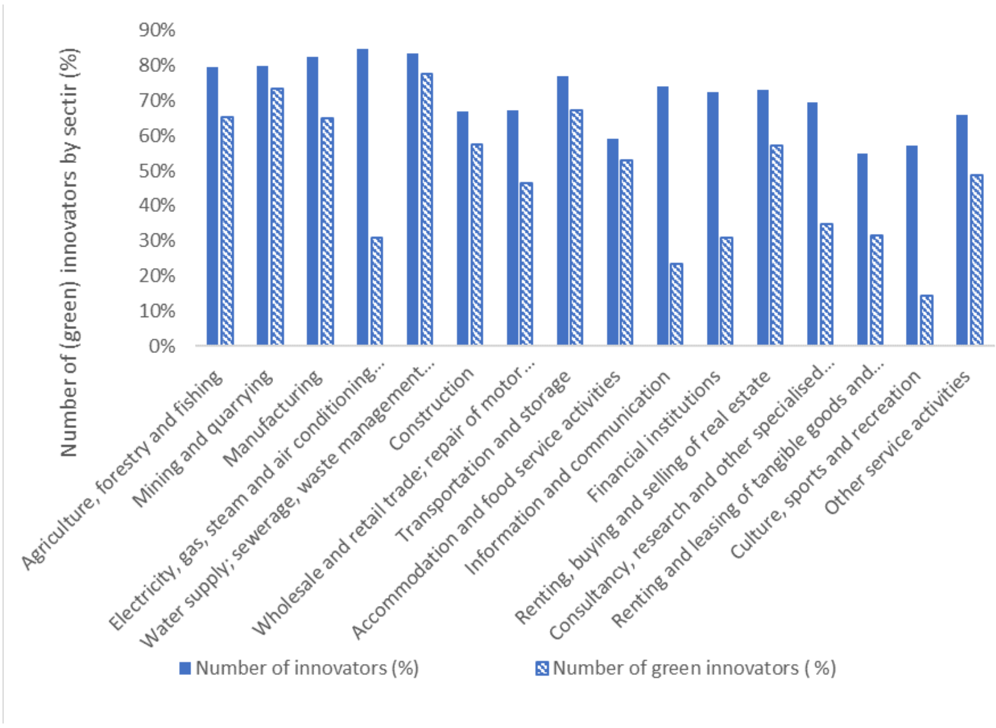

Figure 4: Number of innovators and eco-innovators by sector

References

Antonucci, T. & Pianta, M. (2002), 'Employment effects of product and process innovation in Europe', *International Review of Applied Economics* **16**(3), 295–307.

Baum, C., Schaffer, M. & Stillman, S. (2010), 'ivreg2: Stata module for extended instrumental variables/2SLS, GMM and AC/HAC, LIML and k-class regression. statistical software components s425401, boston college department of economics, boston college, boston'.

Berrone, P., Fosfuri, A., Gelabert, L. & Gomez-Mejia, L. R. (2013), 'Necessity as the mother of 'green'inventions: Institutional pressures and environmental innovations', *Strategic Management Journal* **34**(8), 891–909.

Bogliacino, F. & Pianta, M. (2010), 'Innovation and employment: A reinvestigation using revised Pavitt classes', *Research Policy* **39**(6), 799–809.

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

Cai, W., Wang, C., Chen, J. & Wang, S. (2011), 'Green economy and green jobs: Myth or reality? the case of China's power generation sector', *Energy* **36**(10), 5994–6003.

Cainelli, G., Mazzanti, M. & Zoboli, R. (2011), 'Environmentally oriented innovative strategies and firm performance in services: Micro-evidence from Italy', *International Review of Applied Economics* **25**(1), 61–85.

Cecere, G. & Mazzanti, M. (2017), 'Green jobs and eco-innovations in European SMEs', *Resource and Energy Economics* **49**, 86–98.

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

Dachs, B. & Peters, B. (2014), 'Innovation, employment growth, and foreign ownership of firms: A European perspective', *Research Policy* **43**(1), 214–232.

Deschenes, O. (2013), Green jobs, Technical report, IZA Policy Paper.

Dierdorff, E. C., Norton, J. J., Drewes, D. W., Kroustalis, C. M., Rivkin, D. & Lewis, P. (2009), 'Greening of the world of work: Implications for O* NET-SOC and new and emerging occupations', *O*NET* .

Dowell, G. W. & Muthulingam, S. (2017), 'Will firms go green if it pays? The impact of disruption, cost, and external factors on the adoption of environmental initiatives', *Strategic Management Journal* **38**(6), 1287–1304.

Duanmu, J.-L., Bu, M. & Pittman, R. (2018), 'Does market competition dampen environmental performance? Evidence from China', *Strategic Management Journal* **39**(11), 3006–3030.

EIO (2010), Eco-innovation in Netherlands, Technical report, Eco-Innovation Observatory.

Elliott, R. J. & Lindley, J. K. (2017), 'Environmental jobs and growth in the United States', *Ecological Economics* **132**, 232–244.

Elliott, R. J. R., Jabbour, L. & Vanino, E. (2019), 'Innovation and the creative destruction of trade: A study of the intensive and extensive margins of trade for French firms', *Oxford Bulletin and Economics and Statistics* **82**(1), 180–208.

ETAP (2020), 'Econ-innovationat the heart of European policies', `https://ec.europa.eu/environment/ecoap/about-action-plan/etap-previous-action-plan_en`. Accessed at: June 2019.

Eurostat (2009), The environmental goods and services sector: a data collection handbook, Technical report, Technical report. http://ec. europa. eu/eurostat/documents/3859598/5910217.

Evangelista, R. & Savona, M. (2003), 'Innovation, employment and skills in services: Firm and sectoral evidence', *Structural Change and Economic Dynamics* **14**(4), 449–474.

Gagliardi, L., Marin, G. & Miriello, C. (2016), 'The greener the better? Job creation effects of environmentally-friendly technological change', *Industrial and Corporate Change* **25**(5), 779–807.

Harrison, R., Jaumandreu, J., Mairesse, J. & Peters, B. (2014), 'Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries', *International Journal of Industrial Organization* **35**, 29–43.

Horbach, J. & Rennings, K. (2013), 'Environmental innovation and employment dynamics in different technology fields–an analysis based on the German Community Innovation Survey 2009', *Journal of Cleaner Production* **57**, 158–165.

Hughes, G. (2011), *The myth of green jobs*, Global Warming Policy Foundation,GWPF Report 2.

ILO/UNEP (2012), *Working towards sustainable development: Opportunities for decent work and social inclusion in a green economy*, International Labour Organization.

Isogawa, D., Niskikawa, K. & Ohashi, H. (2012), 'Innovation height and firm performance: Using innovation survey from Japan', *RIETI Discussion Paper Series* (12-E-077).

Kunapatarawong, R. & Martínez-Ros, E. (2016), 'Towards green growth: How does green innovation affect employment?', *Research Policy* **45**(6), 1218–1232.

Lachenmaier, S. & Rottmann, H. (2011), 'Effects of innovation on employment: A dynamic panel analysis', *International Journal of Industrial Organization* **29**(2), 210–220.

Licht, G. & Peters, B. (2013), The impact of green innovation on employment growth in Europe, Technical report, WWWforEurope Working Paper.

Lokshin, M. & Sajaia, Z. (2004), 'Maximum likelihood estimation of endogenous switching regression models', *The Stata Journal* **4**(3), 282–289.

Maddala, G. S. (1986), *Limited-dependent and qualitative variables in econometrics*, number 3, Cambridge university press.

OECD (2008), 'Sustainable manufacturing and eco-innovation: First steps in building a common analytical framework', *OECD, Paris* .

OECD (2012), 'Green growth and eco-innovation', `http://www.oecd.org/sti/ind/greengrowthandeco-innovation.htm`. Accessed at: June 2019.

OECD (2018), 'Employment/population ratio, by sex and age group', `https://stats.oecd.org/index.aspx?queryid=54742`. Accessed at: June 2019.

Peters, D. J. (2014), 'Understanding green occupations from a task-based approach', *Applied Economic Perspectives and Policy* **36**(2), 238–264.

Poirier, D. J. & Ruud, P. A. (1981), 'On the appropriateness of endogenous switching', *Journal of Econometrics* **16**(2), 249–256.

Rennings, K., Ziegler, A. & Zwick, T. (2004), 'The effect of environmental innovations on employment changes: An econometric analysis', *Business Strategy and the Environment* **13**(6), 374–387.

Rennings, K. & Zwick, T. (2002), 'Employment impact of cleaner production on the firm level: Empirical evidence from a survey in five European countries', *International Journal of Innovation Management* **6**(03), 319–342.

Stock, J. H. & Yogo, M. (2002), Testing for weak instruments in linear IV regression, Technical report, National Bureau of Economic Research.

UN (2017), Report on the implementation of the Sustainable Development Goals, Kingdom of the Netherlands, Technical report, United Nations High-Level Political Forum on Sustainable Development.

UNEP (2011), 'Towards a green economy: Pathways to sustainable development and poverty eradication', *Geneva: United Nations Environmental Programme* .

Van Reenen, J. (1997), 'Employment and technological innovation: Evidence from UK manufacturing firms', *Journal of Labor Economics* **15**(2), 255–284.

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

Vona, F., Marin, G., Consoli, D. & Popp, D. (2018), 'Environmental regulation and green skills: An empirical exploration', *Journal of the Association of Environmental and Resource Economists* **5**(4), 713–753.

Wang, C., Zhang, W., Cai, W. & Xie, X. (2013), 'Employment impacts of CDM projects in China's power sector', *Energy Policy* **59**, 481–491.

WB (2017*a*), 'Agriculture, forestry, and fishing, value added (`https://data.worldbank.org/indicator/NV.AGR.TOTL.ZS`. Accessed at: June 2019.

WB (2017*b*), 'Industry (including construction), value added (`https://data.worldbank.org/indicator/NV.IND.TOTL.ZS`. Accessed at: June 2019.

WB (2018*a*), 'Manufacturing, value added (https://data.worldbank.org/indicator/NV.IND.MANF.ZS?locations=NL. Accessed at: June 2019.

WB (2018*b*), 'Services, value added (of GDP)', https://data.worldbank.org/indicator/NV.SRV.TOTL.ZS?locations=NL. Accessed at: June 2019.

WB (2019), 'Employment to population ratio, 15+, total (https://data.worldbank.org/indicator/SL.EMP.TOTL.SP.ZS?end=2010&locations=NL&start=2006. Accessed at: June 2019.

Yi, H. (2013), 'Clean energy policies and green jobs: An evaluation of green jobs in US metropolitan areas', *Energy Policy* **56**, 644–652.

Yi, H. (2014), 'Green businesses in a clean energy economy: Analyzing drivers of green business growth in US states', *Energy* **68**, 922–929.

Yi, H. & Liu, Y. (2015), 'Green economy in China: Regional variations and policy drivers', *Global Environmental Change* **31**, 11–19.

Appendix

A Mapping O*NET green occupations to the Dutch LFS

The O*NET database contains detailed information on the tasks and skills associated with a given occupation. In order to investigate the effect of a greening economy on occupational requirements, the National Centre of O*NET development conducted an extensive research and screening process to identify what it believes to be green jobs. O*NET complied a list of green occupation titles, and identified 12 broad sectors.[19] Similar job titles, with similar work content, are grouped together to match with O*NET SOC codes. For details to see Dierdorff et al. (2009).

Following the process outlined above, three types of green occupation are identified in the O*NET-SOC system: (1) Green increased demand (Green ID) occupations; (2) Green enhanced skills (Green ES) occupations; and (3) Green new and emerging jobs (Green NE) occupations. For the broad definition of green jobs, we use a binary measure and include all three type of green occupation. To calculate a measure of core green jobs, we still use a binary measure but exclude Green ID occupations (which are commonly considered to be indirect green occupations).

The third approach, and central to this paper, is to generate a task based measure which calculates the greenness of each Green ES and Green NE occupation.[20] Following Vona et al. (2019), the measure is a weighted average of green and non-green tasks (which is the ratio of the importance of green occupational tasks over the total number of occupational tasks (importance weighted)) [21]. The importance value for each task come directly from O*NET based on reports from both O*NET analysts and those employees that are

[19]The 12 broad sectors are: (1) Renewable Energy Generation; (2) Transportation; (3) Energy Efficiency; (4) Green Construction; (5) Energy Trading; (6) Energy/Carbon Capture and Storage; (7) Research, Design, and Consulting Services; (8) Environment Protection; (9) Agriculture and Forestry; (10) Manufacturing; (11) Recycling and Waste Reduction; and (12) Governmental and Regulatory Administration.

[20]Our task-based occupational greenness index can be calculated using information from the Green Task Statements and Task Rating files which are available at the O*NET resource centre. See link: https://www.onetcenter.org/reports/GreenTask.html.

[21]For example, assume an occupation has four tasks, two green and two non-green. If the importance score for each task one to four are 0.1, 0.3. 0.4 and 0.2 respectively, then the weighted greenness is 0.4. Without weighting it would be 0.5.

doing the jobs (incumbents).[22] The reason to use a task based measure is that not all of the tasks for those occupations labelled "green" in a binary sense can really be considered green tasks. Our task-based approach provides a continuous measure that we argue is a good proxy for the time a worker spends on green activities.

We now explain how our green job definitions can be used to identify green jobs in the Dutch Labor Force Survey (LFS). To do this we compile a green occupation list based on ISCO. This means we follow a number of stages. First, we match O*NET-SOC with SOC. A crosswalk between O*NET-SOC and SOC is readily available. However, because the O*NET-SOC code is at the 8-digit level and the SOC code is only available at the 6-digit level, matching O*NET green occupation with SOC is a challenge. Our solution is to calculate the average greenness of each 6-digit SOC code from the 8-digit SOC values. For example, consider our broad green job definition. For SOC “11-1011, Chief Executives”, there are two corresponding O*NET-SOC “11-1101.00, Chief Executives” that is defined as a non-green job and “11-1101.03, Chief Sustainability officers” which, not surprisingly, is defined as a green job. In this paper we calculate the average broad greenness for SOC “11-1011” as the simple average between of the two O*NET-SOC codes, which in this case would be 0.5. Our core greenness index and task-based greenness index for each SOC occupation is calculated using the same procedure.

The second step is to use a crosswalk between SOC and ISCO. This is more challenging as the crosswalk between SOC and ISCO does not provide a simple one-to-one matching. Our solution is to again calculate the average greenness of each ISCO code based on the greenness value of each SOC code. For example, ISCO “1112, Senior Government Officials”, is made up of three SOC occupations, “11-1101, Chief Executives” with a SOC broad greenness score of 0.5 (from above), “11-1021, General and Operations Managers” with a SOC broad greenness score of 1, and “11-9161, Emergency Management Directors” with a SOC broad greenness score of 0. Hence, the average broad greenness score for ISCO “1112” is 0.5. Following this approach, of the 436 ISCO occupations, 161 have a greenness index value greater than 0, 106 have a core greenness index of greater than 0 (excluding Green ID jobs), and 83 task-based occupations have a greenness index greater than 0. The full list of ISCO green occupations with their corresponding greenness score is given

[22] Details of the rating statistics for incumbents can be found at https://www.onetcenter.org/dictionary/24.2/excel/appendix_incumbent.html, and for analyst at https://www.onetcenter.org/dictionary/24.2/excel/appendix_analyst.html.

in Table A1.

[Table A1 about here]

In the Dutch LFS2010, there are 109,344 people surveyed. Of those people, 3,907 have no occupation information and are therefore dropped from the sample. Another 21,299 individuals only have occupation information available at the 2 or 3-digit level. To include these individuals in our sample we aggregate our ISCO 4-digit greenness indices to the 2 and 3-digit level. Based on the ISCO greenness scores associated with each occupation at the 4-digit level, we calculate the sample average greenness score for each group. For example, ISCO "1110, Legislators and Senior Officials", includes four occupations, "1111, Legislators" with an ISCO broad greenness score of 0, "1112, Senior Government Officials" with an ISCO broad greenness score of 0.5, "1113, Traditional Chiefs and Heads of Village" with an ISCO broad greenness score of 0.25, and "1114, Senior Officials of Special-interest Organizations" with an ISCO broad greenness score of 0.53. As a result, the overall broad greenness score for "1110" is 0.32. This process is repeated for each of our three greenness indices.

At the end of this process, each individual has a greenness index for both their current and previous job. In this paper we consider an individual to be a green worker if their corresponding occupational greenness score is greater than the average greenness. That is to say, broad green jobs are those occupations with a greenness index greater than 0.189. Core green jobs are those occupations with a greenness index greater than 0.115. Finally, task-based green jobs are occupations with a greenness index greater than 0.034 [23]. Based on these three different definitions of a green occupation, Table A3 reports the total number of occupation categories and number of occupations that are classified as different green occupations by 1-digit ISCO code. As we can see from Table A3, green occupations are more prevalent in the high skilled occupations which may involve more analytic and technical skills such as managers, professionals and technicians and associate professionals, while green occupations are less prevalent in service occupations, especially for task-based measurement of green occupations. When we compare three types of green occupations horizontally, occupations that are considered as Green ID jobs are mainly in primary sectors and some services sectors. For instance, there are 12 broad green occupation categories in ISCO category 6

[23] Details see tableA2

"Skilled agricultural, forestry and fishery workers", but no core green occupations and task-based green occupations, which indicates these 12 occupations must be Green ID occupations.

[Table A2 about here]

[Table A3 about here]

Table A1: Green occupation in ISCO system by greenness

ISCO	Occupation title	Task-based greenness	Core greenness	Broad greenness
2143	Environmental engineers	1	1	1
9612	Refuse sorters	1	1	1
1321	Manufacturing managers	0.5714	0.7143	0.8571
7119	Building frame and related trades workers not elsewhere classified	0.5333	0.5333	0.5333
7411	Building and related electricians	0.5000	0.5000	1
2631	Economists	0.5000	0.5000	0.5000
3123	Construction supervisors	0.5000	0.5000	0.5000
3141	Life science technicians (excluding medical)	0.5000	0.5000	0.5000
9611	Garbage and recycling collectors	0.5000	0.5000	0.5000
2112	Meteorologists	0.4624	0.7500	0.7500
1223	Research and development managers	0.4612	0.6667	0.8333
2164	Town and traffic planners	0.3604	1	1
1213	Policy and planning managers	0.3268	0.6000	0.6000
1322	Mining managers	0.3268	0.6000	0.6000
1349	Professional services managers not elsewhere classified	0.3268	0.6000	0.6000
1439	Services managers not elsewhere classified	0.3268	0.6000	0.6000
1120	Managing directors and chief executives	0.3067	0.7500	0.7500
2422	Policy administration professionals	0.2857	0.2857	0.2857
2433	Technical and medical sales professionals (excluding ICT)	0.2781	0.5000	0.5000
2161	Building architects	0.2683	1	1
2162	Landscape architects	0.2601	1	1
1323	Construction managers	0.2510	1	1
7111	House builders	0.2510	1	1
1113	Traditional chiefs and heads of villages	0.2500	0.2500	0.2500
2132	Farming, forestry and fisheries advisers	0.2073	0.3333	0.6667
1112	Senior government officials	0.2045	0.5000	0.5000
2434	Information and communications technology sales professionals	0.1854	0.3333	0.3333
1324	Supply, distribution and related managers	0.1662	0.7500	0.7500
1431	Sports, recreation and cultural centre managers	0.1634	0.3000	0.3000
2151	Electrical engineers	0.1607	1	1
2412	Financial and investment advisers	0.1593	1	1
3132	Incinerator and water treatment plant operators	0.1500	0.2000	0.4500
8114	Cement, stone and other mineral products machine operators	0.1500	0.2000	0.4500
3119	Physical and engineering science technicians not elsewhere classified	0.1477	0.3679	0.3679
1114	Senior officials of special-interest organizations	0.1467	0.5333	0.5333
2149	Engineering professionals not elsewhere classified	0.1308	0.3833	0.4333
9329	Manufacturing labourers not elsewhere classified	0.1250	0.1250	0.3750

9333	Freight handlers	0.1250	0.1250	0.3750
3131	Power production plant operators	0.1195	0.5	1
1420	Retail and wholesale trade managers	0.1134	1	1
5221	Shopkeepers	0.1134	1	1
7233	Agricultural and industrial machinery mechanics and repairers	0.1111	0.1111	0.4444
3257	Environmental and occupational health inspectors and associates	0.1107	0.3125	0.5625
2153	Telecommunications engineers	0.0984	0.5000	0.5000
1221	Sales and marketing managers	0.0860	0.5000	0.5000
3323	Buyers	0.0828	0.3333	0.6667
2421	Management and organization analysts	0.0823	0.3333	0.3333
7126	Plumbers and pipe fitters	0.0804	0.3333	0.3333
3116	Chemical engineering technicians	0.0797	0.8462	0.8462
7213	Sheet-metal workers	0.0714	0.3333	0.6667
3114	Electronics engineering technicians	0.0668	0.3333	0.6667
3522	Telecommunications engineering technicians	0.0668	0.3333	0.6667
3155	Air traffic safety electronics technicians	0.0668	0.1667	0.3333
8211	Mechanical machinery assemblers	0.0648	0.5000	1
3117	Mining and metallurgical technicians	0.0638	0.7564	0.7564
3115	Mechanical engineering technicians	0.0628	0.5865	0.5865
2131	Biologists, botanists, zoologists and related professionals	0.0622	0.1000	0.2000
2114	Geologists and geophysicists	0.0581	0.5000	0.8333
1343	Aged care services managers	0.0567	0.5000	0.5000
1346	Financial and insurance services branch managers	0.0567	0.5000	0.5000
1219	Business services and administration managers not elsewhere classified	0.0545	0.1000	0.1000
3113	Electrical engineering technicians	0.0531	0.6667	0.8333
3112	Civil engineering technicians	0.0528	0.2000	0.2000
8332	Heavy truck and lorry drivers	0.0428	0.5000	0.5000
3111	Chemical and physical science technicians	0.0410	0.3889	0.7222
3339	Business services agents not elsewhere classified	0.0390	0.1107	0.1107
3142	Agricultural technicians	0.0367	0.3333	0.3333
1311	Agricultural and forestry production managers	0.0361	0.2500	0.2500
1312	Aquaculture and fisheries production managers	0.0361	0.2500	0.2500
2619	Legal professionals not elsewhere classified	0.0281	1	1
7513	Dairy-products makers	0.0270	0.5000	0.5000
2633	Philosophers, historians and political scientists	0.0225	0.1667	0.1667
2642	Journalists	0.0193	0.5000	0.5000
8131	Chemical products plant and machine operators	0.0180	0.3333	0.6667
9313	Building construction labourers	0.0172	0.1250	0.2500
8111	Miners and quarriers	0.0153	0.1250	0.1250
7231	Motor vehicle mechanics and repairers	0.0151	0.1333	0.2333

8113	Well drillers and borers and related workers	0.0083	0.1667	0.1667
2519	Software and applications developers and analysts not elsewhere classified	0.0057	0.1538	0.1538
7223	Metal working machine tool setters and operators	0.0055	0.0833	0.3333
3311	Securities and finance dealers and brokers	0.0050	0.1250	0.1250
3324	Trade brokers	0.0033	0.2500	0.2500
2529	Database and network professionals not elsewhere classified	0.0028	0.0769	0.0769
2142	Civil engineers	0	1	1
2356	Information technology trainers	0	1	1
2424	Training and staff development professionals	0	1	1
2432	Public relations professionals	0	1	1
7121	Roofers	0	1	1
7543	Product graders and testers (excluding foods and beverages)	0	1	1
3331	Clearing and forwarding agents	0	0.7500	0.7500
2133	Environmental protection professionals	0	0.5000	0.6250
2144	Mechanical engineers	0	0.5000	0.5000
3121	Mining supervisors	0	0.5000	0.5000
9622	Odd job persons	0	0.3750	0.6250
3322	Commercial sales representatives	0	0.3750	0.3750
2413	Financial analysts	0	0.3333	0.3333
4321	Stock clerks	0	0.3333	0.3333
1222	Advertising and public relations managers	0	0.2500	0.2500
2152	Electronics engineers	0	0.2500	0.2500
2643	Translators, interpreters and other linguists	0	0.2500	0.2500
2113	Chemists	0	0.1667	0.8333
7127	Air conditioning and refrigeration mechanics	0	0.1667	0.8333
2111	Physicists and astronomers	0	0.1667	0.1667
3353	Government social benefits officials	0	0.0714	0.0714
3354	Government licensing officials	0	0.0714	0.0714
3351	Customs and border inspectors	0	0.0476	0.0476
2145	Chemical engineers	0	0	1
3122	Manufacturing supervisors	0	0	1
3133	Chemical processing plant controllers	0	0	1
3143	Forestry technicians	0	0	1
3359	Regulatory government associate professionals not elsewhere classified	0	0	1
4322	Production clerks	0	0	1
4323	Transport clerks	0	0	1
7413	Electrical line installers and repairers	0	0	1
8182	Steam engine and boiler operators	0	0	1
9624	Water and firewood collectors	0	0	1
7115	Carpenters and joiners	0	0	0.6667

7214	Structural-metal preparers and erectors	0	0	0.6667
2141	Industrial and production engineers	0	0	0.5000
2263	Environmental and occupational health and hygiene professionals	0	0	0.5000
2512	Software developers	0	0	0.5000
7124	Insulation workers	0	0	0.5000
7232	Aircraft engine mechanics and repairers	0	0	0.5000
7234	Bicycle and related repairers	0	0	0.5000
7312	Musical instrument makers and tuners	0	0	0.5000
7515	Food and beverage tasters and graders	0	0	0.5000
8219	Assemblers not elsewhere classified	0	0	0.5000
8344	Lifting truck operators	0	0	0.5000
9215	Forestry labourers	0	0	0.5000
2163	Product and garment designers	0	0	0.3333
7114	Concrete placers, concrete finishers and related workers	0	0	0.3333
7212	Welders and flamecutters	0	0	0.3333
9312	Civil engineering labourers	0	0	0.3333
7421	Electronics mechanics and servicers	0	0	0.2857
2146	Mining engineers, metallurgists and related professionals	0	0	0.2500
4222	Contact centre information clerks	0	0	0.2500
8312	Railway brake, signal and switch operators	0	0	0.2500
8331	Bus and tram drivers	0	0	0.2500
6210	Forestry and related workers	0	0	0.2333
6111	Field crop and vegetable growers	0	0	0.2000
6112	Tree and shrub crop growers	0	0	0.2000
6114	Mixed crop growers	0	0	0.2000
6121	Livestock and dairy producers	0	0	0.2000
6122	Poultry producers	0	0	0.2000
6123	Apiarists and sericulturists	0	0	0.2000
6129	Animal producers not elsewhere classified	0	0	0.2000
6221	Aquaculture workers	0	0	0.2000
6222	Inland and coastal waters fishery workers	0	0	0.2000
6223	Deep-sea fishery workers	0	0	0.2000
6224	Hunters and trappers	0	0	0.2000
7311	Precision-instrument makers and repairers	0	0	0.2000
8212	Electrical and electronic equipment assemblers	0	0	0.2000
8342	Earthmoving and related plant operators	0	0	0.2000
8181	Glass and ceramics plant operators	0	0	0.1667
8311	Locomotive engine drivers	0	0	0.1667
7412	Electrical mechanics and fitters	0	0	0.1538
8142	Plastic products machine operators	0	0	0.1538

7422	Information and communications technology installers and servicers	0	0	0.1429
6130	Mixed crop and animal producers	0	0	0.1333
5419	Protective services workers not elsewhere classified	0	0	0.1250
3118	Draughtspersons	0	0	0.0667

Table A2: Average greenness by different type of green jobs

Variable	Obs	Mean	Std. Dev.	Min	Max
Broad Greenness	580	0.189	0.288	0	1
Core Greenness	580	0.115	0.233	0	1
Task-based Greenness	580	0.034	0.103	0	1

Table A3: Number of green occupations by 1-digit ISCO code

ISCO1	Occupation title	Total #	Broad green#	Core green #	Task-based green #
0	Armed forces occupations	3	0	0	0
1	Managers	31	20	20	20
2	Professionals	92	35	31	17
3	Technicians and associate professionals	84	25	22	18
4	Clerical support workers	29	4	1	0
5	Service and sales workers	40	1	1	1
6	Skilled agricultural, forestry and fishery workers	18	12	0	0
7	Craft and related trades workers	66	24	10	6
8	Plant and machine operators, and assemblers	40	11	6	3
9	Elementary occupations	33	9	6	4

B Green jobs in the LFS

Figures B1 and B2 present the annual average wage against greenness indices for occupations based on LFS2010. The positive slop of the fitted lines in both graphs suggest that the greener an occupation is, the higher the average wage. The slope of fitted line for core green occupations is steeper than that of broad green occupations. Figure B3 and B4 present the relationship between skill intensity and the greenness of occupations. The circles in both graphs are a fairly dispersed, nevertheless, the upward slopping fitted lines also indicate a positive relationship between skill intensity and the greenness of occupations. Similarly, we found the slope of core green occupations is steeper than that of broad green occupations. In general, green jobs, as defined by O*NET, pay both higher wages and require a higher level of skills. As such it is fairly reasonable for policymakers to consider green jobs to be “better jobs".

[Figure B1 about here]

[Figure B2 about here]

[Figure B3 about here]

[Figure B4 about here]

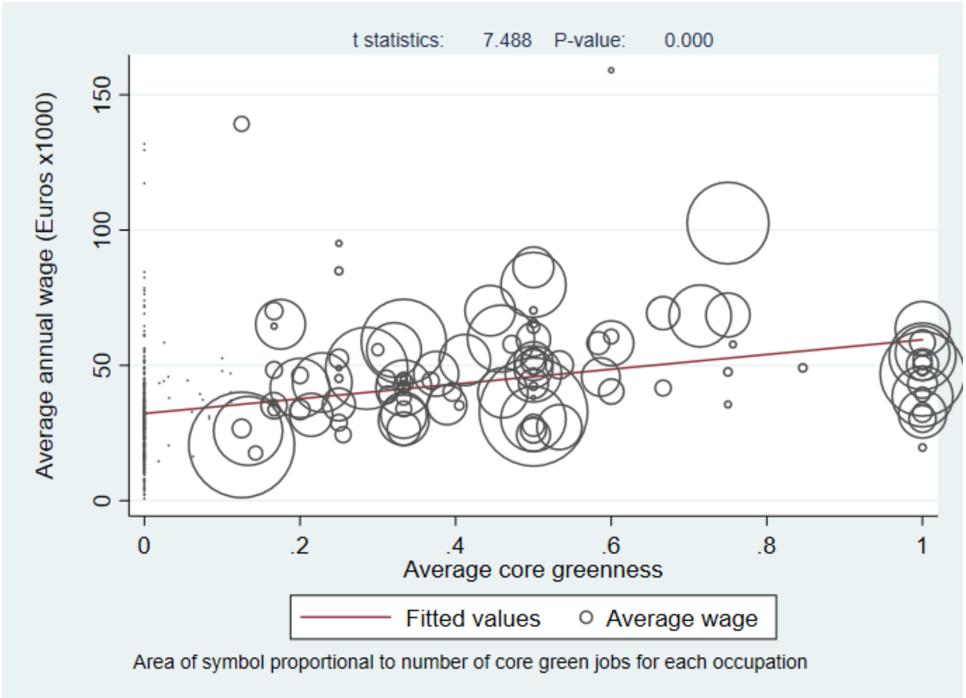

Figure B1: Wage and core greenness

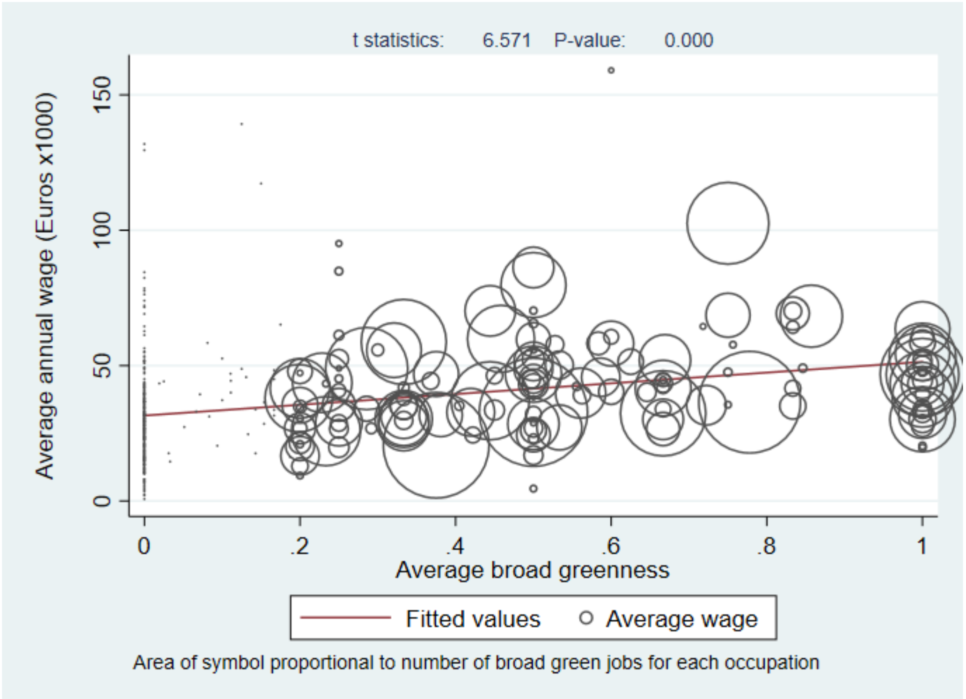

Figure B2: Wage and broad greenness

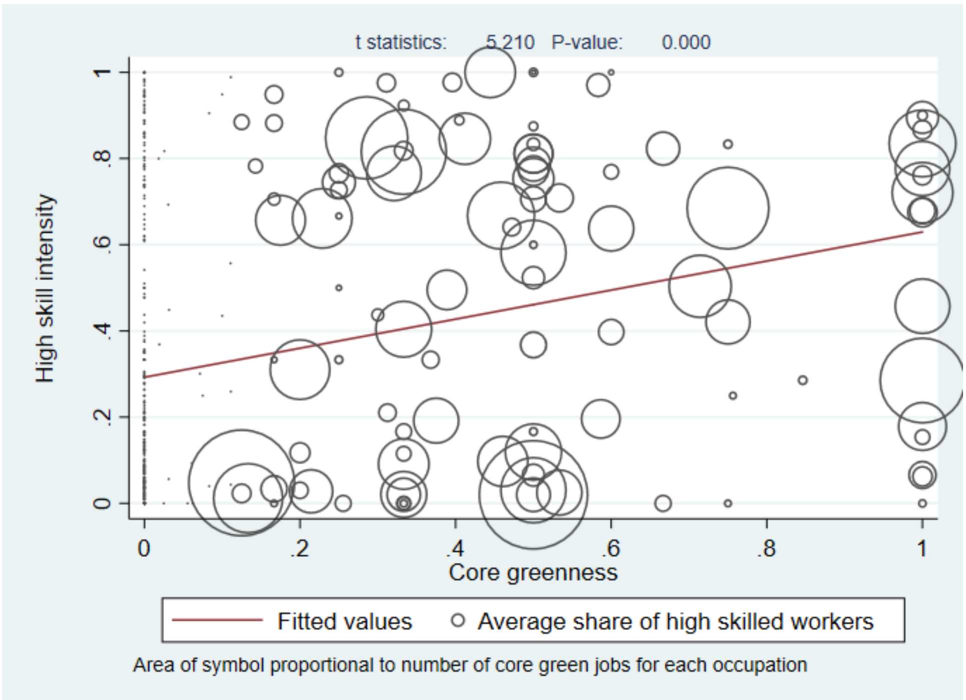

Figure B3: High skill intensity and core greenness

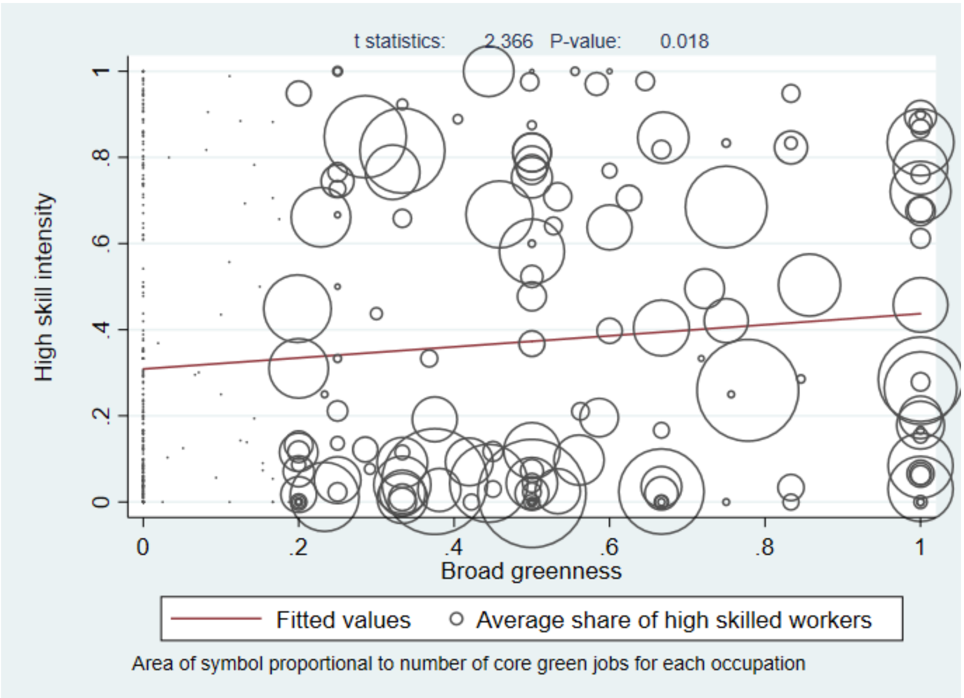

Figure B4: High skill intensity and broad greenness

C Firm distribution by size and industries

Figure C1 reports the distribution of firms by size. In our final sample, medium sized firms, with 50 to 250 employees, account for the largest proportion of firms (53.36%). Large firms, with at least 250 employees, account for 24.83% of the firms while small firms, with 10 to 50 employees, account for just 21.82%.

[Figure C1 about here]

Figure C2 presents the sectoral distribution of firms. Based on 2-digit SBI2008 codes, we have 16 sectors in our sample. The largest proportion of firms are in manufacturing (27%) while Wholesale and retail trade; repair of motor vehicles and motorcycles is the second largest industry (21%) with construction being the third largest (10%).

[Figure C2 about here]

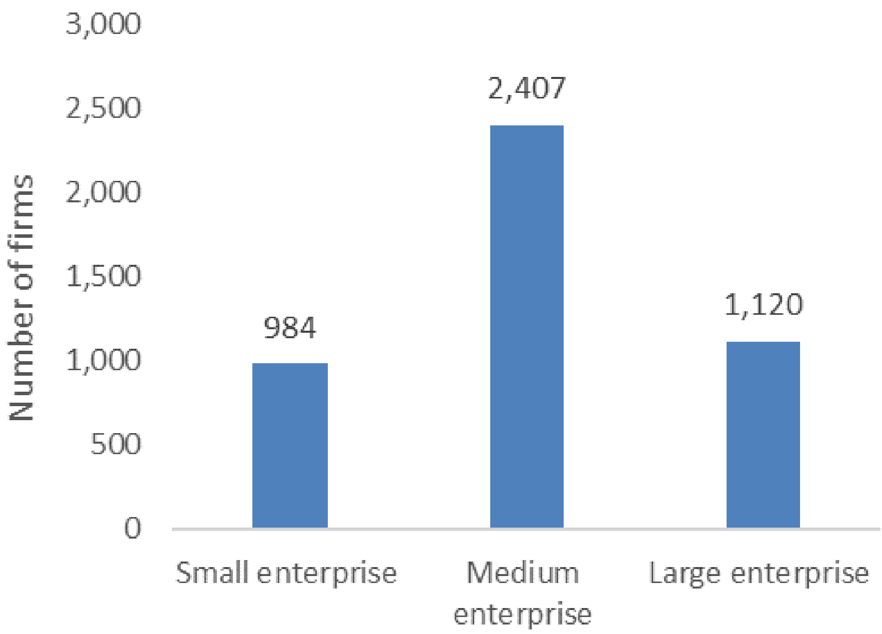

Figure C1: Firm size distribution

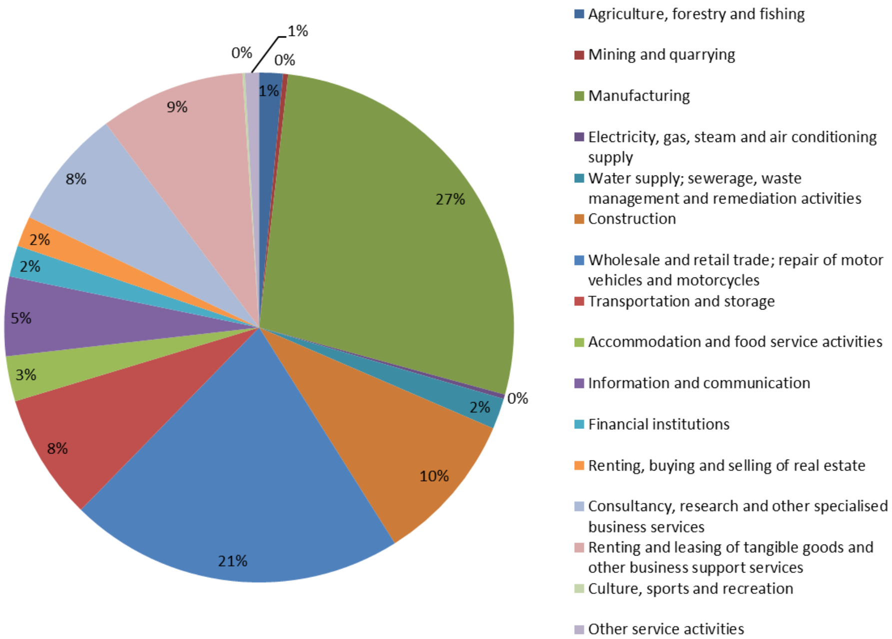

Figure C2: Sector distribution

D Descriptive statistics and correlation coefficients

[Table D1 about here]

[Table D2 about here]

Table D1: Descriptive statistics and variable description

Variables	Description	Mean	S.D.
Toal employment	Natural log of total employment in 2010	4.823	1.177
Green employment (Task-based)	Inverse hyperbolic sine of green employment in 2010	2.617	2.662
Green employment (Core green)	Inverse hyperbolic sine of green employment in 2010	2.672	2.668
Green employemnt (Broad green)	Inverse hyperbolic sine of green employment in 2010	3.451	2.624
Share of gree jobs (Task-based)	Share of green jobs in 2010	0.299	0.371
Share of gree jobs (Core green)	Share of green jobs in 2010	0.317	0.383
Share of gree jobs (Broad green)	Share of green jobs in 2010	0.473	0.418
Eco-innovator	Dummy = 1 if firm engage in green innovation during 2006 to 2008	0.527	0.499
Eco-product innovator	Dummy = 1 if firm engage in green product innovation during 2006 to 2008	0.353	0.478
Eco-process innovator	Dummy = 1 if firm engage in green process innovation during 2006 to 2008	0.466	0.499
Policy driven	Dummy = 1 if green innovation is driven by policy	0.205	0.404
Subsidy driven	Dummy = 1 if green innovation is driven by government subsidy	0.081	0.272
Regulation driven	Dummy = 1 if green innovation is driven by current or future regulation	0.178	0.382
Voluntary	Dummy = 1 if firm engage in green innovation voluntarily	0.235	0.424
Product innovator	Dummy = 1 if firm engage in product innovation during 2006 to 2008	0.290	0.454
Process innovator	Dummy = 1 if firm engage in process innovation during 2006 to 2008	0.277	0.447
Organisation innovator	Dummy = 1 if firm engage in organisation innovation during 2006 to 2008	0.317	0.465
Marketing innovator	Dummy = 1 if firm engage in marketing innovation during 2006 to 2008	0.243	0.429
Innovator	Dummy = 1 if firm engage in any innovation activities during 2006 to 2008	0.724	0.447
Wage	Natural log of average daily wage in 2008	4.900	0.420
Group	Dummy = 1 if firm is part of enterprise group	0.593	0.491
Headoffice	Dummy = 1 if the headoffice of firm is located outside the Netherlands	0.205	0.404
Export	Dummy = 1 if firm export to other country	0.497	0.500
Turnover	Natural log of total turnover in 2008	9.460	1.638
R&D	Inverse hyperbolic sine of R&D expenditure in 2010	1.477	2.741
Funding	Dummy = 1 if firm receives public funding	0.123	0.329

Note: minimum and maximum value of variables are not reported due to confidential restrictions.

Table D2: Correlation Coefficients

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1.Total employment	1													
2.Green employment (Task-based)	0.4524*	1												
3.Share of green jobs(Task-based)	-0.0439*	0.7454*	1											
4.Eco-innovator	0.0747*	0.1098*	0.0811*	1										
5.Eco-product innovator	0.0613*	0.1016*	0.0823*	0.7001*	1									
6.Eco-process innovator	0.0772*	0.1077*	0.0729*	0.8843*	0.5341*	1								
7.Policy driven	0.1001*	0.1172*	0.0681*	0.4809*	0.4157*	0.4888*	1							
8.Voluntary	0.1043*	0.1127*	0.0542*	0.5245*	0.5116*	0.5176*	0.5345*	1						
9.Regulation driven	0.0918*	0.1040*	0.0552*	0.4406*	0.3892*	0.4576*	0.9162*	0.5034*	1					
10.Subsidy driven	0.0679*	0.0933*	0.0747*	0.2807*	0.2596*	0.2832*	0.5837*	0.3201*	0.3774*	1				
11.Product innovator	0.1345*	0.1178*	0.0327	0.1916*	0.1401*	0.2048*	0.1538*	0.1871*	0.1424*	0.0708*	1			
12.Process innovator	0.1368*	0.1072*	0.0256	0.1949*	0.1185*	0.2136*	0.1613*	0.1617*	0.1479*	0.1006*	0.4927*	1		
13.Organisation innovator	0.2150*	0.1533*	0.0361	0.1537*	0.1170*	0.1564*	0.1326*	0.1561*	0.1146*	0.0922*	0.3724*	0.4385*	1	
14.Marketing innovator	0.1546*	0.0725*	-0.0227	0.1361*	0.1059*	0.1345*	0.1146*	0.1427*	0.1043*	0.0618*	0.3306*	0.2932*	0.3953*	1

E Additional regression tables

[Table E1 about here]

Table E1: Eco-innovation and green employment(task-based)-OLS estimation

	Whole smaple			Innovator only		
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	Total employment	Green employment	Share of green jobs	Total employment	Green employment	Share of green jobs
Eco-innovator	-0.0381	0.147*	0.0324***	-0.0558	0.196*	0.0332**
	(0.0287)	(0.0802)	(0.0115)	(0.0401)	(0.108)	(0.0149)
Product innovator	0.101***	0.240**	0.0138	0.115***	0.273***	0.0158
	(0.0351)	(0.101)	(0.0146)	(0.0362)	(0.104)	(0.0149)
Process innovator	0.0428	-0.000415	-0.0137	0.0392	0.00735	-0.0128
	(0.0349)	(0.102)	(0.0145)	(0.0354)	(0.103)	(0.0146)
Organisation innovator	0.236***	0.381***	0.0139	0.242***	0.390***	0.0111
	(0.0342)	(0.0975)	(0.0132)	(0.0354)	(0.101)	(0.0139)
Marketing innovator	0.0438	-0.0545	-0.0236*	0.0551	-0.0264	-0.0236*
	(0.0356)	(0.0991)	(0.0134)	(0.0362)	(0.102)	(0.0138)
Turnover	0.446***	0.468***	-0.00421	0.448***	0.469***	-0.00752*
	(0.0163)	(0.0311)	(0.00364)	(0.0197)	(0.0379)	(0.00430)
Wage	-0.803***	0.231**	0.152***	-0.751***	0.236	0.142***
	(0.0471)	(0.114)	(0.0147)	(0.0618)	(0.148)	(0.0181)
Group	0.261***	0.452***	0.0330***	0.219***	0.395***	0.0344**
	(0.0325)	(0.0880)	(0.0127)	(0.0382)	(0.106)	(0.0152)
Headoffice	0.108***	-0.0794	-0.0230	0.0852**	-0.0408	-0.0132
	(0.0371)	(0.111)	(0.0152)	(0.0421)	(0.127)	(0.0171)
Export	-0.105***	0.0820	0.0451***	-0.109***	0.101	0.0429***
	(0.0338)	(0.0902)	(0.0132)	(0.0404)	(0.108)	(0.0155)
Sectoral effect	Yes	Yes	Yes	Yes	Yes	Yes
Regional effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.792***	-3.870***	-0.502***	3.557***	-3.929***	-0.431***
	(0.241)	(0.598)	(0.0831)	(0.306)	(0.761)	(0.103)
Observations	4,511	4,511	4,511	3,265	3,265	3,265
R-squared	0.455	0.164	0.102	0.452	0.157	0.101

Note: robust standard errors in parentheses; $***p < 0.01, **p < 0.05, *p < 0.1$

F Test for validity of IVs

F.1 Test of over-identifying restrictions

To test the validity of the instrumental variables used on our endogenous switching model, we first need to test whether our instruments are uncorrelated with the error term and whether the excluded instrument is correctly excluded from the estimation equation.[24] In order to do so, we first perform the Sargan-Hansen test, which is a test of over-identification restrictions for all instruments. The null hypothesis of Sargan-Hansen test is that the instruments are overall exogenous. A Hansen J statistic is reported in Table F1 and a rejection of the null could represent either an invalid IV or an incorrectly specified structural equation. Then we implement an orthog option which allows a test of the exogeneity of one or more instruments. Under the null hypothesis, the one or smaller set of instruments are exogenous. C statistics are reported for *R&D* and *Funding* respectively, and a rejection of null indicates that the suspect instruments are invalid. As we can see from Table F1, the Hansen J statistics are insignificant for all three structural equations, which means the instruments can be considered to be exogenous. The C statistics for both *R&D* and *Funding* are also insignificant which indicates each of instruments is exogenous.

[Table F1 about here]

F.2 Tests of under- and week identifications

The next stage was to perform a under-identification test to see whether the instruments are correlated with the endogenous regressor. Under the null, the equation is under-identified. With heteroskedastic robust errors, a Kleibergen-Paap rk LM statistic is reported in Table F2. A rejection of the null means that the equation is identified, i.e. the excluded instruments are correlated with endogenous regressor. We then perform a weak identification test, which is a test of whether the instruments are correlated with endogenous variable but only weakly. This is important as the estimators can perform poorly if the instruments are just weakly correlated with the endogenous variable Baum et al. (2010). With heteroskedastic robust errors, a Kleibergen-Paap rk Wald F statistic is reported in Table F2. The null hypothesis of a weak identification test is that the equation is weakly identified. We also report Stock-Yogo critical values. According to (Stock & Yogo 2002),

[24] Green jobs in this section are based on our task-based measure of green jobs.

weak instruments have two characteristics: (1) weak instruments could lead to biased instrumental-variables estimator; (2) a severe size distortion will occur if the hypothesis tests of parameters are estimated by an instrumental-variables estimator. So we first need to choose the largest relative bias of estimator and the largest size distortion we are willing to tolerate. If the test statistics exceed the critical value, we then can conclude our instruments are not weak. As we can see from Table F2, the test statistics are the same for the three models as the first stage regressions are the same. The P value of all Kleibergen-Paap rk LM statistics are 0.000, which strongly rejects the null hypothesis that the equation is under-identified. In addition, all the Kleibergen-Paap rk Wald F statistics exceed the Stock-Yogo critical values, which suggest that our instruments are not weak.

[Table F2 about here]

F.3 Testing instrument redundancy

Finally, we perform a redundancy test for *R&D* and *Funding*, respectively. The redundancy test is a test of whether a subset of an excluded instrument is redundant. Under the null, the tested instrument is redundant, and a rejection of null indicates that the excluded instrument is not redundant. With heteroskedastic robust errors, IV redundant test statistics are reported in Table F3. As we can see, IV redundant test statistics are the same for all three models. The P value for redundant test of R&D is 0.000, which rejects the null that R&D is redundant, and the P value for redundant test of Funding is 0.009, which also rejects the null that Funding is redundant.

[Table F3 about here]

Table F1: Testing over-indentification restrictions

	Total employment	Green employment	Share of green jobs
Over-identification test for all instruments			
Hansen J statistic	0.834	0.557	0.124
Chi-sq(1) P-val	0.3612	0.4556	0.7245
Exogeneity test of R&D			
C statistic	0.834	0.557	0.124
Chi-sq(1) P-val	0.3612	0.4556	0.7245
Exogeneity test of Funding			
C statistic	0.834	0.557	0.124
Chi-sq(1) P-val	0.3612	0.4556	0.7245

Table F2: Under- and weak identification test

	Total employment	Green employment	Share of green jobs
Under-identification test			
Kleibergen-Paap rk LM statistic	406.214	406.214	406.214
Chi-sq(2) P-val	0.000	0.000	0.000
Weak identification test			
Kleibergen-Paap rk Wald F statistic	259.135	259.135	259.135

Stock-Yogo weak ID test critical values:

Maximal IV relative bias	5%	10%	20%	30%
	16.85	10.27	6.71	5.34
Maximal IV size	10%	15%	20%	25%
	19.93	11.59	8.75	7.25

Table F3: Redundancy test

	Total employment	Green employment	Share of green jobs
Redundant test for R&D			
IV redundant test statistics	317.526	317.526	317.526
Chi-sq(1) P-val	0.000	0.000	0.000
Redundant test for Funding			
IV redundant test statistics	6.769	6.769	6.769
Chi-sq(1) P-val	0.009	0.009	0.009